Mortgage Lenders' Diversity Policies and Mortgage Lending to Minorities

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ABSTRACT

Credit access is central to homeownership, yet racial disparities in mortgage lending persist. While lender have increasingly adopted diversity policies, it is unknown whether and how such policies impact mortgage lending disparities. Using a robust difference-in-differences design, we find that diversity policies widen approval disparities, reducing origination rates for minority borrowers. Results from an instrumental variables approach and event-study design support a causal relation. Ex-post loan performance suggests the widened disparities cannot be fully explained by application risks. Mechanism analysis indicates that a stigma effect in approval decisions, triggered by an increase in risky minority applications, likely plays a role.

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Mortgages play a critical role in Americans' home purchases. As of 2022, residential mortgage debt in the U.S. totaled $11.92 trillion. A large literature in economics and finance has documented the existence of racial disparities in access to mortgage credit (Munnell, Tootell, Browne, and McEneaney 1996; Ladd 1998). Such disparities stem from a complex interplay of structural, economic, and historical factors. In response to these disparities, and the increasing diversity of the U.S. population, many mortgage lenders have adopted diversity-related policies in recent decades. These policies are often motivated by a mix of legal, reputational, and business considerations, including the need to address demographic shifts in their customer bases. However, the actual impact of such policies on racial disparities in mortgage lending remains largely unexplored. Broadly speaking, it is unclear whether and how diversity policies address race-related outcome gaps.

At the same time, diversity policies themselves have garnered significant attention and debate. Diversity policies may serve as window dressing, publicly stated for public relations or legal compliance purposes. Alternatively, such policies may overshoot, incorporating controversial features such as quotas, which can raise concerns about lower standards for minorities and reverse discrimination against majority-group members. Policies that are perceived to overshoot can also create a stigma against minority individuals and cause backlash which paradoxically makes minorities worse off. Despite these potential problems, it is also possible that diversity policies are effective in reducing race-related outcome gaps. We examine this broad range of possibilities, investigating the realized effects of mortgage lenders' diversity policies on race-related differences in mortgage lending outcomes.

We combine home-mortgage-lending data from the Home Mortgage Disclosure Act (HMDA) with newly available diversity policy data from Refinitiv and hand-collected diversity policy disclosures. Our analysis focuses on 2018-2021, a sample period for which we have both application data and detailed borrower and mortgage characteristics. We start by examining the effects of diversity policies on application completion and approval rates, while controlling for a host of borrower and mortgage characteristics. In addition to examining effects for minority borrowers in aggregate, we examine the impact of diversity policies on outcomes for Black, Hispanic, and other minority borrowers (predominantly Asian), separately.

Our main analysis employs a rich set of fixed effects to control for other factors which might affect lending outcomes, including lender, year, borrower-characteristic, loan-characteristic, and census tract fixed effects. The results capture the incremental effects of diversity policies, controlling for these factors. Our most stringent specifications include a race by lender interacted fixed effect, which allows us to capture the incremental effects of diversity policies on race-related outcome gaps at a given lender. We find that lenders adopting diversity policies have *lower* approval rates for minority borrowers, in particular, Black borrowers. The Black-White approval rate disparity is wider by 3.04 percentage points after a lender adopts a diversity policy. Although we find an incremental increase in application completion rates for minority borrowers after policy adoption, this effect is more than offset by lower approval rates. Together, the combined effect leads to a reduction in origination rates for minority borrowers relative to White borrowers.

To strengthen the causal inference between diversity policy adoption and the examined outcomes, we implement an instrumental variables (IV) approach. We instrument lenders' diversity policy adoption using changes in the diversity commitments of lenders' major shareholders, which likely drives variation in policy adoption that is exogenous to lender-specific diversity issues. The first stage shows that the instrument strongly predicts lenders' subsequent adoption of diversity policies. Using predicted values of policy adoption from the first stage, we find consistent results that both approval and origination disparities between minority and majority borrowers widen following lenders' diversity policy adoption. This effect is particularly pronounced among Black borrowers.

We also use an event study design to visualize the dynamics of the diversity policy effect and to test the parallel trend assumption which the difference-in-differences (DID) model relies on. The event study uses the initial adoption of a diversity policy at 12 lenders with clear policy adoption dates between 2010 and 2021. Following diversity policy adoption, we find an incremental increase in application completion rates, but a decrease in approval and origination rates. These results are consistent with both the fixed effects model and the IV approach, pointing more strongly to a causal relation.

While we control for a comprehensive set of risk measures, it remains possible that unobservable risk factors, not included in our model, might lead to the increased approval rate gap we find. To address this concern, we examine ex-post loan performance. We find a significant decrease in default rates for minority borrowers at lenders adopting diversity policies, relative to the default rate for White borrowers, driven mostly by Black and Hispanic borrowers. While we cannot examine the quality of denied mortgages, the decrease in ex-post defaults suggests that lenders could accept additional marginal minority applications and maintain the same average quality as without a diversity policy. This evidence suggests that risk does not fully explain the lower approval rates, and suggests the possibility of heightened underwriting standards for minority applicants post policy adoption. Further evidence shows that approved minority loans under a diversity policy tend to have significantly higher FICO scores than approved loans without a policy, consistent with increasing standards for minority borrowers.

This leads to an obvious question: Why would a diversity policy lead to higher underwriting standards for minority applicants? One of the main ways diversity policies can lead to higher standards for minorities is by triggering a stigma or backlash effect. Under a diversity policy, a lender might more aggressively solicit minority applications and support minority application completions. This could result in a larger number of high-risk minority applications reaching the back office. The back office observes the increase in higher-risk minority applications and responds by being more cautious when evaluating minority applications. While this heightened scrutiny could be a rational response, problems arise if the back office overreacts, raising standards beyond what actual risks warrant. This occurs when the perception of minority applicant risk increases more than the actual increase in risk, a phenomenon described in the literature as a "stigma" effect, in which the existence of the diversity policy stigmatizes the minority group – leading to more negative perceptions/beliefs about the group than are justified. We conduct several tests to examine whether such a backlash or stigma effect occurs, and whether such an effect plays a role in the decreasing approval rates for minorities.

Supporting a potential stigma mechanism, we observe an increase in the overall riskiness of completed mortgage applications after policy adoption, as measured by common risk factors such as debt-to-income (DTI) and loan-to-value (LTV) ratios. We find similar patterns when measuring predicted risk using a machine learning-based approach. Thus, the first step in the stigma process – an increased prevalence of riskier minority applications post policy – occurs, which may lead the back office to associate minority status with heightened risk.

To examine whether this leads to stricter underwriting standards for *all* minority applicants, not just higher-risk applicants, we examine approval rates across risk bins. Consistent with a stigma effect, we find increased approval disparities across all predicted risk bins, including for minority applicants with the lowest predicted default risks. This is consistent with stigma driving higher underwriting standards for *all* minorities, affecting even lower-risk borrowers.

Taken together, these results provide evidence of the effects of lenders' diversity policies on race-related disparities in mortgage lending. We find evidence that lenders' diversity policies increase the disparities in loan approvals and originations, even after controlling for a host of borrower and loan characteristics. Additional analyses suggest that one mechanism for these effects is a stigma effect. Diversity policies result in an increase in the riskiness of completed applications from minority applicants. However, the increase in risk itself does not fully account for the widened approval disparity, suggesting that the association of minority status with heightened risk under diversity policies could unintentionally increase the effect of racial stigma in approval decision-making.

To provide further evidence for the potential role of racial stigma in the mortgage outcomes, we examine the impact of diversity policies in situations with higher documented racial disparities in mortgage access. Following prior literature, we exploit three types of variation. First, we use geographic variation in racial animus. Conklin, Gerardi, and Lambie-Hanson (2025) find that approval disparities are most significant in areas with high racial animus, suggesting that discrimination contributes to such disparities. Consistent with their work, we find that diversity policies widen approval and origination disparities more for high racial animus areas.

Second, we compare the impact of diversity policies on disparities for conventional and non-conventional mortgages. Non-conventional loans, unlike conventional mortgages, often involve less standardized underwriting processes and require additional reviews to ensure compliance with specific government regulations. The additional required scrutiny increases time pressure and stress on the back office, which creates conditions for exacerbated implicit biases and stigma effects (Chugh 2004; Bertrand, Chugh, and Mullainathan 2005; Kamath, Ng, and Shanthikumar 2024). Consistent with this expectation, we find a significantly stronger effect of diversity policies on racial disparities in both approval and origination rates for non-conventional loans.

Third, we investigate whether the widened approval disparities following diversity policies extend to home equity loans. Prior studies document significant and persisted approval disparities in home equity loans (Conklin et al. 2025). Our findings confirm that the stigma effect of diversity policies extend to the home equity loan market as well.

Finally, we explore variations in the impact of diversity policies along four core policy dimensions: diversity training, diversity targets and commitments, designated diversity leadership and oversight, and customer-focused diversity efforts. Using hand-coded policy data, we find that policies with these features are associated with more cautious front-end outreach and attenuated downstream backlash, captured by smaller increases in approval- and origination-rate disparities. Overall, these findings highlight the importance of thoughtful diversity policy design and suggest that progress in reducing lending disparities may depend significantly on the specific characteristics of the associated policies.

Our paper makes several contributions. First, our paper contributes to literature examining race-related differences in access to financial services. A growing body of research documents the existence and drivers of race-related disparities in mortgage lending (e.g., Munnell et al. 1996; Ambrose, Conklin, and Lopez 2021; Bhutta and Hizmo 2021; Bartlett, Morse, Stanton, and Wallace 2022; An, Bushman, Kleymenova, and Tomy 2024; Frame, Huang, Jiang, Lee, Liu, Mayer, and Sunderam 2025), and other financial services (e.g., Morse and Pence 2021; Begley and Purnanandam 2021; Erel and Liebersohn, 2022; Butler, Mayer, and Weston 2023; Ambrose, Conklin, Coulson, Diop, and Lopez 2025). Our study is one of the first, to our knowledge, to examine the effect of diversity policies on racial disparities in financial service access.

Our paper also contributes to research examining the Environmental, Social, and Governance (ESG) initiatives of companies, by examining whether lenders' diversity policies have real effects on their lending decisions and interactions with customers. There is mixed evidence in the ESG literature about the effectiveness of firms' ESG policies and efforts (e.g., Basu, Vitanza, Wang and Zhu 2022; Thomas, Yao, Zhang, and Zhu 2022). We contribute to the literature by providing evidence on the consequences of diversity policies in the banking sector.

More broadly, our paper contributes to the nascent literature on the effectiveness of diversity policies and other actions which can potentially address existing disparities (e.g., Paluck, Porat, Clark, and Green 2020; Begley and Purnanandam 2021; Devine and Ash 2022; Goldsmith-Pinkham and Shue 2023; Ru and Schoar 2023). While a significant body of research has established the existence of different forms of race- and other characteristic-related disparities, there is still little understanding of what actions can address these differences. Moreover, the dramatic increase in the number and prominence of diversity policies has prompted growing backlash, and questions about whether these policies go too far (e.g., Chen and Smith 2023). As such, there is a need for rigorous research into the real-world effects of diversity policies.

This paper is organized as follows. Section I describes mortgage lenders' diversity policies and discusses the implications of such policies on mortgage lending outcomes. Section II outlines the data used in this study and discusses the identification strategy. Section III reports our main results. Section IV explores possible mechanisms. Section V concludes.

I. Mortgage Lenders' Diversity Policies and Predictions for Mortgage Lending

In this section, we discuss the adoption of diversity policies at banks and other mortgage lenders, characteristics of these policies, and how they might affect mortgage lending outcomes.

A. Diversity Policy Adoption

Over the late 20th and early 21st centuries, the share of the United States (U.S.) population identifying as a member of a racial or ethnic minority group has increased significantly, highlighting the growing economic importance of addressing potential race-related frictions in the economy. In 1980, 20% of the U.S. population identified as a racial or ethnic minority; by 2020, that share had risen to 40%.[1] Yet research has documented continuing economic disparities with respect to race (e.g., Dougal, Gao, Mayew, and Parsons 2019; Fairlie, Robb, and Robinson 2022; Kline, Rose, and Walters 2022).

Diversity policies have arisen as a common response to the increasing diversity of the U.S. population, to attract and support a diverse employee and customer base, and to mitigate legal risk. Our data indicates that an increasing number of mortgage lenders have implemented diversity policies. There is a significant variation in the timing of adoption, indicating that adoption is likely not driven by a single event. Legal, investor, and social pressures all contribute to the adoption of policies, as do strategic decisions to invest in diversity initiatives. As shown in Figure 1, in 2009, 58% of the 36 public mortgage lenders in our data had an identifiable diversity policy. By 2021, 92% had such a policy.

To better understand diversity policy adoption decisions at our sample lenders, we reviewed companies' press releases, media coverage, and company websites to identify lenders' stated reasons for diversity policy adoption. Lenders consistently discuss attracting and retaining top talent, fostering a productive work environment, and better serving their customers and communities as reasons for adopting a diversity policy. Many explicitly cite the growing diversity of their customer bases.

We describe these policies in more detail below and discuss their possible effects on mortgage lending outcomes.

B. Diversity Policy Characteristics and Hypothesized Effects

Diversity policies and initiatives have a variety of labels within firms, from "Anti-discrimination" policies to "Diversity, Equity, Inclusion and Belonging" (DEIB) policies. These policies vary in their specific characteristics and dimensions. We provide two examples of lenders' diversity policy statements in Appendix A.

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[1] Source: The nation is diversifying even faster than predicted, according to new census data. https://www.brookings.edu/articles/new-census-data-shows-the-nation-is-diversifying-even-faster-than-predicted/

To better understand lender diversity policies, we hand collect and code characteristics of diversity policies for 36 large public mortgage lenders in our sample, covering 105 different policy documents. We focus on the following four key dimensions: (1) diversity training – mentioning of diversity or inclusion-related employee training in the policy disclosure; (2) diversity target – mentioning of specific goals or commitments related to demographic diversity; (3) designated diversity leadership and oversight – establishment of an individual or team responsible for diversity efforts. The person or team in charge can be a designated executive (e.g., Chief Diversity Officer) or any other person or group appointed to manage diversity initiatives.[2] Finally, given our focus on customer-focused mortgage lending outcomes, we include (4) customer diversity efforts – discussion of any specific actions or commitments to promote mortgage lending specifically to minorities and women. We document the coding criteria of the four dimensions in Appendix B and provide illustrative examples regarding these four dimensions in Table B1.

Each of these four dimensions identifies meaningful variation across lenders in diversity policy design. In addition, each of these dimensions may plausibly affect mortgage lending outcomes. Diversity training should improve mortgage lending outcomes for minorities if it provides loan officers with knowledge and tools to facilitate improved customer service for minority borrowers. The loan application process is almost always assisted by loan officers, who play an important role in helping borrowers complete loan applications, ensuring that borrowers provide necessary documentation, and determining appropriate interest rates and closing costs for the applications. Diversity training and education on minority-associated circumstances and application/negotiation styles could allow loan officers to better serve minority applicants. Of the policies in our coded data, 65% include some form of diversity or anti-discrimination training.

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[2] These first three dimensions build on Kalev et al. (2006), which develops a sociological framework for describing and evaluating diversity policies. Kalev et al. (2006) include the following dimensions of diversity policies: diversity training; diversity targets and leadership/oversight; and mentoring and social connection. We code diversity targets and leadership/oversight separately as we find that many policies report one but not the other. We do not code mentoring and social connection, as we find that it is difficult to evaluate using publicly available data – particularly given that it is more subjective and varied. Additional details are available upon request.

Kalev, Dobbin, and Kelly (2006) find that accountability interventions – programs that typically embed explicit goals or targets – have strong impact on increasing minority representation, suggesting that clear commitments can drive follow-through on diversity efforts. In our sample, a substantial share of policies (62%) includes some explicit diversity target or future commitment. By publicly declaring such targets, firms generate accountability pressures across the organization. As such, policies with such explicit goals are likely to be fundamentally different from policies which lack such goals. Explicit diversity goals have also become one of the most controversial aspects of diversity policies, raising concerns with reverse discrimination against majority-group members, which we discuss more below.

Evidence suggests that establishing responsibility for diversity initiatives has a strong impact on managerial diversity (Kalev et al. 2006), creating both a direct effect and strengthening the effects of other diversity efforts. Lenders frequently establish such responsibility: 64% of the policies in our data include the appointment of a Diversity Officer or a Diversity Council (DEO). Of those, a quarter have a specific Chief Diversity Officer (CDO) - an individual in the upper management with a title indicating responsibility for diversity initiatives (Harding, Joe and Rhodes 2024). Such leadership is intended to increase the effectiveness of diversity policy implementation.

While diversity policies often focus internally, they can also contain elements which are explicitly related to customers. We find that 64% of the policies we code discuss specific actions or goals regarding customer diversity, such as goals of increasing the number of loans made to minority and/or women borrowers. Such policies are most likely to directly impact lending to minority borrowers.

It is also plausible that diversity policies will have no impact on lending outcomes for minority borrowers. Recent research suggests that firms often engage in diversity washing, in which their public discussion of diversity does not align with corporate practices such as hiring (Baker, Larcker, McClure, Saraph, and Watts 2024). In the mortgage setting, Basu et al. (2022) find that banks with high ESG ratings, including high social ratings, reject more applications and issue fewer mortgages in higher-poverty areas. While Basu et al. (2022) do not explicitly examine minority borrowing or diversity policies, their evidence suggests that lenders engage in ESG and social washing. If those lenders also engage in diversity washing, we would not expect stated diversity policies to have a positive impact on minority borrowers' outcomes, particularly after controlling for loan- and borrower- characteristics.

Finally, it is possible that diversity policies can drive backlash. There are concerns that diversity policies have gone too far, focusing on specific diversity targets rather than the more general elimination of discrimination. In 2023, the Supreme Court ruled that using race in deciding college admissions is unconstitutional. The majority opinion lays out the reasoning and specific concerns with race-based admissions. Additional legal challenges to race-based programs are in progress.[3] While the intention of implementing the diversity policies might be to counter the higher bar set for minority groups, the concern is that the bar can be lowered too much, such that majority group members now face reverse discrimination. Another concern is that not all members of a given minority group face the same discrimination, such that considering race alone may fail to achieve the underlying goal of addressing race-related discrimination.

Research shows that diversity policies often create concerns of reverse discrimination (Dover, Major, and Kaiser 2016). Such concerns can paradoxically lead to worse outcomes for minorities. In particular, several studies show that affirmative action induces a negative stigma on women and minority employees, decreasing evaluations of their performance and abilities, even when evidence suggests strong performance (e.g., Heilman, Block, and Lucas 1992; Heilman, Block, and Stathatos 1997). Thus, the negative stigma associated with a diversity policy can hurt even high-performing minority group members. In the setting of mortgage lending, if the back office, which is responsible for making loan approval decisions, believes that lower-quality minority applicants are being encouraged to apply for loans due to the diversity policy, the back office may be more careful and stringent in their treatment of such applicants. This can lead to more negative outcomes for minority applicants.

Together, it is unclear what effects diversity policies will have on mortgage lending outcomes for minorities. Proponents would suggest that policies will reduce disparities. Diversity washing suggests no

[3] See, for example, Monea (2024), https://www.supremecourt.gov/opinions/22pdf/20-1199_hgdj.pdf, and https://www.wsj.com/politics/policy/appeals-court-blocks-venture-firms-grant-program-for-black-women-476fc8f7.

effect. And potential backlash would suggest a paradoxical worsening of outcomes for minorities. As such, we do not make directional predictions.

II. Data and Empirical Methodology

Our sample combines diversity policy data, sourced from Refinitiv and verified through hand collection, with home-mortgage lending data released by the Federal Financial Institutions Examination Council (FFIEC) under the Home Mortgage Disclosure Act (HMDA), which captures almost the universe of mortgage applications in the U.S. Our entire sample period spans from 2010 through 2021, however the bulk of our analyses focus on a shorter period – 2018 through 2021 – for which we have more detailed loan and borrower information, as we discuss below. We supplement the HMDA data with additional mortgage attributes and post-origination performance details from Fannie Mae Single-Family Loan Performance Data and Freddie Mac Single-Family Loan-Level Dataset, which cover loans purchased by Fannie Mae and Freddie Mac.

A. Diversity Policy Data

We obtain initial data on lenders' diversity policies from Refinitiv (Thomson Reuters). Refinitiv uses a large collection of publicly available sources to collect ESG information and determine if a firm has a diversity policy.[4] However, such information is most likely to be publicly disclosed for publicly traded mortgage lenders. Private companies have lower disclosure requirements, and do not face the same investor pressures for additional public disclosure. As such, we focus our study on lenders which are publicly traded or have a public parent.

[4] These sources include: 1. Non-Financial Report/Corporate Social Responsibility Report (CSR); 2. Annual Report Or 10K; 3. Company Website & Circular; 4. Registration Report; 5. Integrated Report- This includes financial and Non-Financial information; 6. Financial Statement;7. Reference Document; 8. GRI Report; 9. DEF14-Proxy Statement; 10. 20F; 11. Audit Committee Charter/ Terms of Reference; 12. Notice of Annual Meeting; 13. Bylaw; 14. Constitution; 15. Corporate governance guidelines; 16. Corporate governance report; 17. Code of Conduct report; 18. CDP Report-Carbon Disclosure Project (if reported on the company website).

For lenders marked by Refinitiv as having diversity policies, we first verified the provided URLs and collected the policy content. Despite many policies dating back over a decade, we were able to validate most of them, suggesting strong accuracy in Refinitiv's diversity policy indicators. Second, we also hand-checked the adoption year for each diversity policy adoption event used in our event study analysis. To ensure the precision of the event years, we carefully search for any existing diversity policies in the year preceding the identified event year. Our hand collection leads to updates of two of the twelve events. Thus, while Refinitiv is generally quite accurate, hand collection appears to be important for event date accuracy.[5] Finally, we used the hand-collected policy content to classify across four core dimensions: diversity training, diversity targets and commitments, designated diversity leadership and oversight, and customer-focused diversity initiatives. In Appendix B, we document the data collection and verification process in detail.

As a validation that the diversity policies we identify capture variation in diversity-related behavior at the lender level, we examine whether the total volume of initiated applications, completed applications, and mortgage originations increase for minority borrowers, post-adoption, at the lender-year level in Table C1. We find significant increases in the volumes of both total and completed applications for minority applicants, but no significant increase in total origination volumes. In the remainder of the paper, we focus on outcomes at the application level, to control for borrower and loan characteristics.

B. HMDA Data

The Home Mortgage Disclosure Act (HMDA) mandates that the vast majority of mortgage lenders disclose extensive details about the loan applications they process, making it the most exhaustive repository of mortgage application data. Furthermore, it discloses racial and ethnic backgrounds of borrowers, enabling us to compare mortgage outcomes across different racial groups. We also use the detailed borrower and mortgage characteristics, as outlined in Table 1 and Table 2, to control for observed variation in

[5] The two adoption date corrections are for Prime Lending and First National Bank of Pennsylvania. We found earlier adoption years than those indicated by Refinitiv for both lenders, utilizing the Wayback Machine Internet Archive (http://web.archive.org/). Our results are robust if we use the adoption years from Refinitiv.

mortgage applications. We rely on this dataset to perform our long panel analysis from 2010 through 2021, where we examine the impact of diversity policy adoption on racial disparities in approval rates and other related outcomes.[6]

The HMDA data underwent a significant transformation in 2018, resulting in a much more detailed disclosure of reported mortgages. Specifically, the updated dataset introduces several additional attributes, such as the age of borrowers, loan-to-value ratio, debt-to-income ratio, and an indicator for conforming mortgages. The newly added information allows us to analyze potential variation in examined outcomes across different racial groups with more extensive controls for borrower and loan attributes.[7] We rely on HMDA panel data from 2018 through 2021 for the majority of our analyses.

We construct our sample following prior research (Bartlett et al. 2022; Bhutta, Hizmo, and Ringo 2025; Frame et al. 2025). Specifically, our analysis centers on first-lien, 30-year, fixed-rate mortgages for the purchase of owner-occupied single-family homes. Because 30-year fixed-rate mortgages predominate in the U.S. market, this restriction entails limited loss of coverage while minimizing heterogeneity in contract terms and borrower selection. We focus on purchase mortgages because loan denials in this segment have the most significant impact on borrowers' ability to obtain housing. In addition, we restrict the sample to applications submitted directly to lenders (excluding those routed through intermediaries) to avoid additional screening layers that could confound lender-level decisions. Finally, we exclude entries where the applicant/borrower's race is not specified, which accounts for 23.0% of the applications.

C. Loan Performance Data

In the ex-post loan performance analyses, we incorporate loan performance data from the two government-sponsored enterprises (GSEs): Fannie Mae and Freddie Mac. These two entities jointly

[6] We constrain our sample to begin in 2010 to minimize the influence from potential confounding factors correlated with the 2008 financial crisis.
[7] Our use of the public HMDA dataset precludes observing FICO scores, loan officer IDs, and AUS recommendations. These fields appear only in the confidential HMDA employed by Bhutta et al. (2025) and Frame et al. (2025). We utilize loan performance data to examine the potential effects of this data constraint on our inferences.

guarantee around 70% of the mortgages in the U.S. and make performance data for these mortgages available to the public.[8] Their datasets include the borrower's credit score (FICO) at mortgage origination, which is one of the most important risk factors determining the approval decision. The GSE performance data also reports mortgage performance metrics, particularly whether a loan has been prepaid or defaulted after origination.

We follow prior literature to merge the GSE loan performance data with the HMDA data, using overlapping variables including year, loan amount, county and ZIP code (3 digit), interest rate, LTV, and DTI. We can only merge the loan performance data with the short panel HMDA data (2018-2021) since the HMDA data prior to 2018 lacks a set of crucial matching variables, such as interest rate, LTV, and DTI.

D. Sample Mortgage Lenders: Merging Refinitiv with HMDA Data

We start with 138 mid-to-large size mortgage lenders with a national market share above 0.1% during 2018-2021.[9] For the 30 public lenders, we follow the process discussed in Section II.A to collect their diversity policy information. For the remaining lenders, we search for the diversity policy of their parent firms if they have a public parent. We exclude private lenders without a public parent, due to the lower levels of public disclosure for such lenders, making it less likely that we will be able to determine whether such lenders have diversity policies. Altogether, we collect diversity policies for 44 mortgage lenders with an aggregate market share of 25.3%. We further drop eight lenders that experienced mergers and acquisitions during the sample period, to make sure that the policy changes we observe are not due to mergers and acquisitions.[10] Our final sample includes 36 mortgage lenders, with an aggregate market share of 21.4%.

E. Difference-in-Differences Estimation Framework

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[8] See data on Fannie Mae & Freddie Mac (GSEs) from National Association of Realtors (https://www.nar.realtor/fannie-mae-freddie-mac-gses).
[9] These 138 mortgage lenders have an aggregate market share of 67.1%.
[10] Table S6 of the Online Appendix shows the main regression results when we do not drop the eight lenders that experienced mergers and acquisitions. The effects are similar.

Our main analysis focuses on the impact of a lender's diversity policy on racial disparities in lending outcomes. In particular, we estimate the following model, for a sample period from 2018 through 2021.

$$Y_{ijt} = \sum_{R \in \mathbb{M}} \beta_R R_i DI_{jt-1} + \delta DI_{jt-1} + \gamma' X_{ijt} + \theta_{j \times R(i)} + \eta_t + \epsilon_{ijt}. \qquad (1)$$

Our observations are at the mortgage (i.e., borrower-lender-year) level. The treatment group is composed of the lenders that have implemented diversity policies during the sample period. The control group includes lenders that do not experience diversity policy changes during the same period. The outcome variables (Y_{ijt}) are loan application completion, loan approval, and loan origination (extensive margin). Equation (1) represents a linear probability model for the outcome.

Our main independent variables include the lagged diversity policy dummy (DI_{jt-1}) and its interactions with minority borrower race groups ($\mathbb{M}$). In our main specification, we focus on racial and ethnic minority borrowers, that is, those who are non-White, and break them into three groups: $R_i \in \mathbb{M} = \{Black, Hispanic, Other\ Minority\}$.[11] We also include a specification that merges the three minority groups as one ($\mathbb{M} = \{Minority\}$) to test the average minority borrower effect. We use the lagged Diversity Policy dummy to ensure that the diversity policy is in place before the associated outcome being measured. Our primary coefficients of interest are the interaction coefficients between the racial groups and the policy dummy (i.e., β_R). These coefficients capture the differences in racial disparities for each specific minority borrower category versus the benchmark White borrowers, for lenders with a diversity policy relative to lenders without a policy. In our most stringent model, these coefficients can be interpreted as the change in racial disparity for minority borrowers after adoption of a diversity policy relative to the disparity for minority borrowers at the same lender before the policy's adoption.

Following Frame et al. (2025), we include control variables (X_{ijt}) such as log(loan amount), indicators for LTV bins, DTI bins, conforming loans, loan type, joint applications, centile bins of the applicant income-to-MSA median income ratio, ten-year bins of applicant age, and property census tracts.

[11] Our Black and Other minority group refers to Non-Hispanic Black and Non-Hispanic other minority borrowers.

In addition, we flexibly control for lender-race fixed effects ($\theta_{j\times R}$) to allow for time-invariant lender heterogeneities in serving borrowers of different races. Lastly, we also control for year fixed effects (η_t). We cluster the standard errors at the county level to allow for ambiguous within-county correlations.

F. Additional Approaches for Identification of Diversity Policy Effects

Our primary approach uses a robust lender-race-FE specification with a variety of application-level controls. Thus, the effects identified using our primary approach are driven by within lender-race variation in race-related outcome gaps not explained by observed application characteristics. However, as with any examination of corporate policies, the potential endogeneity of policy adoption is still a concern. To address this concern, in addition to our main DID design, we implement an instrumental variables (IV) strategy and an event study approach.

F.1. Identifying Causal Effects of Diversity Policies: Exploiting Quasi-Exogenous Variation in Diversity Policy Adoption

Policy adoption is a managerial choice that may correlate with unobserved factors, such as internal priorities and evolving external pressures, which raises concerns about omitted variables that jointly move diversity policy adoption and race-related outcomes, as well as reverse causality from performance to adoption timing. These concerns make it difficult to isolate the policy's causal effect on race-related outcomes. To strengthen causal interpretation of the diversity policy effects, we implement an IV approach that instruments diversity policy adoption with external triggers plausibly exogenous to lender-specific conditions and unrelated to contemporaneous minority-lending performance.

Cronqvist and Fahlenbrach (2008) identify strong institutional investor fixed effects in corporate policies. In other words, institutional investors exhibit different preferences, which in turn affect the policies of the companies they invest in. We exploit this insight to develop an instrument for diversity policy adoption. Specifically, we construct an instrument based on changes in the diversity commitments of the major shareholders of the lenders (or their public parent). If a large shareholder is significantly increasing its own public diversity commitments, that shareholder is likely to place pressure on portfolio companies to adopt similar policies. At the same time, the shareholder does not have a direct impact on race-related mortgage outcomes – they can only influence such outcomes by influencing corporate policies and oversight. Thus, by leveraging shareholder-level variation in diversity policy adoption, we can more effectively isolate and understand the causal impact of diversity policies on lending outcomes.

We define the instrumental variable *Shareholder_Diversity_Initiative*$_{jt}$ (*SDI*$_{jt}$) as an indicator that equals 1 if either of the following events occurred between 2014 and the beginning of year t.

Event 1: more than 25% of the lender *j*'s major public shareholders adopt a diversity policy in a calendar year.

Event 2: more than 25% of the lender *j*'s major public shareholders adopt diversity targets in a calendar year.

This instrument captures significant increases shareholders' commitment to diversity, which likely translate into policy adoption pressure on the lender and, in turn, predict lenders' subsequent policy adoption.

A potential concern with this IV approach is the possibility of investor selection bias, i.e., shareholders committed to diversity might strategically acquire stakes in lenders without existing diversity policies. To ensure that the instrument is not affected by endogenous changes in institutional ownership, for our main specification we base *SDI* on shareholders as of 2014.

F.2. Examining Time-Series Dynamics: An Event Study Approach

To visualize the dynamics of the diversity policy effect, and to test the parallel trend assumption which the DID model relies on, we conduct an event study analysis at the lender level. We estimate the following event study regression specification:

$$Y_{ijt} = \sum_{R \in \mathbb{M}} \sum_{\substack{\tau=-5 \\ \tau \neq -1}}^{4} \beta_R^{(\tau)} R_i DI_{jt,\tau} + \sum_{\substack{\tau=-5 \\ \tau \neq -1}}^{4} \delta^{(\tau)} DI_{jt,\tau} + \rho' Z_{ijt} + \theta_{j \times R(i)} + \eta_t + \varepsilon_{ijt}. \quad (2)$$

where $DI_{jt,\tau}$ is a dummy variable that equals 1 if lender j implemented the diversity policy in year $t - \tau$, and 0 otherwise.

Several papers have raised concerns about potential biases in estimated event study dynamics with fixed-effects estimated using both treated and untreated observations (e.g., De Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021; Callaway and Sant'Anna 2021; Borusyak, Jaravel, and Spiess 2024; De Chaisemartin and d'Haultfoeuille 2024). The literature has advanced multiple error-corrected techniques. In this paper, we adopt the approach recommended by Gardner (2022), which is a two-stage estimation technique. Under this approach, we first estimate fixed effects only from untreated units, to avoid any contamination from the treated lenders. In the second stage, these estimated fixed effects are used to generate fitted values that residualize the dependent variable for the second stage estimation. This approach is appealing for both its transparency and computational simplicity.

In the event study analysis, we rely on a longer time window (2010-2021) to include more policy adoption events. However, several mortgage characteristics are only included in HMDA data after 2018, and thus cannot be included as control variables in the event study regressions. These characteristics include LTV bins, DTI bins, joint application and conforming loan indicators, as well as ten-year bins of applicant age.

III. Results

Table 3 presents the result of estimating Equation (1) for loan application completion and approval decisions under the DID estimation framework. Columns (1)-(3) present the results for whether the loan application is completed, a result of both the applicant's and loan officer's efforts. We are not able to control for mortgage LTV and DTI in this analysis since these two risk factors are not available unless the applications are completed. Columns (4)-(6) present the results for whether the loan is approved, conditional on application completion, where LTV and DTI are controlled for. Columns (7)-(9) present the results for the final origination of the loan, with missing values for LTV and DTI grouped into their own indicator bins.

A. Racial Disparities in Application Completion Rates

Consistent with prior research, we find lower completion and approval rates for minority borrowers, absent diversity policies, captured by the significantly negative coefficients on minority group indicators. The effect is particularly strong for Black and non-Black non-Hispanic minority borrowers (primarily Asian), as indicated by the negative and statistically significant coefficients on *Black Borrower* and *Other Minority Borrower* in Column (1) and (4). Column (3) shows that diversity policies improve completion rates for minority applicants in general. The policies are associated with the greatest improvement in completion rate for Black borrowers. The improvement is captured by a significant positive coefficient on the interaction term between *Black Borrower* and *Diversity Policy*$_{-1}$ in Column (2), which shows a reduced Black-White completion rate gap of 1.89 percentage points.

B. Racial Disparities in Application Approval/Origination Rates

Columns (4) through (6) of Table 3 present results for application approval rates. The results presented in Column (4) indicate that there is inconsistency in approval rate disparities without a diversity policy: Black and non-Black non-Hispanic minority borrowers face lower approval rates, however Hispanic borrowers experience higher approval rates. Focusing on diversity policies, we find that policies are associated with a decrease in approval rates for all minority borrowers. Specifically, we find significantly negative coefficients on the interaction term between *Minority Borrow* and *Diversity Policy*$_{-1}$ in Column (6), indicating a widening of the racial disparities in approval rates between minority and White borrowers. The effect is particularly strong for Black borrowers and is also significant for other minority borrowers. As indicated by the coefficient on the interaction term between *Black Borrower* and *Diversity Policy*$_{-1}$ in Column (5), the approval rate racial disparity increases by 3.04 percentage points. This outpaces the reduction in the completion rate disparity and results in an overall increase in the mortgage origination disparity of 2.45%, as shown in Column (8).

C. Identifying Causal Effects of Diversity Policies: Instrumental Variables Analysis

As described in Section II.F.1, we develop an instrument for lenders' diversity policy adoption based on changes in large shareholders' policies. We obtain lenders' institutional holdings from Form 13F data from LSEG. We define major institutional shareholders as those that hold over 1% of the outstanding shares of lenders (or their public parents). On average, lenders have approximately 13 major shareholders, collectively owning around 41% of equity. We focus on publicly traded shareholders and obtain their diversity policy adoption (Event 1) and diversity target (Event 2) data from the Refinitiv database to define *SDI*, significant shareholder diversity adoption events. We identify an average of eight public shareholders per lender who collectively own approximately 24% of equity. To address the concern that shareholders committed to diversity strategically acquire stakes in lenders without existing diversity policies, we construct *SDI* using shareholders identified as of 2014.[12]

Our regression sample includes lenders without any formal diversity policy prior to 2017. Table C2 presents the first-stage regression result, which shows a strong predictive relationship between *SDI* and lenders' subsequent adoption of diversity policies. Table 4 presents the two-stage-least-square IV regressions using predicted values of lenders' diversity policy adoption from the first stage. We find consistent results that both approval and origination disparities between minority and majority borrowers widen following lenders' diversity policy adoption. This effect is particularly pronounced among Black borrowers. Overall, the results from the IV approach are closely aligned with our main analysis.

D. Examining Time-Series Dynamics: Event-Study

As described in Section II.F.2, we conduct an event study analysis with a staggered DID design at the lender level. Figures 2 through 4 present the results for the event study analysis. Figure 2 presents the results for application completion. Consistent with the findings in Table 3, we observe an increase in the application completion rate for minority borrowers after lenders' adoption of diversity policies, compared to their White peers, but no pre-adoption trend. On average, the increase reaches its peak around the third

[12] In an alternative specification, we relax the restriction that institutional ownership is fixed in 2014. Results based on this alternative approach (Table S8 of the Online Appendix) closely mirror our primary IV findings reported in Table C2.

year after policy adoption, with a 2-percentage-point improvement in closing completion gaps between minority and majority borrowers.

Figure 3 presents an event study analysis of mortgage approval likelihood. We observe no significant difference in the approval rates between White and minority borrowers prior to the introduction of the diversity policies, and no clear pre-policy trend. After adoption, we observe a drop in approval rates for minority borrowers relative to White borrowers, with a significant difference in years one through four. Four years into policy implementation, the difference in approval rates between minority and White applicants is wider by 5.5 percentage points.

Figure 4 presents the event study result for overall mortgage originations rates. Consistent with the main regression results, we document a decrease in origination rates for minority borrowers compared with White borrowers after the adoption of diversity policies.

We find consistent evidence that diversity policy adoption leads to subsequent racial disparities in lending outcomes across a range of specifications – including models with rich fixed effects, an IV approach, and an event study framework. Taken together, these findings reinforce the connection between the adoption of lenders' diversity policy and the observed lending disparities.

E. Robustness to Post-2020 Policy Adoption

During the sample period (2018–2021), the murder of George Floyd intensified the Black Lives Matter movement and shifted social attention toward racial disparities. A potential concern is that lenders with weaker diversity performance may have been pressured to adopt diversity policies during this period, which could drive the widening racial disparity in mortgage approvals. To address this, we conduct a robustness test excluding the two lenders that adopted diversity policies after 2020. The results, reported in Table C3, are very similar to our primary specification.

IV. The Potential Role of Application Riskiness

A. Unobserved Risks or Rising Standards: Evidence from Ex-Post Performance and FICO Scores

The evidence presented in Section III suggests that minority borrowers experience lower approval rates at lenders following diversity policy adoption. This increase in approval rate disparities, even after controlling for a comprehensive set of risk factors, suggests that risk alone may not fully explain the widened gap. However, it remains plausible that unobservable risk factors, not captured in our main model and correlated with race, may also contribute to these changes. To address this concern, we analyze ex-post loan performance outcomes.

Following prior studies (Adelino, Gerardi, and Willen 2014; Hurst, Keys, Seru, and Vavra 2016), we measure ex-post loan performance using a standard indicator of mortgage default, which equals 100% if the borrower misses payments for 2 consecutive months within 2 years after loan origination. Table 5 reports results for the effect of the diversity policy on mortgage default. The results indicate a significant reduction in default rates for Black borrowers (by 1.3 percentage points) after lenders adopt a diversity policy. While we cannot examine the quality of denied mortgages, the decrease in ex-post defaults suggests that the decrease in minority loan approvals is not entirely explained by actual risks.

Next, we examine FICO scores, as a measure of quality that is observable to the back office at origination, for approved loans. Table 5, Columns (5)-(6), present the results. We find a significant increase in FICO scores for minority loans approved after diversity policy adoption (an increase of 5.3 points for Black borrowers and 2.5 points for Hispanic Borrowers). The evidence indicates an increase in underwriting standards for minority applicants.

The decreasing default rate and increasing FICO score, together, suggest that lenders may be "raising the bar" for approval of loans to minority borrowers after adopting a diversity policy. In particular, the results suggest that lenders with a diversity policy in place could approve a larger number of minority loan applications without increasing default rates above what the rates were without a diversity policy, or decreasing FICO scores.

B. Possible Drivers of Rising Standards: Racial Stigma Due to Policy Adoption

The above evidence suggests that the widened approval gap is at least partially attributable to a higher underwriting standard towards minority applicants - standards that are not warranted by their ex-post loan performance. What could explain this heightened standard following the adoption of diversity policies? A possible explanation is that diversity policies unintentionally trigger a backlash or racial stigma within the back office. This stigma arises from overgeneralization. If there is an increased prevalence of riskier minority applications after diversity policy adoption, this shift may foster a stigma on all minority applications, leading to the impression that all minority applications are riskier. In response, the back office would impose stricter underwriting standards on all minority applicants. In other words, the stigma effect can be a correct reaction to an incorrect generalization, which is triggered by a real shift.

B.1. Application Riskiness Measured by Common Risk Factors

To explore this possibility, we start by analyzing the risk profiles of minority applications arriving at the back office after diversity policy adoption. Our first question is whether there is an increase in risky minority applications – a real shift in risk which could potentially trigger an overgeneralization. We use two approaches. In the first approach, we examine changes in two common and observable risk factors after the policy adoption for all completed loan applications. Specifically, we use a linear regression model to analyze changes in the proportion of applicants classified as "risky" borrowers based on debt-to-income (DTI) ratio and loan-to-value (LTV) ratio. We adopt two widely accepted thresholds: a DTI ratio exceeding 36% and an LTV ratio exceeding 80%. Table 6 summarizes the findings. We find a 1.4 percentage point increase in the proportion of applications from Black and Hispanic borrowers with high DTI ratios and a 1-2 percentage point increase from these groups with high LTV ratios in completed applications. Overall, the results suggest a relative increase in minority applicant riskiness for completed applications, implying that the back office will observe more high-risk minority applications following policy adoption.

B.2. Application Riskiness Under a Machine Learning Approach

Our second approach employs a machine learning model to provide a more comprehensive assessment of the changes in applicants' risk profiles without focusing on specific risk factors. Specifically, we train a random forest model to predict each mortgage applicant's default risk using the default outcomes and a rich set of characteristics of approved mortgage applications, including loan amount, loan-to-value ratio (LTV), debt-to-income ratio (DTI), income, relative income ratio within the metropolitan statistical area (MSA), loan type, year, and county. By considering multiple dimensions simultaneously, our model is able to form a more accurate portrait of the applicant's default risk compared with traditional linear models. We then apply the trained model to all completed mortgage applications to estimate a predicted default risk for each application. In the Online Appendix, we describe the full details of the random forest model, and demonstrate the model's accuracy in closely tracking realized default outcomes.

We present the machine estimated default risk for mortgage applications arriving at the back office. Figure 5 compares the distributions of predicted default risk for minority and White borrowers' applications, before and after the adoption of diversity policies, for the lenders who adopt the diversity policies during our sample period. Table 7 provides a regression analysis of distribution changes in predicted default risks for minority applications post-policy adoption, with more comprehensive controls. Consistent with the risk factor analysis in Table 6, we find an increase in the overall riskiness of minority applications under the machine learning model following policy adoption. The increase is primarily driven by a rise in minority applications within the highest predicted default risk bin (i.e., those with a probability of default greater than 15%), along with an increase in riskiness within this bin.

C. Possible Racial Stigma – Evaluating Approval Standards Across All Risk Bins

Next, we examine the changes in approval disparities between minority and White applicants following the adoption of diversity policies, conditional on the machine-learning-based risk assessment. While we cannot observe the back office's perception of risk, and thus whether they overgeneralize, we can observe approval rates conditional on assessed risk. If the increase in risky applications has triggered an overgeneralization, we should observe more stringent approval standards even for lower-risk minority applications. Figure 6 highlights a general widening of approval disparities between minority and White applicants with the same predicted default risks. In the more detailed regression analysis with appropriate controls, we find consistent results that approval disparities persist even after controlling for predicted default risks.

We find that approval disparities widen across all risk bins, as shown in Columns (1) through (6) of Table 8. The widening in approval gaps is most pronounced in higher-risk categories, as we might expect from the increase in high-risk minority applicants. However, the widened gap exists even in the lowest risk bins, consistent with a stigma effect.

V. Additional Mechanisms

A. Identifying Possible Racial Stigma – Variation in Diversity Policy Effects

The above evidence reveals the complexity of the effects of diversity policies on mortgage lending. While more minority borrowers complete loan applications following the adoption of diversity policies, a disproportionate share of these completed applications comes from higher-risk borrowers. In response, back-office risk management practices tighten approval standards across all minority applicants, leading to a widened approval rate gap between minority and White applicants. The gap persists even after controlling for applicants' riskiness, suggesting a backlash/stigma effect – specifically, the perceived riskiness of minority applicants appears to exceed their actual risk levels, driving approval rates to drop below what underlying risks justify.

To provide additional suggestive evidence of the role and scope of potential stigma effects of diversity policies in driving the back-office approval disparities, we examine whether the effect of diversity policies on minority approval rates is particularly significant in situations with higher documented disparities. Following prior literature, we exploit three specific settings: geographic variation in racial animus; non-conventional versus conventional mortgages; and home equity loans. These capture situations in which lenders may be more susceptible to a stigma effect, and in which back-office judgement may play a bigger role.

A.1. Geographic Variation in Racial Animus

In the first additional analysis, we exploit geographic variation in racial animus and examine whether the effect of diversity policies on approval decisions varies in areas with different levels of racial animus. Conklin et al. (2025) find that approval disparities are most significant in areas with high racial animus, suggesting that discrimination contributes to such disparities. We expect the sigma effect to be more pronounced in areas with greater racial animus.

Following Conklin et al. (2025), we measure local racial animus using the Racial Animus Index, an index based on Google search queries containing racially charged language constructed by Stephens-Davidowitz (2014). Higher levels of the index indicate greater racial bias against Black individuals. We generate a tercile indicator based on the Racial Animus Index in borrowers' local media market (Nielsen-DMAs). Since the Racial Animus Index exclusively focuses on Black minorities, we augment our main model by including a three-way interaction term of *Black Borrower# Diversity Policy# Racial Animus Indicator*.

The results are presented in Table 9. Column (1) reports variation in the effect of diversity policies on loan application completion rate, while Columns (2) and (3) focus on variation in the effects of diversity policies on approval rates and origination rates. Consistent with our prediction, the approval disparity post policy adoption exhibits a larger increase in areas with high racial animus. In areas with the highest racial animus, the Black-White racial disparities experienced a 50% larger increase compared with areas with the lowest racial animus. This indicates a heightened overreaction from the back-office in areas with elevated racial animus, which supports the inference that racial stigma plays a role in the approval outcomes we observe.

A.2. Non-Conventional Mortgages

In the second additional analysis, we repeat our main analysis, dividing the sample into conventional and non-conventional mortgages. The non-conventional mortgage sample is comprised of three categories: (1) loans insured by the FHA, which primarily assists borrowers with smaller down payments and lower credit scores; (2) loans insured by the VA for military families; and (3) loans guaranteed by the USDA, which aims to support rural areas.

Unlike conventional mortgages, non-conventional loans target riskier borrowers and often require additional review from lenders to ensure compliance with specific government regulations. These additional review requirements can increase time pressure and stress on the back office, which can exacerbate the effects of implicit biases (Chugh 2004; Bertrand et al. 2005; Kamath et al. 2024). The potentially higher-risk pool can also lead to stronger stigma effects. Consequently, implicit biases, including stigma effects, are most likely to influence approval decisions for non-conventional loans.

Consistent with this expectation, we find that the racial disparities in both approval and origination rates are significantly larger for non-conventional loans following diversity policy adoption. As shown in Column (3) and (5) of Table 10, the widening of approval and origination disparities nearly doubles for non-conventional loans, compared with conventional loans, following diversity policy adoption. These results are consistent with a more pronounced stigma effect in the non-conventional mortgage market.

A.3. Home Equity Loans

Our main analysis focuses on first-lien, 30-year, fixed-rate mortgages for the purchase of owner-occupied single-family homes since these loans make up the bulk of mortgage borrowing in the U.S. and are offered by all mortgage lenders to their clients. A small proportion of mortgage lenders also actively provide another type of house-collateralized credit: home equity loans. Conklin et al. (2025) report significant racial disparities in the home equity loan market, which are one-degree-of-magnitude higher than those identified by Bhutta et al. (2025) in the purchase mortgage market. To explore whether the stigma effect of diversity policies extends to the market for home equity loans, we repeat our main analysis using home equity loan products. Consistent with our main findings, we observe similar effects: improved completion rates and decreased approval and origination rates for minority applicants compared to White applicants, following policy adoption.[13] We present the results in Table S3 and describe the data construction and summary statistics for home equity loans in Section II of the Online Appendix.

B. Variation in Racial Stigma Across Different Diversity Policy Dimensions

While our main analysis focuses on whether a firm has a disclosed diversity policy, as discussed in Section I.B., the content and nature of such policies can vary significantly, potentially leading to differential impacts on policy effectiveness and the extent to which the policy drives racial stigma. To explore this variation, we hand-code firms' public diversity policy disclosures across four core dimensions: diversity training, diversity targets and commitments, designated diversity leadership and oversight, and customer-focused diversity initiatives. Details of the coding process are provided in Appendix B.

Table 11 presents evidence exploring how variations in these four dimensions relate to lending outcomes. Panel A presents the results for completion-rate disparities, while Panels B and C report findings on approval and origination rates, respectively. Our results suggest that policies featuring these four policy dimensions generally result in smaller reductions in completion-rate disparities, indicating more cautious outreach to minority borrowers at the front office level. However, the results in Panel B indicate that they are associated with smaller increases in approval-rate disparities, consistent with a milder backlash effect in downstream lending processes. The combined effect is a smaller increase in origination rate disparities for policies with these features.

We further observe that among the four dimensions, customer diversity efforts appear to have the most positive effects for minority borrowers, with no overall reduction in approval and originations for minority borrowers in general, and improvements for Hispanic and Other Minority borrowers.

[13] Conklin et al. (2025) examines Home Equity Loans, Home Equity Lines of Credit, and Cash-out Refinances. In our sample, the lenders that adopted diversity policies between 2017 and 2020 rarely issue Home Equity Lines of Credit, so we cannot test the diversity effect on the Home Equity Lines of Credit. We do examine Cash-out Refinances in Table S5 of the Online Appendix. Similar to Home Equity Loans, minority applicants for Cash-out Refinances are less likely to be approved after lenders adopt diversity policies.

Overall, our findings highlight the inherent complexity in diversity policy effectiveness. They suggest that progress in reducing lending disparities may depend significantly on the characteristics of the diversity policies and initiatives lenders put in place. Our results suggest that policies combining clear accountability structures with targeted customer-focused commitments are most likely to be effective.

VI. Conclusion

In this paper, we examine the impact of mortgage lenders' diversity policies on racial disparities in mortgage lending. Using rich fixed effects specifications, we find that lenders with diversity policies have lower approval rates for minority borrowers. Even though diversity policies narrow differences in application completion rates, this effect is more than offset by the lower approval rates, resulting in an incremental decrease in mortgage origination rates for minority borrowers. Our results are robust to an instrument-variable approach and event study design, pointing to a causal relation between lenders' policy adoption and documented lending outcomes.

The increase in approval disparities persists after we control for a comprehensive set of risk variables, raising the possibility that changes in the risk factors are not the only reason behind widened disparities. Examining subsequent loan performance, we find a significant decrease in default rates and higher FICO scores for minority loans at lenders with diversity policies. The results support that the disparities are not solely driven by unobservable risk factors. Instead, they are consistent with a higher underwriting standard towards minority applicants post policy adoption - standards that are not warranted by the ex-post loan performance.

We further examine a potential driver of this effect: racial stigma. In particular, we examine whether diversity policies trigger an increase in risky minority applicants, which could trigger stigma, and an over-adjustment to this shift – the stigma effect. We find evidence consistent with a racial stigma effect. Specifically, we observe an increase in the overall riskiness of completed mortgage applications after policy adoption, measured by both easily visible risk factors of debt-to-income (DTI) and loan-to-value (LTV) ratios, as well as predicted default risks under a machine learning model. The back office, observing this increase in risky minority applications, is likely to scrutinize minority applications more closely. The question is whether this leads to an overreaction – raising standards even for lower-risk minority borrowers. Consistent with a racial stigma effect, we find increased approval disparities for minority applicants across all predicted risk bins, including for those with the lowest predicted default risk.

In additional analysis, we provide further evidence consistent with a stigma effect driving increased approval gaps. Specifically, we find a stronger effect of diversity policies in widening approval rate disparities in geographic areas with high racial animus. We also find a stronger effect for non-conventional loans, which require additional resources from the back office and create conditions for increased implicit bias. In addition, we find that the racial stigma effect extends to the home equity loans, a market with stronger previously documented approval disparities.

Finally, we shed light on how differences in policy features can lead to heterogeneous effects on the extent to which policies drive racial stigma. Using hand-coded policy disclosures, we find that specific policy features result in more cautious front-end outreach but attenuated downstream backlash. Overall, the effectiveness of diversity policies in reducing lending disparities appears to depend critically on their design.

Given the economic importance of mortgage lending in the United States, these results should be of interest to a broad swath of the economy. However, our results also have implications beyond mortgage lending. As organizations throughout the economy examine how to address growing diversity, without excluding or hurting majority-group members, our results provide specific insights. Diversity policies can help significantly, as we find with application completion rates. But it is important to consider potential overreaction, stigmas, and backlash effects when designing and implementing such policies. Finally, our paper indicates the potential importance of careful analyses of diversity policy effects in other settings, to provide insight into how to improve such policies. It should not be assumed that all policies do what they claim.

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Table 1 Variable Definitions and Data Sources

Application and Performance Outcomes	Source	Definition
Completion	HMDA	Indicator equal to 100 (%) if the application is completed and submitted for decision
Approval (given completion)	HMDA	Indicator equal to 100 (%) if the loan is originated or the application is approved but not accepted, given the application is completed
Origination	HMDA	Indicator equal to 100 (%) if the loan is originated, meaning the borrower decides to take the loan after approval
Default (within 2 years)	Loan Performance	Indicator equal to 100 (%) if the borrower fails to make payments or misses the deadlines for two consecutive months
Key Independent Variables		
Diversity Policy$_{-1}$	Refinitiv, Hand Collection	Indicator equal to one if the lender has a diversity policy in the past calendar year
Minority Borrower	HMDA	Indicator equal to one if the borrower is a racial or ethnic minority
Black Borrower	HMDA	Indicator equal to one if the race of the borrower is Black, and the ethnicity is not Hispanic
Hispanic Borrower	HMDA	Indicator equal to one if the ethnicity of the borrower is Hispanic
Other Minority Borrower	HMDA	Indicator equal to one if the borrower is a racial or ethnic minority, but not Black or Hispanic
Borrower and Mortgage Characteristics		
Loan Amount ($K)	HMDA	The amount of the covered loan in dollars
Income Ratio	HMDA	The ratio of the applicant gross annual income and the local county median income, controlled for with percentile of income ratio. The county median income come from the Census Small Area Income and Poverty Estimates (SAIPE).
Joint Application	HMDA	Indicator equal to one if there are multiple people on the application
Conforming Loan	HMDA	Indicator equal to one if the loan amount is below the conforming loan limit in the county
Borrower Age - less than 25	HMDA	The age, in years, of the first co-applicant or co-borrower is less than 25 (not included). Only available post-2018.
Borrower Age - 25-34	HMDA	The age, in years, of the first co-applicant or co-borrower is between 25 and 34. Only available post-2018.
Borrower Age - 35-44	HMDA	The age, in years, of the first co-applicant or co-borrower is between 35 and 44. Only available post-2018.
Borrower Age - 45-54	HMDA	The age, in years, of the first co-applicant or co-borrower is between 45 and 54. Only available post-2018.
Borrower Age - 55-64	HMDA	The age, in years, of the first co-applicant or co-borrower is between 55 and 64. Only available post-2018.
Borrower Age - 65-74	HMDA	The age, in years, of the first co-applicant or co-borrower is between 65 and 74. Only available post-2018.
Borrower Age - greater than 74	HMDA	The age, in years, of the first co-applicant or co-borrower is greater than 74 (not included). Only available post-2018.

Loan Type - Conventional	HMDA	Indicator equal to one if the type of covered loan or application is conventional (not insured or guaranteed by FHA, VA, RHS, or FSA)
Loan Type - FHA	HMDA	Indicator equal to one if the type of covered loan or application is Federal Housing Administration insured (FHA)
Loan Type - VA	HMDA	Indicator equal to one if the type of covered loan or application is Veterans Affairs guaranteed (VA)
Loan Type - USDA	HMDA	Indicator equal to one if the type of covered loan or application is USDA Rural Housing Service or Farm Service Agency guaranteed (RHS or FSA)
Combined Loan-to-Value (LTV)	HMDA	Loan-to-Value ratio, controlled for with 20-percentage bins ranging from 0 to 120
Debt-to-Income (DTI)	HMDA	Debt-to-Income ratio, controlled for with bins as provided by HMDA
FICO	Loan Performance	Continuous dependent variable as FICO score and control variable as 40-point bins ranging from 580 to 820 and with bins less than 580 and higher than 820.
Random Forest Predicted Default Risk (%)	Authors' Calculation	The predicted default likelihood estimated by a random forest model
Racial Animus	Stephens-Davidowitz (2014)	This is percent of Google searches at the DMA level, from 2004-2007, that included the word "nigger(s)." Each DMA's score is multiplied by a constant.

Table 2 Summary Statistics

	Mean	S.D.	P1	P25	P50	P75	P99	Obs.
Application and Performance Outcomes								
Completion	82.4	38.1	0	100	100	100	100	2,266,015
Approval (given completion)	89.5	30.7	0	100	100	100	100	1,866,616
Origination	72.1	44.9	0	0	100	100	100	2,266,015
Default (within 2 years)	2.9	16.9	0	0	0	0	100	863,996
Prepaid (within 2 years)	26.1	43.9	0	0	0	100	100	863,996
Key Independent Variables								
Diversity Policy$_{-1}$	0.90	0.30	0	1	1	1	1	2,266,015
Minority Borrower	0.37	0.48	0	0	0	1	1	2,266,015
Black Borrower	0.09	0.29	0	0	0	0	1	2,266,015
Hispanic Borrower	0.14	0.35	0	0	0	0	1	2,266,015
Other Minority Borrower	0.13	0.34	0	0	0	0	1	2,266,015
Borrower and Mortgage Characteristics								
Loan Amount ($K)	352.7	308.7	55	185	275	405	1605	2,266,015
Income Ratio	1.71	10.40	0.31	0.86	1.27	1.94	7.81	2,266,015
Joint Application	0.45	0.50	0	0	0	1	1	2,266,015
Conforming Loan	0.90	0.30	0	1	1	1	1	2,266,015
Borrower Age - less than 25	0.05	0.21	0	0	0	0	1	2,266,015
Borrower Age - 25-34	0.32	0.47	0	0	0	1	1	2,266,015
Borrower Age - 35-44	0.27	0.45	0	0	0	1	1	2,266,015
Borrower Age - 45-54	0.17	0.37	0	0	0	0	1	2,266,015
Borrower Age - 55-64	0.11	0.31	0	0	0	0	1	2,266,015
Borrower Age - 65-74	0.06	0.24	0	0	0	0	1	2,266,015
Borrower Age - greater than 74	0.02	0.13	0	0	0	0	1	2,266,015
Loan Type - Conventional	0.76	0.43	0	1	1	1	1	2,266,015
Loan Type - FHA	0.14	0.35	0	0	0	0	1	2,266,015
Loan Type - VA	0.08	0.27	0	0	0	0	1	2,266,015
Loan Type - USDA	0.02	0.13	0	0	0	0	1	2,266,015
Combined Loan-to-Value (%) (LTV)	85.7	24.2	33.3	80.0	90.0	96.5	102.4	1,864,296
Debt-to-Income (%) (DTI)	35.1	12.0	10.0	30.0	38.0	44.0	60.0	1,864,673
FICO	754.5	43.5	639.0	726.0	763.0	790.0	817.0	863,996
Random Forest Predicted Default Risk (%)	4.76	5.10	0.1	1.1	2.9	6.7	22.5	1,835,149
Racial Animus	63.97	19.78	30.1	50.6	61.3	73.0	141.4	195

Table 3 The Effect of Diversity Policy on Lending Outcomes

This table reports regression results for mortgage lending outcomes from estimating Equation (1). The observations are from the short panel HMDA data (2018-2021). The variables are defined in Table 1. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. ∗, ∗∗, ∗∗∗ indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

	Completion (in %)			Approval (Given Completed, in %)			Origination (in %)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Black Borrower # Diversity Policy$_{-1}$	1.83***	1.89***		-4.49***	-3.04***		-3.20***	-2.45***	
	(5.00)	(3.31)		(-14.15)	(-5.49)		(-11.55)	(-5.45)	
Hispanic Borrower # Diversity Policy$_{-1}$	-0.59*	0.10		-3.78***	-0.11		-2.87***	-0.05	
	(-1.72)	(0.19)		(-10.12)	(-0.26)		(-9.11)	(-0.14)	
Other Minority Borrower # Diversity Policy$_{-1}$	-0.09	0.74		-1.46***	-0.93**		-0.93***	-0.62	
	(-0.18)	(1.16)		(-5.99)	(-2.40)		(-3.98)	(-1.62)	
Minority Borrower # Diversity Policy$_{-1}$			0.91**			-1.38***			-1.09***
			(2.50)			(-4.01)			(-3.76)
Diversity Policy$_{-1}$	2.70***	2.56***	2.56***	0.20	-0.59***	-0.59***	-0.32*	-0.86***	-0.86***
	(10.69)	(10.08)	(10.07)	(1.00)	(-3.86)	(-3.86)	(-1.72)	(-5.17)	(-5.16)
Black Borrower	-3.51***			-0.62**			-1.22***		
	(-10.20)			(-2.05)			(-4.68)		
Hispanic Borrower	-0.96***			0.70**			0.25		
	(-2.89)			(2.02)			(0.87)		
Other Minority Borrower	-4.12***			-1.15***			-1.38***		
	(-8.31)			(-5.45)			(-6.82)		
log(Loan Amount)	x	x	x	x	x	x	x	x	x
LTV Bin FE				x	x	x	x	x	x
DTI Bin FE				x	x	x	x	x	x
Conforming Loan	x	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x	x
Income Ratio Percentile FE	x	x	x	x	x	x	x	x	x
Borrower Age Bin FE	x	x	x	x	x	x	x	x	x
Loan Type FE	x	x	x	x	x	x	x	x	x
Property Tract FE	x	x	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x	x	x
Lender FE	x			x			x		
Lender*Race FE		x	x		x	x		x	x
Dependent Var. Mean	82.38	82.38	82.38	89.50	89.50	89.50	72.08	72.08	72.08
R^2	0.05	0.05	0.05	0.32	0.32	0.32	0.67	0.67	0.67
Obs.	2,263,663	2,263,662	2,263,662	1,863,724	1,863,723	1,863,723	2,263,663	2,263,662	2,263,662

Table 4 IV Regression: The Effect of Diversity Policy on Lending Outcomes

This table reports two-stage-least-square IV regression results for mortgage lending outcomes. The instrumental variables are increases in shareholder diversity initiatives, based on 2014 shareholders, and its interactions with borrower race or minority indicators. The first stage results are reported in Table C3. The observations are from the short panel HMDA data (2018-2021). The variables are defined in Table 1. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. *, **, *** indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

	Completion (in %)		Approval (Given Completed, in %)		Origination (in %)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\text{Black \# Diversity Policy}}_{-1}$	-0.14*		-3.80***		-3.38***	
	(-1.79)		(-7.21)		(-7.30)	
$\widehat{\text{Hispanic \# Diversity Policy}}_{-1}$	0.02		-1.18***		-1.20***	
	(0.33)		(-3.01)		(-2.71)	
$\widehat{\text{Other Minority \# Diversity Policy}}_{-1}$	0.02		-0.68		-0.47	
	(0.28)		(-1.59)		(-1.13)	
$\widehat{\text{Minority \# Diversity Policy}}_{-1}$		-0.04		-2.10***		-1.89***
		(-0.93)		(-6.23)		(-6.19)
$\widehat{\text{Diversity Policy}}_{-1}$	-0.40***	-0.40***	-0.85**	-0.90**	-1.68***	-1.72***
	(-8.73)	(-8.73)	(-2.11)	(-2.20)	(-3.91)	(-3.96)
log(Loan Amount)	x	x	x	x	x	x
LTV Bin FE			x	x	x	x
DTI Bin FE			x	x	x	x
Conforming Loan	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x
Income Ratio Percentile FE	x	x	x	x	x	x
Borrower Age Bin FE	x	x	x	x	x	x
Loan Type FE	x	x	x	x	x	x
Property Tract FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x
Dependent Var. Mean	83.80	83.80	93.72	93.72	76.27	76.27
First Stage: Kleibergen-Paap rk F	88.77	176.5	96.82	192.1	88.77	176.5
First Stage: Anderson-Rubin p-val	0	0	0	0	0	0
Obs.	495,741	495,741	412,495	412,495	495,741	495,741

Table 5 The Effect of Diversity Policy on Ex post Mortgage Default Performance and Borrower Quality

This table reports regression results for ex-post mortgage performance and borrower quality for originated loans. Columns (1)-(4) examine mortgage default (within 2 years of loan origination). Columns (5)-(6) examine FICO scores. The observations are all originated mortgages in the short panel HMDA data (2018-2021) that can be matched with Fannie Mae and Freddie Mac Performance Data. The variables are defined in Table 1. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. *, **, *** indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

	Default (within 2 years, in %)				FICO	
	(1)	(2)	(3)	(4)	(5)	(6)
Black Borrower # Diversity Policy$_{-1}$	-1.53**		-1.28*		5.32***	
	(-2.19)		(-1.86)		(4.42)	
Hispanic Borrower # Diversity Policy$_{-1}$	-1.46***		-1.31**		2.48**	
	(-2.74)		(-2.51)		(2.55)	
Other Minority Borrower # Diversity Policy$_{-1}$	-0.92*		-0.90*		0.43	
	(-1.82)		(-1.80)		(0.43)	
Minority # Diversity Policy$_{-1}$		-1.29***		-1.16***		2.46***
		(-3.84)		(-3.49)		(3.62)
Diversity Policy$_{-1}$	-0.02	-0.02	-0.06	-0.06	-1.05***	-1.05***
	(-0.13)	(-0.13)	(-0.41)	(-0.42)	(-2.92)	(-2.92)
log(Loan Amount)	x	x	x	x	x	x
LTV Bin FE	x	x	x	x	x	x
DTI Bin FE	x	x	x	x	x	x
FICO Bin FE			x	x		
Conforming Loan	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x
Income Ratio Percentile FE	x	x	x	x	x	x
Borrower Age Bin FE	x	x	x	x	x	x
Loan Type FE	x	x	x	x	x	x
Property Tract FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x
Dependent Var. Mean	2.93	2.93	2.93	2.93	754.63	754.63
R^2	0.10	0.10	0.11	0.11	0.20	0.20
Obs.	857,503	857,503	857,502	857,502	857,502	857,502

Table 6 The Effect of Diversity Policy on Riskiness of Mortgage Applications – Evidence from Directly Observable Risk Factors

This table reports results for the changes in proportions of applications with high Debt-to-Income (DTI) and Loan-to-Value (LTV) Ratios in completed applications. In column (1) and (2), the dependent variable is a dummy that equals 100% if the applicant's Debt-to-Income Ratio is above 36%, or 0 otherwise. In column (3) and (4), the dependent variable is a dummy that equals 100% if the applicant's Loan-to-Value Ratio is above 80%, or 0 otherwise. The variables are defined in Table 1. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. ∗, ∗∗, ∗∗∗ indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

	Debt-to-Income Ratio >36% (in %)		Loan-to-Value Ratio >80% (in %)	
	(1)	(2)	(3)	(4)
Black Borrower # Diversity Policy$_{-1}$	1.43**		1.95***	
	(2.16)		(4.37)	
Hispanic Borrower # Diversity Policy$_{-1}$	1.36*		1.17**	
	(1.95)		(2.47)	
Other Minority Borrower # Diversity Policy$_{-1}$	-1.98**		3.51***	
	(-2.29)		(3.23)	
Minority # Diversity Policy$_{-1}$		0.64		1.98***
		(1.31)		(4.76)
Diversity Policy$_{-1}$	-0.44	-0.44	-0.84**	-0.84**
	(-1.23)	(-1.23)	(-2.55)	(-2.55)
log(Loan Amount)	x	x	x	x
Year FE	x	x	x	x
Lender*Race FE	x	x	x	x
Dependent Var. Mean	54.79	54.79	59.72	59.72
R^2	0.05	0.05	0.16	0.16
Obs.	1,864,672	1,864,672	1,864,296	1,864,296

Table 7 The Effect of Diversity Policy on Riskiness of Mortgage Applications – Evidence from a Machine Learning Model

This table reports the distributions in predicted default risk bins under a machine learning model for completed applications. The default risk bins are set at 5% intervals, ranging from 0% to 15%, with all risks above 15% grouped into a combined bin. The variables are defined in Table 1. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. ∗, ∗∗, ∗∗∗ indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

	Distribution by Random Forest Predicted Default Risk Bins (Given Completion, in %)							
	Default Risk 0-5%		Default Risk 5-10%		Default Risk 10-15%		Default Risk >15%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black Borrower # Diversity Policy$_{-1}$	-1.70*		-2.98***		-1.80***		6.48***	
	(-1.73)		(-3.10)		(-2.68)		(10.17)	
Hispanic Borrower # Diversity Policy$_{-1}$	3.00***		-4.15***		-2.30***		3.45***	
	(4.20)		(-4.38)		(-3.42)		(4.88)	
Other Minority Borrower # Diversity Policy$_{-1}$	1.09		-0.40		-0.49		-0.20	
	(0.93)		(-0.47)		(-0.83)		(-0.46)	
Minority # Diversity Policy$_{-1}$		0.79		-2.96***		-1.75***		3.91***
		(1.28)		(-4.62)		(-3.74)		(9.06)
Diversity Policy$_{-1}$	-0.60	-0.60	-0.81**	-0.81**	-0.09	-0.09	1.50***	1.50***
	(-1.24)	(-1.24)	(-2.31)	(-2.31)	(-0.36)	(-0.36)	(7.36)	(7.37)
log(Loan Amount)	x	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x	x	x
Dependent Var. Mean	66.32	66.32	19.19	19.19	9.08	9.08	5.41	5.41
R^2	0.21	0.21	0.06	0.06	0.06	0.06	0.10	0.10
Obs.	1,835,149	1,835,149	1,835,149	1,835,149	1,835,149	1,835,149	1,835,149	1,835,149

Table 8 The Effect of Diversity Policy on Approval Decisions for Applications in Different Predicted Default Risk Categories

This table reports regression results for mortgage application approval for each predicted default risk bin. The default risk bins are set at 5% intervals, ranging from 0% to 15%, with all risks above 15% grouped into a combined bin. The variables are defined in Table 1. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. ∗, ∗∗, ∗∗∗ indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

	Approval (Given Completion, in %)							
	Default Risk 0-5%		Default Risk 5-10%		Default Risk 10-15%		Default Risk >15%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black Borrower # Diversity Policy$_{-1}$	-2.63***		-4.17***		-2.52**		-4.98***	
	(-3.48)		(-4.50)		(-2.40)		(-3.20)	
Hispanic Borrower # Diversity Policy$_{-1}$	-0.45		0.95		0.07		-0.09	
	(-0.77)		(1.15)		(0.07)		(-0.06)	
Other Minority Borrower # Diversity Policy$_{-1}$	-0.04		-1.41		0.27		-1.53	
	(-0.08)		(-1.30)		(0.14)		(-0.95)	
Minority Borrower # Diversity Policy$_{-1}$		-1.01**		-1.54**		-1.09		-2.38**
		(-2.41)		(-2.41)		(-1.40)		(-2.05)
Diversity Policy$_{-1}$	-0.28*	-0.28*	-1.41***	-1.41***	-1.91***	-1.91***	-1.84*	-1.86*
	(-1.75)	(-1.74)	(-3.62)	(-3.61)	(-2.89)	(-2.89)	(-1.81)	(-1.82)
log(Loan Amount)	x	x	x	x	x	x	x	x
LTV Bin FE	x	x	x	x	x	x	x	x
DTI Bin FE	x	x	x	x	x	x	x	x
Conforming Loan	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x
Income Ratio Percentile FE	x	x	x	x	x	x	x	x
Borrower Age Bin FE	x	x	x	x	x	x	x	x
Loan Type FE	x	x	x	x	x	x	x	x
Property Tract FE	x	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x	x	x
Dependent Var. Mean	92.89	92.89	85.57	85.57	80.59	80.59	80.26	80.26
R^2	0.31	0.31	0.39	0.39	0.43	0.43	0.45	0.45
Obs.	1,212,068	1,212,068	340,221	340,221	149,674	149,674	113,908	113,908

Table 9 The Effect of Diversity Policy on Lending Outcomes for Applications in Areas with Varying Racial Animus

This table reports regression results for mortgage lending outcomes, for geographic areas with different levels of racial animus. The variables are defined in Table 1. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. *, **, *** indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

	Completion (in %)	Approval (Given Completion, in %)	Origination (in %)
	(1)	(2)	(3)
Black Borrower # Diversity Policy$_{-1}$	1.46**	-2.39***	-1.90***
	(2.34)	(-3.99)	(-3.96)
Black Borrower # Diversity Policy$_{-1}$ # Racial Animus Tercile 2	0.52*	-0.69**	-0.57**
	(1.73)	(-2.24)	(-2.29)
Black Borrower # Diversity Policy$_{-1}$ # Racial Animus Tercile 3	0.75**	-1.32***	-1.17***
	(2.30)	(-3.19)	(-3.28)
Hispanic Borrower # Diversity Policy$_{-1}$	0.10	-0.10	-0.05
	(0.19)	(-0.26)	(-0.14)
Other Minority Borrower # Diversity Policy$_{-1}$	0.74	-0.93**	-0.62
	(1.16)	(-2.40)	(-1.62)
Diversity Policy$_{-1}$	2.56***	-0.59***	-0.86***
	(10.08)	(-3.87)	(-5.17)
Other Race Interactions	x	x	x
log(Loan Amount)	x	x	x
LTV Bin FE		x	x
DTI Bin FE		x	x
Conforming Loan	x	x	x
Joint Application	x	x	x
Income Ratio Percentile FE	x	x	x
Borrower Age Bin FE	x	x	x
Loan Type FE	x	x	x
Year FE	x	x	x
Property Tract FE	x	x	x
Lender*Race FE	x	x	x
Dependent Var. Mean	82.38	89.50	72.08
R^2	0.05	0.32	0.67
Obs.	2,263,662	1,863,723	2,263,662

Table 10 The Effect of Diversity Policy for Conventional and Non-Conventional Mortgages

This table reports regression results for mortgage lending outcomes, for conventional and non-conventional mortgages. The variables are defined in Table 1. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. *, **, *** indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

	Completed (in %)		Approved (Given Completed, in %)		Originated (in %)	
	(1)	(2)	(3)	(4)	(5)	(6)
Black Borrower # Diversity Policy$_{-1}$ # Conventional	1.77**		-1.19*		-0.91*	
	(2.50)		(-1.91)		(-1.71)	
Hispanic Borrower # Diversity Policy$_{-1}$ # Conventional	0.01		0.59		0.60	
	(0.01)		(1.39)		(1.47)	
Other Minority Borrower # Diversity Policy$_{-1}$ # Conventional	0.97		-0.94**		-0.52	
	(1.40)		(-2.41)		(-1.31)	
Minority # Diversity Policy$_{-1}$ # Conventional		0.88**		-0.41		-0.20
		(2.19)		(-1.18)		(-0.70)
Black Borrower # Diversity Policy-1 # FHA, VA, USDA	1.85***		-2.52***		-2.10***	
	(2.95)		(-4.06)		(-4.24)	
Hispanic Borrower # Diversity Policy-1 # FHA, VA, USDA	0.12		0.30		0.17	
	(0.20)		(0.57)		(0.35)	
Other Minority Borrower # Diversity Policy-1 # FHA, VA, USDA	0.28		-2.15***		-1.85***	
	(0.34)		(-3.29)		(-3.24)	
Minority # Diversity Policy-1 # FHA, VA, USDA		0.90**		-1.30***		-1.13***
		(2.07)		(-3.10)		(-3.17)
Diversity Policy$_{-1}$	2.45***	2.44***	0.57***	0.57***	0.03	0.03
	(8.78)	(8.78)	(3.91)	(3.93)	(0.18)	(0.19)
Diversity Policy$_{-1}$ # FHA, VA, USDA	2.73***	2.73***	-2.58***	-2.58***	-2.40***	-2.39***
	(9.27)	(9.26)	(-11.24)	(-11.24)	(-10.97)	(-10.96)
Other Race Interactions	x	x	x	x	x	x
log(Loan Amount)	x	x	x	x	x	x
LTV Bin FE			x	x	x	x
DTI Bin FE			x	x	x	x
Conforming Loan	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x
Income Ratio Percentile FE	x	x	x	x	x	x
Borrower Age Bin FE	x	x	x	x	x	x
Loan Type FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
Property Tract FE	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x
Dependent Var. Mean	82.38	82.38	89.50	89.50	72.08	72.08
R^2	0.05	0.05	0.32	0.32	0.67	0.67
Obs.	2,263,662	2,263,662	1,863,723	1,863,723	2,263,662	2,263,662

Table 11 The Effect of Diversity Policy on Lending Outcomes for Varying Policy Features

This table reports regression results for diversity policies interacted with specific features, including diversity targets, diversity training, the appointment of a DEO or CDO, and consumer actions. The sample is from the short-panel HMDA data (2018–2021). Panels A, B, and C present results for mortgage application completion, approval, and origination, respectively. The variables are defined in Table 1. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. ∗, ∗∗, ∗∗∗ indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

Panel A Effects of Diversity Policy Features on Mortgage Completion

	Completion (in %)							
Policy Feature(s)	Diversity Target		Diversity Training		Feature: Has DEO Feature 2: Has CDO		Customer Diversity Efforts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black # Diversity Policy$_{-1}$	2.08***		1.93***		2.05***		2.03***	
	(3.61)		(3.30)		(3.48)		(3.55)	
Hispanic # Diversity Policy$_{-1}$	0.13		0.14		0.19		0.16	
	(0.25)		(0.27)		(0.37)		(0.30)	
Other Minority # Diversity Policy$_{-1}$	0.81		0.80		0.93		0.76	
	(1.26)		(1.27)		(1.44)		(1.20)	
Minority # Diversity Policy$_{-1}$		1.00***		0.96***		1.08***		0.97***
		(2.73)		(2.65)		(2.87)		(2.66)
Black # Diversity Policy$_{-1}$ # Policy Feature	-0.67*		-0.08		0.10		-3.01***	
	(-1.88)		(-0.23)		(0.27)		(-5.50)	
Hispanic # Diversity Policy$_{-1}$ # Policy Feature	-0.06		-0.03		-0.43		-1.56***	
	(-0.20)		(-0.09)		(-1.34)		(-3.60)	
Other # Diversity Policy$_{-1}$ # Policy Feature	-0.17		-0.13		-0.51		-0.46	
	(-0.57)		(-0.44)		(-1.52)		(-1.01)	
Minority # Diversity Policy$_{-1}$ # Policy Feature		-0.24		-0.08		-0.34		-1.38***
		(-1.12)		(-0.34)		(-1.55)		(-4.31)
Black # Diversity Policy$_{-1}$ # Policy Feature 2					-1.07***			
					(-3.19)			
Hispanic # Diversity Policy$_{-1}$ # Policy Feature 2					-0.60**			
					(-2.33)			
Other # Diversity Policy$_{-1}$ # Policy Feature 2					-0.92***			
					(-2.66)			
Minority # Diversity Policy$_{-1}$ # Policy Feature 2						-0.84***		
						(-4.09)		
Diversity Policy$_{-1}$	2.26***	2.26***	2.41***	2.41***	2.26***	2.26***	2.55***	2.55***
	(8.62)	(8.62)	(9.59)	(9.58)	(8.79)	(8.79)	(10.12)	(10.10)
Diversity Policy$_{-1}$ # Policy Feature	0.86***	0.85***	0.48***	0.48***	-0.17	-0.17	0.67***	0.66***
	(6.40)	(6.39)	(3.53)	(3.53)	(-1.09)	(-1.08)	(3.75)	(3.74)
Diversity Policy$_{-1}$ # Policy Feature 2								
log(Loan Amount)	x	x	x	x	x	x	x	x
LTV Bin FE								
DTI Bin FE								
Conforming Loan	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x
Income Ratio Percentile FE	x	x	x	x	x	x	x	x
Borrower Age Bin FE	x	x	x	x	x	x	x	x
Loan Type FE	x	x	x	x	x	x	x	x
Property Tract FE	x	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x	x	x
Dependent Var. Mean	82.38	82.38	82.38	82.38	82.38	82.38	82.38	82.38
R^2	0.05	0.05	0.05	0.05	0.05	0.05	0.32	0.32
Obs.	2,263,662		2,263,662		2,263,662		2,263,662	

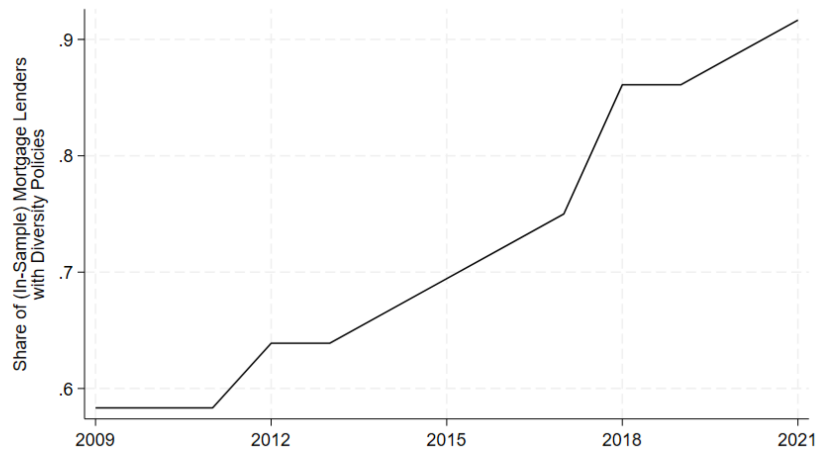
Panel B Effects of Diversity Policy Features on Mortgage Approval

Policy Feature(s)	Approval (Given Completed, in %)							
	Diversity Target		Diversity Training		Feature: Has DEO Feature 2: Has CDO		Customer Diversity Efforts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black # Diversity Policy$_{-1}$	-3.21***		-3.17***		-3.22***		-3.12***	
	(-5.84)		(-5.67)		(-5.74)		(-5.75)	
Hispanic # Diversity Policy$_{-1}$	-0.21		-0.29		-0.36		-0.16	
	(-0.51)		(-0.69)		(-0.85)		(-0.39)	
Other Minority # Diversity Policy$_{-1}$	-1.03***		-1.04***		-1.17***		-1.01**	
	(-2.64)		(-2.62)		(-2.87)		(-2.57)	
Minority # Diversity Policy$_{-1}$		-1.50***		-1.54***		-1.62***		-1.46***
		(-4.30)		(-4.38)		(-4.58)		(-4.24)
Black # Diversity Policy$_{-1}$ # Policy Feature	0.83***		0.52		0.57		1.33***	
	(2.93)		(1.43)		(1.44)		(2.63)	
Hispanic # Diversity Policy$_{-1}$ # Policy Feature	0.45*		0.86***		1.09***		1.74***	
	(1.80)		(3.48)		(3.91)		(3.83)	
Other # Diversity Policy$_{-1}$ # Policy Feature	0.47**		0.53**		0.76**		1.89***	
	(2.25)		(2.39)		(2.57)		(5.84)	
Minority # Diversity Policy$_{-1}$ # Policy Feature		0.55***		0.66***		0.84***		1.71***
		(3.46)		(3.46)		(4.23)		(6.80)
Black # Diversity Policy$_{-1}$ # Policy Feature 2					0.43			
					(1.28)			
Hispanic # Diversity Policy$_{-1}$ # Policy Feature 2					0.39			
					(1.53)			
Other # Diversity Policy$_{-1}$ # Policy Feature 2					0.74***			
					(2.73)			
Minority # Diversity Policy$_{-1}$ # Policy Feature 2						0.55***		
						(2.86)		
Diversity Policy$_{-1}$	-0.66***	-0.65***	-0.73***	-0.73***	-0.65***	-0.65***	-0.46***	-0.46***
	(-4.17)	(-4.16)	(-4.53)	(-4.52)	(-4.18)	(-4.18)	(-3.09)	(-3.09)
Diversity Policy$_{-1}$ # Policy Feature	0.13	0.13	0.48***	0.48***	0.43***	0.43***	2.23***	2.23***
	(1.37)	(1.39)	(4.98)	(4.98)	(3.65)	(3.63)	(15.19)	(15.19)
Diversity Policy$_{-1}$ # Policy Feature 2					-0.04	-0.05		
					(-0.31)	(-0.34)		
log(Loan Amount)	x	x	x	x	x	x	x	x
LTV Bin FE								
DTI Bin FE								
Conforming Loan	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x
Income Ratio Percentile FE	x	x	x	x	x	x	x	x
Borrower Age Bin FE	x	x	x	x	x	x	x	x
Loan Type FE	x	x	x	x	x	x	x	x
Property Tract FE	x	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x	x	x
Dependent Var. Mean	89.50	89.50	89.50	89.50	89.50	89.50	89.50	89.50
R^2	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32
Obs.	1,863,723		1,863,723		1,863,723		1,863,723	

Panel C Effects of Diversity Policy Features on Mortgage Origination

Policy Feature(s)	Origination (in %)							
	Diversity Target		Diversity Training		Feature: Has DEO Feature 2: Has CDO		Customer Diversity Efforts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black # Diversity Policy$_{-1}$	-2.59***		-2.52***		-2.64***		-2.54***	
	(-5.77)		(-5.57)		(-5.94)		(-5.81)	
Hispanic # Diversity Policy$_{-1}$	-0.15		-0.17		-0.26		-0.09	
	(-0.38)		(-0.42)		(-0.65)		(-0.24)	
Other Minority # Diversity Policy$_{-1}$	-0.70*		-0.72*		-0.85**		-0.69*	
	(-1.80)		(-1.82)		(-2.13)		(-1.76)	
Minority # Diversity Policy$_{-1}$		-1.18***		-1.19***		-1.30***		-1.15***
		(-4.00)		(-4.03)		(-4.33)		(-3.99)
Black # Diversity Policy$_{-1}$ # Policy Feature	0.64***		0.28		0.53		1.24***	
	(2.80)		(0.98)		(1.53)		(2.88)	
Hispanic # Diversity Policy$_{-1}$ # Policy Feature	0.42*		0.58**		0.75***		1.43***	
	(1.92)		(2.52)		(2.98)		(3.38)	
Other # Diversity Policy$_{-1}$ # Policy Feature	0.31*		0.44**		0.66***		1.40***	
	(1.68)		(2.20)		(2.60)		(5.13)	
Minority # Diversity Policy$_{-1}$ # Policy Feature		0.43***		0.45***		0.66***		1.37***
		(3.13)		(2.58)		(3.63)		(6.32)
Black # Diversity Policy$_{-1}$ # Policy Feature 2					0.50*			
					(1.73)			
Hispanic # Diversity Policy$_{-1}$ # Policy Feature 2					0.46**			
					(2.08)			
Other # Diversity Policy$_{-1}$ # Policy Feature 2					0.60***			
					(2.75)			
Minority # Diversity Policy$_{-1}$ # Policy Feature 2						0.52***		
						(3.29)		
Diversity Policy$_{-1}$	-0.88***	-0.87***	-0.98***	-0.98***	-0.91***	-0.91***	-0.75***	-0.75***
	(-5.18)	(-5.16)	(-5.64)	(-5.63)	(-5.24)	(-5.24)	(-4.60)	(-4.60)
Diversity Policy$_{-1}$ # Policy Feature	-0.01	-0.01	0.39***	0.39***	0.16	0.16	2.03***	2.03***
	(-0.07)	(-0.06)	(4.37)	(4.38)	(1.53)	(1.52)	(15.48)	(15.48)
Diversity Policy$_{-1}$ # Policy Feature 2					-0.33***	-0.34***		
					(-2.86)	(-2.89)		
log(Loan Amount)	x	x	x	x	x	x	x	x
LTV Bin FE	x	x	x	x	x	x	x	x
DTI Bin FE	x	x	x	x	x	x	x	x
Conforming Loan	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x
Income Ratio Percentile FE	x	x	x	x	x	x	x	x
Borrower Age Bin FE	x	x	x	x	x	x	x	x
Loan Type FE	x	x	x	x	x	x	x	x
Property Tract FE	x	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x	x	x
Dependent Var. Mean	72.08	72.08	72.08	72.08	72.08	72.08	72.08	72.08
R^2	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67
Obs.	2,263,662		2,263,662		2,263,662		2,263,662	

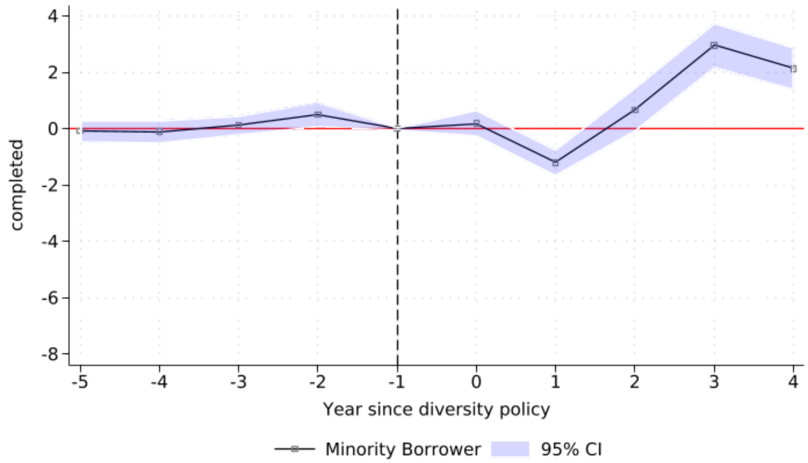
Figure 1 Share of Mortgage Lenders with a Diversity Policy



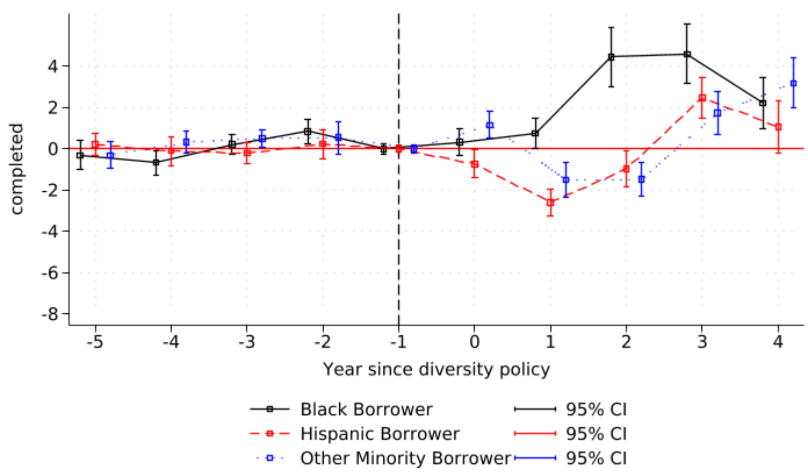
This figure plots the time trend of the proportion of the mortgage lenders in our sample which report having diversity policies, as identifiable from public documents, by year, for the period 2009 through 2021.

Figure 2 Event Study on Minority Borrowers' Application Completion Rate

Panel A Disparity between Minority and White Borrowers



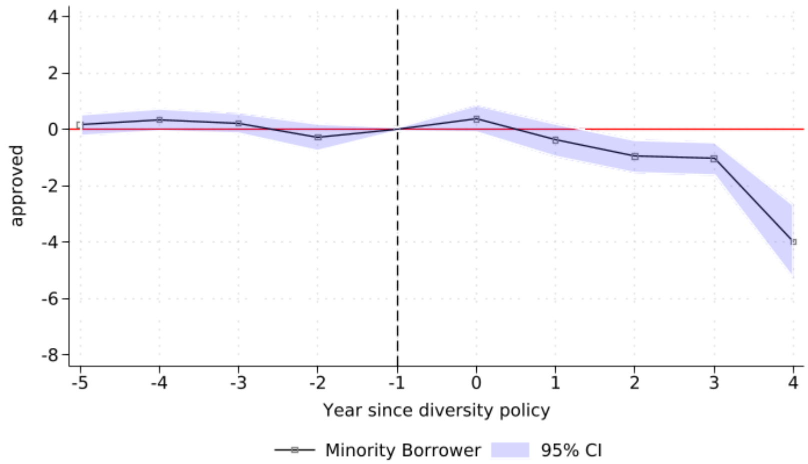
Panel B Disparity By Racial Groups



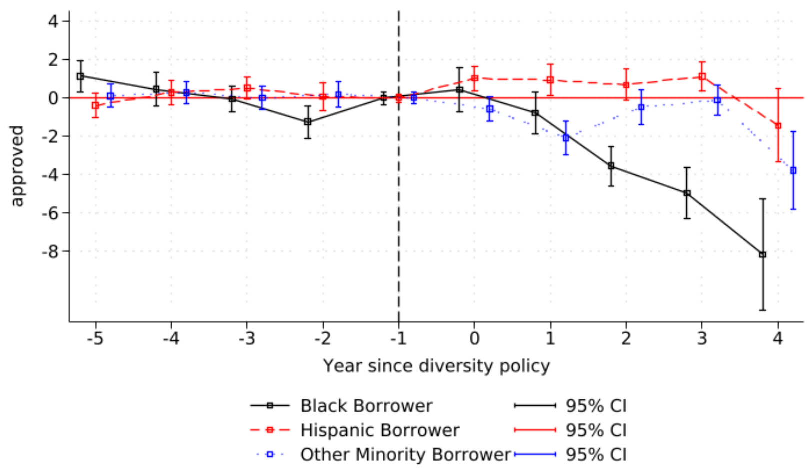
This figure plots the event study of the impact of the diversity policy on minority borrowers' probability of application completion. The observations are from the long panel HMDA data (2010-2021). The estimation applies the bias-corrected DID approach in Gardner (2021). The control variables include loan type fixed effects, income ratio percentile fixed effects, county fixed effects, lender fixed effects, and year fixed effects. The variables are defined in Table 1. The standard errors are clustered at the county level. The dots show the point estimates, and the shaded area indicates the 95% confidence interval.

Figure 3 Event Study on Minority Borrowers' Approval Rate

Panel A Disparity between Minority and White Borrowers



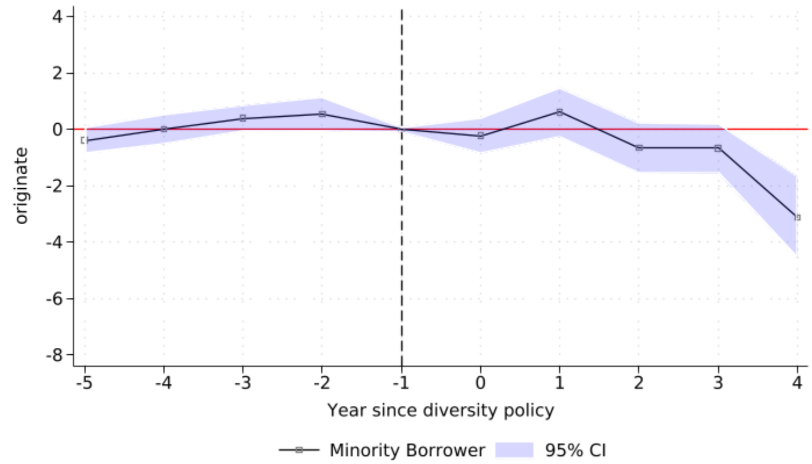
Panel B Disparity By Racial Groups



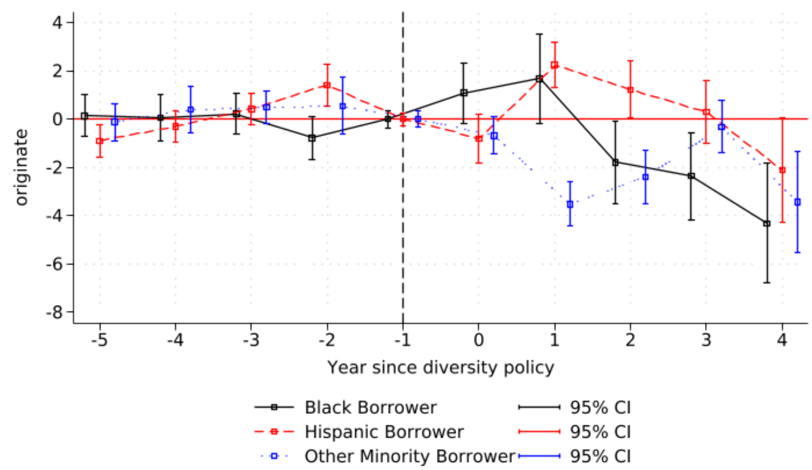
This figure plots the event study of the impact of the diversity policy on minority borrowers' probability of application approval. The observations are from the long panel HMDA data (2010-2021). The estimation applies the bias-corrected DID approach in Gardner (2021). The control variables include loan type fixed effects, income ratio percentile fixed effects, county fixed effects, lender fixed effects, and year fixed effects. The variables are defined in Table 1. The standard errors are clustered at the county level. The dots show the point estimates, and the shaded area indicates the 95% confidence interval.

Figure 4 Event Study on Minority Borrowers' Origination Rate

Panel A Disparity between Minority and White Borrowers

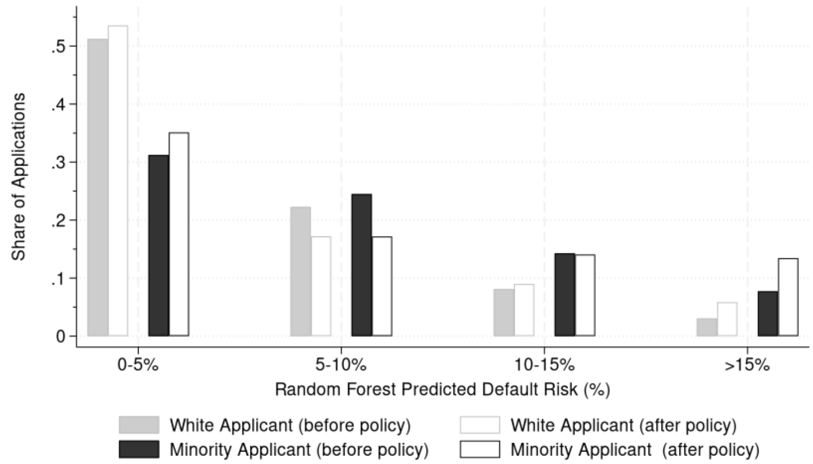


Panel B Disparity By Racial Groups



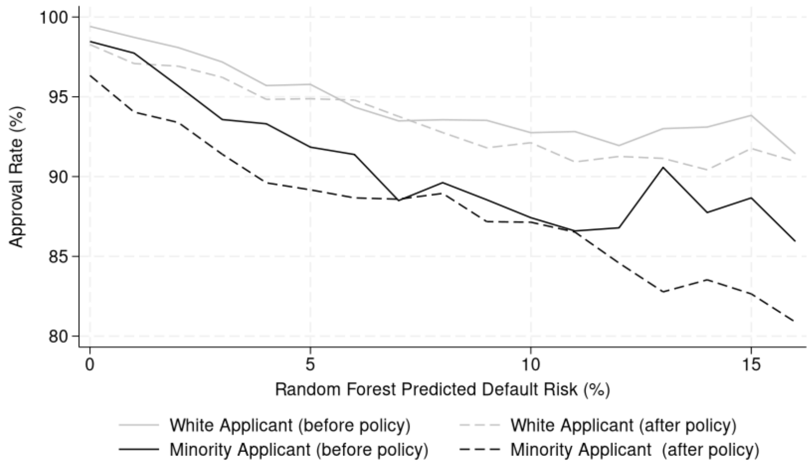
This figure plots the event study of the impact of the diversity policy on minority borrowers' probability of origination. The observations are from the long panel HMDA data (2010-2021). The estimation applies the bias-corrected DID approach in Gardner (2021). The control variables include loan type fixed effects, income ratio percentile fixed effects, county fixed effects, lender fixed effects, and year fixed effects. The variables are defined in Table 1. The standard errors are clustered at the county level. The dots show the point estimates, and the shaded area indicates the 95% confidence interval.

Figure 5 Applicant Default Risk Distribution by Race



This figure plots the distribution of predicted default risk for minority and White applicants prior to and after diversity policy adoption, for lenders that adopt policies during our sample period. The default risk is predicted by the random forest model using the observed characteristics in the data. The sample includes completed applications, as DTI and LTV are missing for incomplete applications. Figure A4 in the Online Appendix shows risk distributions of Black, Hispanic and other minority applications, respectively.

Figure 6 Approval Rate by Race and Default Risk



This figure plots the approval rates by predicted default risk for minority and White applications prior to and after diversity policy adoption, for lenders that adopt policies during our sample period. The default risk is predicted by the random forest model using the observed characteristics in the data. The sample includes completed applications, as DTI and LTV are missing for the incomplete applications. Figure A5 in the Online Appendix shows approval rates by predicted default risk for Black, Hispanic and other minority applications, respectively.

Appendix A: Examples of Mortgage Lenders' Diversity Policy Statements

Example 1: Cadence Bank 2021 Environmental Social & Governance Report - Diversity and Workforce Demographics Statement

SOCIAL CAPITAL | HUMAN CAPITAL | SUSTAINABILITY | CORPORATE GOVERNANCE | ENVIRONMENT | COVID-19 RESPONSE | DISASTER RELIEF

Diversity & Workforce Demographics

Our commitment to developing an inclusive culture led us to continue our partnership with the CEO Action For Diversity and Inclusion™, the largest CEO-driven business commitment to advance diversity and inclusion within the workplace.

Our efforts around building a more inclusive workplace culture are guided by our Diversity, Equity and Inclusion (DEI) strategy and dedicated resources headed by our Chief Diversity Officer. Cadence has a Corporate DEI Council (the Council) composed of a diverse cross-section of teammates across all levels of the organization. The Council serves as a powerful network of champions committed to building an inclusive workplace culture at Cadence. Recognizing that bias can significantly negatively impact teammates' sense of inclusion and belonging, our company has invested in educating our teammates on unconscious bias in the workplace and other related topics. Our commitment to DEI starts with our senior management and board of directors.

We are committed to fostering, cultivating and preserving a culture of DEI as a growth strategy for our company and as a celebration of the uniqueness of our teammates' professional talents and individual experiences. As part of this celebration, we launched a "Lift Every Voice" series, which gives teammates the opportunity to share their personal stories and lived experiences as a way to foster community and create a sense of belonging for all teammates. In addition, we introduced "Courageous Conversations" to promote open dialog around tough conversations, helping teammates better understand diverse perspectives and inspiring allyship. Cadence also provided a new holiday during 2021 in recognition of Juneteenth and other important cultural events.

All teammates are expected to create a collaborative and inclusive environment that encourages teammate engagement and establishes our company as a diverse and productive member of the communities we serve. This means we do not differentiate in how we serve customers, their needs, the products we offer, or the people we recruit, hire, retain or promote based upon any protected status, including gender, race, religion, veteran status, sexual orientation, gender identity, socio-economic status, political affiliation, ethnic origin or disability. This also applies to our third-party vendor relationships with which our company does business. We are committed to our DEI strategy for vendor and supplier procurement, and we hired a dedicated Supplier Diversity Manager to further develop these important initiatives. We further implemented a DEI dashboard to monitor and track key metrics for supplier diversity and representation, and to guide program development.

Our mission is to have our company be a reflection of the communities and the people it serves. We believe our teammates are our most valuable asset. The collective sum of the individual differences, life experiences, knowledge, inventiveness, innovation of thought, self-expression, workforce engagement, unique capabilities and talent that our teammates invest in their work represents a significant part of not only our culture, but our reputation and our company's achievements as well. Our DEI efforts provide initiatives and perspectives that promote improved products and services for our customers and increased value for our shareholders.

(continued)

All teammates are expected to exhibit conduct that reflects inclusion during work, at work functions on or off the worksite, and all other company-sponsored and participative events. All teammates must also attend and complete annual diversity awareness training to enhance their knowledge to fulfill this responsibility. We work to build a culture that is diverse, inclusive and free of discrimination or harassment.

Cadence is intentional about having its workforce reflect the diversity of the communities it serves. To that end, we actively recruit prospective teammates from diverse sources, including Historically Black Colleges and Universities (i.e., HBCUs), understanding that a diverse workforce is, among other things, an essential driver of revenue generation and increased shareholder value. In addition, we created a hiring toolkit, providing hiring managers with equitable interview standards to facilitate an interview process that aligns with our intent to be an inclusive organization and to create an equivalent interview experience that mitigates as much bias as possible. Likewise, we added questions pertaining to DEI to our exit interviews in order to measure the impact of our DEI efforts and to gauge employee experience during tenure that is measured by a net performance score.

> Our mission is to have our company be a reflection of the communities and the people it serves. We believe our teammates are our most valuable asset.

Cadence recognizes the importance of having its board and management reflect the diversity of its teammates and communities. Under-represented groups (women and minorities) make up 44% and 20% of our continuing directors and executive management team, respectively.

Example 2: Associated Bank 2021 Environmental Social & Governance Report – DE&I Approach

DE&I Approach

REFINING OUR FOCUS

Events of the past few years have reinforced that we must accelerate our efforts with respect to DE&I programming. In 2021, we evolved our approach through the elevation of our strategy, new engagement opportunities and advocacy initiatives.

Included in these initiatives are the established specific, executive-level goals, primarily focused on attracting, developing and advancing talent that reflects the diversity of our customers and the communities we serve.

In support of these goals, Associated has established DE&I Champions within each line of business in 2022. As liaisons to DE&I leadership, these individuals will help establish and set strategies in support of line of business goals and objectives. They will also create strategies to promote and encourage engagement in line of business and companywide DE&I programs.

Tracked Line of Business Workforce Diversity Metrics

POPULATION METRICS

- People of color population and population change
- People of color in senior vice president or higher roles
- Women in senior vice president or higher roles
- LGBTQ+ population
- People with disabilities

HIRING METRICS

- Women in candidate slate
- People of color in candidate slate
- Protected veteran new hires

2021 DE&I Select Actions	
Strategy Elevation	• Established executive-level DE&I goals for each business line and support area • Elevated Director of DE&I to report directly to an executive officer • Conducted periodic DE&I town hall-style meetings
DE&I Engagement	• Increased community engagement to drive brand awareness and build colleague recruitment pipeline • Increased colleague engagement through series of Courageous Conversation events • Established Black Colleague Resource Group to promote the hiring, retention, advancement and development of Black and African American talent at Associated and to better represent and support our communities
DE&I Advocacy	• Created unique learning opportunities for colleagues to increase cultural competencies • Expanded demographic tracking to inform and support program relevancy • Showcased Associated's commitment to DE&I and promoted public advocacy through the sponsorship of external programs and events, and greater social media engagement

Appendix B: Diversity Policy Data Verification, Collection, and Coding Process

We obtain proprietary data on lenders' diversity policies from Refinitiv, a subsidiary of Thomson Reuters. Refinitiv collects data on companies' ESG performance along a variety of dimensions. One can think of Refinitiv's data as forming a pyramid, in which components at the lower levels are inputs into the higher-level more aggregated ratings. Our measure is based on lower-level detailed data, which we verify through hand collection.

At the highest level, Refinitiv provides an overall ESG rating, as used in Basu et al. (2022). While Refinitiv's rating methodology is proprietary, Refiniv provides a breakdown of different components which go into the overall measure. At the next level, Refinitiv provides ratings of several components, including a diversity and inclusion (D&I) rating. Refinitiv's D&I rating captures firms' performance across four dimensions, which they call pillars: diversity, inclusion, people development, and controversies.

Underlying the first diversity pillar, which is most strongly related to our intended research question, are measures in the following eight dimensions: (1) Board Diversity (2) Diversity Policy (3) Diversity Target (4) Women Employees (5) New Women Employees (6) Women Managers (7) Female Board (8) Board Gender Diversity. We focus on item (2), Diversity Policy. The Diversity Policy measure takes a value of "True" if the lender has a policy, program, or practice, to promote diversity, and a value of "False" if not.

B.1. Manual Verification of Source Data

Based on discussions with Refinitiv representatives and data scientists, we learn that Refinitiv identifies firms' diversity policies using a wide range of publicly available sources, including: (1) non-financial/CSR reports; (2) annual reports or Form 10-K; (3) company websites and circulars; (4) registration reports; (5) integrated reports (financial and non-financial); (6) financial statements; (7) reference documents; (8) GRI reports; (9) DEF 14A proxy statements; (10) Form 20-F; (11) audit committee charters/terms of reference; (12) notices of annual meetings; (13) bylaws; (14) constitutions; (15) corporate governance guidelines; (16) corporate governance reports; (17) codes of conduct; and (18) CDP (Carbon Disclosure Project) reports posted on company websites. Because such disclosures are far more common among publicly traded mortgage lenders, who face higher reporting requirements and investor scrutiny, our analysis focuses on lenders that are publicly listed or have a publicly traded parent.

For lenders identified as having diversity policies, we obtain information on Refinitiv's source and the specific content of the policy, as well as URLs to the source information, from Refinitiv. We access each URL to confirm its validity and to ascertain whether it is directed to content pertinent to the lenders' diversity policies. Approximately 50% of the source file URLs were inactive at the time of our verification process, predominantly due to changes in web pages over time. In instances of inactive URLs, we attempted to locate the most current links that would lead to the original source documents by searching for the titles of the source documents and the content of the policies. If we were still unable to find the original source document, we expanded to broadly search for any information that would indicate the existence of a diversity policy. Specifically, we searched lenders' (1) historical ESG or Corporate Social Responsibility (CSR) reports, (2) annual reports, (3) codes of conduct or employee handbooks, and (4) archived web pages.

Through these manual searches, we successfully identified at least one source of diversity policy information for approximately 85% of the lender year observations that Refinitiv had coded as having a diversity policy. Given that many of the policies we were attempting to verify were over a decade old (e.g., from 2010), this verification rate indicates a high level of accuracy for the diversity policy indicators provided by Refinitiv.

B.2. Coding Core Dimensions of Diversity Policies

To better understand lender diversity policies, we also hand collect and code characteristics of diversity policies. As mentioned in Section I.B., we focus on the following four key dimensions: (1) diversity training, (2) diversity target, (3) designated diversity leadership and oversight, and (4) customer diversity efforts.

Specifically, we measure diversity training as a dummy variable equal to 1 if the firm's policy disclosure includes structured programs – such as mandatory workshops, e-learning modules, or facilitated discussions – designed to raise employee awareness of bias, promote inclusive behaviors, and build cultural competence.

We measure diversity targets and commitments as a dummy variable equal to 1 if the policy explicitly mentions any quantitative or qualitative future targets or commitments aimed at improving diversity.

We use two separate indicators to capture designated diversity leadership and oversight. The first indicator, Chief Diversity Officer (CDO), equals 1 if the individual responsible for diversity initiatives is part of upper management, and 0 otherwise. The second indicator, diversity committee or task force (DEO), equals 1 if the firm identifies a specific person or group in charge of overseeing diversity efforts. Both indicators represent formal governance structures, with the former emphasizing senior executive accountability and the latter capturing broader organizational oversight.

Finally, we measure customer diversity efforts as a dummy variable which equals 1 if the firm discloses specific actions or commitments to promote mortgage lending specifically targeting minorities and women. This includes quantitative lending targets or detailed strategies to expand capital access for these groups.

We provide illustrative examples regarding these four dimensions in Table B1.

Table B1 Examples of Core Dimensions of Diversity Policy Disclosures

Core Policy Dimension	Code	Example
Diversity Training	1	To ensure all Huntington colleagues are able to identify the value of, and exhibit, behaviors that drive diversity, equity, and inclusion, we offer year-round training. In 2020, our colleagues collectively completed more than 14,000 hours of DEI training. The following educational sessions and resources help shape our shared understanding of DEI at Huntington (Source: HBAN 2020 Diversity Policy Disclosure).
Diversity Target	1	OBJECTIVES FOR 2020 AND BEYOND: At least 50% of annual hires to PNC's early career development program to be made up of diverse candidates (Source: PNC 2020 Diversity Policy Disclosure).
Designated Diversity Leadership and Oversight	1	Who has responsibility: BMO's Chief Inclusion Officer (CIO) sets the strategic priorities in partnership with BMO's Leadership Committee for Inclusion and Diversity (LCID), which comprises 25 of the Bank's most senior executives. (Source: BMO 2018 Diversity Policy Disclosure).
Customer Diversity Efforts	1	This effort includes a mix of tools, information, and opportunities, all designed to remove barriers and expand access to homeownership, and support efforts to build stronger communities. Advancing Homeownership includes 10-year commitments to provide \$125 billion in home purchase loans for Hispanic homebuyers and \$60 billion in loans for Black and African American homebuyers. In addition, we've made a commitment to provide a total of \$25 million in funding for homebuyer education and counseling programs in support of these efforts. (Source: WFC 2020 Diversity Policy Disclosure).

Appendix C: Additional Tables

Table C1 The Effect of Diversity Policy on the Volume of Applications and Originations

This table reports regression results for total volume of mortgage applications and originations. The observations are from HMDA data (2018-2021). The mortgage applications and originations are aggregated to the lender-year level. *t*-stats are shown in parentheses. *, **, *** indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

Panel A Total Applications

	Log(# of Applications)				
	All	White	Black	Hispanic	Other Minority
	(1)	(2)	(3)	(4)	(5)
Diversity $Policy_{-1}$	0.17	0.18	0.22*	0.42**	0.15
	(1.46)	(1.61)	(1.90)	(2.06)	(1.15)
Year FE	x	x	x	x	x
Lender FE	x	x	x	x	x
R^2	0.96	0.97	0.98	0.95	0.97
Obs.	144	144	144	144	144

Panel B Completed Applications

	Log(# of Completed Applications)				
	All	White	Black	Hispanic	Other Minority
	(1)	(2)	(3)	(4)	(5)
Diversity $Policy_{-1}$	0.20	0.21*	0.26**	0.50**	0.19
	(1.63)	(1.76)	(2.06)	(2.26)	(1.40)
Year FE	x	x	x	x	x
Lender FE	x	x	x	x	x
R^2	0.96	0.96	0.98	0.95	0.97
Obs.	144	144	144	144	144

Panel C Originated Mortgages

	Log(# of Originations)				
	All	White	Black	Hispanic	Other Minority
	(1)	(2)	(3)	(4)	(5)
Diversity $Policy_{-1}$	0.14	0.16	0.16	0.32	0.10
	(1.09)	(1.28)	(1.38)	(1.52)	(0.71)
Year FE	x	x	x	x	x
Lender FE	x	x	x	x	x
R^2	0.95	0.96	0.97	0.94	0.97
Obs.	144	144	144	144	144

Table C2 First Stage Regressions for the Shareholder Diversity Initiative IV

This table reports regression results for the first stage regressions for the 2014-shareholder diversity initiative and its interactions with races. Panel A, B and C report the first stage results for the completion, approval and origination, respectively. The observations are from the short panel HMDA data (2018-2021). The variables are defined in Table 1. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. ∗, ∗∗, ∗∗∗ indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

Panel A: First stage for Completion Regression

	Diversity Policy$_{-1}$ (1)	Black # Diversity Policy$_{-1}$ (2)	Hispanic # Diversity Policy$_{-1}$ (3)	Other Minority # Diversity Policy$_{-1}$ (4)
Shareholder Diversity Iniative$_{-2}$	0.64***	-0.04***	-0.07***	-0.02***
	(18.75)	(-5.69)	(-6.34)	(-7.48)
Black # Shareholder Diversity Iniative$_{-2}$	-0.00	0.96***	0.00	-0.00
	(-0.34)	(86.31)	(0.13)	(-0.06)
Hispanic # Shareholder Diversity Iniative$_{-2}$	0.02***	-0.00*	0.98***	-0.00**
	(3.95)	(-1.91)	(187.14)	(-1.96)
Other Minority # Shareholder Diversity Iniative$_{-2}$	0.01***	-0.00***	-0.00	0.98***
	(3.24)	(-2.87)	(-1.11)	(180.73)
log(Loan Amount)	x	x	x	x
LTV Bin FE				
DTI Bin FE				
Conforming Loan	x	x	x	x
Joint Application	x	x	x	x
Income Ratio Percentile FE	x	x	x	x
Borrower Age Bin FE	x	x	x	x
Loan Type FE	x	x	x	x
Property Tract FE	x	x	x	x
Year FE	x	x	x	x
Lender*Race FE	x	x	x	x
First Stage: Kleibergen-Paap rk F			88.77	
First Stage: Anderson-Rubin p-val			0	
Obs.	495,741	495,741	495,741	495,741

Panel B: First stage for Approval Regression

	Diversity Policy$_{-1}$ (1)	Black # Diversity Policy$_{-1}$ (2)	Hispanic # Diversity Policy$_{-1}$ (3)	Other Minority # Diversity Policy$_{-1}$ (4)
Shareholder Diversity Iniative$_{-2}$	0.65***	-0.03***	-0.07***	-0.02***
	(19.51)	(-5.44)	(-6.35)	(-7.39)
Black # Shareholder Diversity Iniative$_{-2}$	0.00	0.97***	0.00	0.00
	(0.75)	(111.74)	(1.04)	(1.02)
Hispanic # Shareholder Diversity Iniative$_{-2}$	0.02***	-0.00	0.99***	-0.00
	(4.17)	(-1.30)	(234.74)	(-1.45)
Other Minority # Shareholder Diversity Iniative$_{-2}$	0.01***	-0.00***	-0.00	0.99***
	(3.11)	(2.65)	(-1.02)	(228.59)
log(Loan Amount)	x	x	x	x
LTV Bin FE	x	x	x	x
DTI Bin FE	x	x	x	x
Conforming Loan	x	x	x	x
Joint Application	x	x	x	x
Income Ratio Percentile FE	x	x	x	x
Borrower Age Bin FE	x	x	x	x
Loan Type FE	x	x	x	x
Property Tract FE	x	x	x	x
Year FE	x	x	x	x
Lender*Race FE	x	x	x	x
First Stage: Kleibergen-Paap rk F			96.82	
First Stage: Anderson-Rubin p-val			0	
Obs.	412,495	412,495	412,495	412,495

Panel C: First stage for Origination Regression

	Diversity Policy$_{-1}$ (1)	Black # Diversity Policy$_{-1}$ (2)	Hispanic # Diversity Policy$_{-1}$ (3)	Other Minority # Diversity Policy$_{-1}$ (4)
Shareholder Diversity Iniative$_{-2}$	0.64***	-0.04***	-0.07***	-0.02***
	(18.75)	(-5.69)	(-6.34)	(-7.48)
Black # Shareholder Diversity Iniative$_{-2}$	-0.00	0.96***	0.00	-0.00
	(-0.34)	(86.31)	(0.13)	(-0.06)
Hispanic # Shareholder Diversity Iniative$_{-2}$	0.02***	-0.00*	0.98***	-0.00**
	(3.95)	(1.91)	(187.14)	(-1.96)
Other Minority # Shareholder Diversity Iniative$_{-2}$	0.01***	-0.00***	-0.00**	0.98***
	(3.24)	(-2.87)	(-1.11)	(180.73)
log(Loan Amount)	x	x	x	x
LTV Bin FE	x	x	x	x
DTI Bin FE	x	x	x	x
Conforming Loan	x	x	x	x
Joint Application	x	x	x	x
Income Ratio Percentile FE	x	x	x	x
Borrower Age Bin FE	x	x	x	x
Loan Type FE	x	x	x	x
Property Tract FE	x	x	x	x
Year FE	x	x	x	x
Lender*Race FE	x	x	x	x
First Stage: Kleibergen-Paap rk F			88.77	
First Stage: Anderson-Rubin p-val			0	
Obs.	495,741	495,741	495,741	495,741

Table C3 Robustness: The Effect of Diversity Policy on Lending Outcomes If Dropping Post-2020 Policy Adoption

This table reports regression results for mortgage lending outcomes from estimating Equation (1). The observations are from the short panel HMDA data (2018-2021). The variables are defined in Table 1. Different from Table 3, we drop the two lenders that adopt diversity policies during the COVID period (2020 and 2021). The standard errors are clustered at the county level. *t*-stats are shown in parentheses. *, **, *** indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

	Completion (in %)			Approval (Given Completed, in %)			Origination (in %)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Black Borrower # Diversity Policy$_{-1}$	1.79***	1.80***		-5.34***	-3.07***		-3.93***	-2.65***	
	(3.77)	(2.97)		(-14.95)	(-5.21)		(-12.71)	(-5.54)	
Hispanic Borrower # Diversity Policy$_{-1}$	0.06	0.02		-3.56***	-0.03		-2.64***	-0.04	
	(0.12)	(0.04)		(-8.68)	(-0.07)		(-7.19)	(-0.09)	
Other Minority Borrower # Diversity Policy$_{-1}$	0.30	0.59		-1.79***	-0.91**		-0.94***	-0.53	
	(0.53)	(0.93)		(-5.59)	(-2.33)		(-2.68)	(-1.37)	
Minority Borrower # Diversity Policy$_{-1}$			0.79**			-1.32***			-1.10***
			(2.09)			(-3.75)			(-3.71)
Diversity Policy$_{-1}$	3.00***	2.97***	2.97***	0.25	-0.66***	-0.66***	-0.20	-0.81***	-0.81***
	(11.24)	(11.26)	(11.25)	(1.18)	(-4.00)	(-3.99)	(-1.04)	(-4.73)	(-4.72)
Black Borrower	-3.45***			0.36			-0.39		
	(-7.45)			(1.03)			(-1.31)		
Hispanic Borrower	-1.60***			0.63*			0.12		
	(-3.38)			(1.76)			(0.39)		
Other Minority Borrower	-4.47***			-0.81***			-1.36***		
	(-7.84)			(-2.71)			(-4.22)		
log(Loan Amount)	x	x	x	x	x	x	x	x	x
LTV Bin FE				x	x	x	x	x	x
DTI Bin FE				x	x	x	x	x	x
Conforming Loan	x	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x	x
Income Ratio Percentile FE	x	x	x	x	x	x	x	x	x
Borrower Age Bin FE	x	x	x	x	x	x	x	x	x
Loan Type FE	x	x	x	x	x	x	x	x	x
Property Tract FE	x	x	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x	x	x
Lender FE	x			x			x		
Lender*Race FE		x	x		x	x		x	x
Dependent Var. Mean	82.30	82.30	82.30	89.29	89.29	89.29	71.81	71.81	71.81
R^2	0.05	0.05	0.05	0.32	0.32	0.32	0.67	0.67	0.67
Obs.	2,148,819	2,148,818	2,148,818	1,767,285	1,767,284	1,767,284	2,148,819	2,148,818	2,148,818

Mortgage Lenders’ Diversity Policies and Mortgage Lending to Minorities

Online Appendix

I. The Overall Volume of Mortgage Applications and Originations

In this section, we examine the impact of diversity policies on the total volume of mortgage applications and originations, as summarized in Table C1 of the main paper. For this analysis, we aggregate mortgage applications and originations (of different racial groups) at the lender-year level. Although this aggregation reduces the number of observations and, consequently, the statistical power of the tests, it still reveals clear and meaningful patterns.

In Panel A of Table C1 we find that lenders receive significantly more applications from minority borrowers, particularly Black and Hispanic applicants, after adopting diversity policies. This increase may reflect a shift in market strategies or a growing preference among minority groups to engage with these lenders.

Panel B of Table C1 shows an increase in volumes of completed applications from minority borrowers, particularly Black and Hispanic applicants, at lenders adopting diversity policies. In particular, the growth in completed applications from minority borrowers exceeds the overall growth in total applications. This finding is consistent with the improved completion rates for minority applications documented in the main analysis, suggesting that diversity policies enhance the likelihood of minority applicants completing the application process.

Panel C examines the total volume of originations and reports a positive but statistically insignificant increase in the volume of mortgages originated. This result is consistent with the reduced approval and origination rates for minority applications documented in the main analysis, highlighting that while diversity policies encourage more applications, they do not translate to a significant increase in actual loan origination volumes.

II. Random Forest Model - Predicting Mortgage Default Risk

We assess the riskiness of mortgage applications by predicting default risk using a random forest model. The random forest model offers several advantages over linear regression models when predicting mortgage default due to its ability to capture complex, non-linear relationships. Mortgage default prediction often involves interactions between variables such as loan-to-value (LTV) ratio and income, which may not have a simple linear relationship. The random forest model can naturally model these complex interactions. Additionally, the random forest model is more robust to outliers and noise in the dataset, making it better suited for handling the variability in mortgage data. More importantly, the model's use of ensemble methods (aggregating multiple decision trees) helps reduce the risk of overfitting and provides better generalization to unseen data.

II.1 Default Model Estimation

We apply the random forest model to the full set of completed mortgage applications, encompassing both approved and rejected applications. The data is split into two groups: government-backed mortgages and conventional mortgages. Given the distinct risk profiles of applications and the unique underwriting standards of each category, we estimate the model separately for each subsample.

We use the following covariates as predicting features: loan amount, combined loan-to-value (LTV) ratio, year, debt-to-income (DTI) ratio, count, income, income ratio percentile, loan type. We do not use information, such as FICO scores, that is unavailable for the out of sample loans for which we need to predict default probability. This allows us to build a model that can more effectively predict default probability using only the available information.

We first estimate the model using originated mortgages that are matched with the public GSE performance data, so we can use the observed default performance to make the estimation. To mitigate (in-sample) overfitting issues, we follow a five-fold cross-validation process by equally splitting the dataset into five subsets. In each estimation iteration (out of five iterations), the random forest model is trained using four folds of the data, while the remaining fold is used for validation (testing). This process is repeated five times, with each fold used exactly once as the validation fold. Specifically, in the first iteration, the model trains on folds 1 to 4 and is validated on fold 5. In the second iteration, the model trains on folds 1, 2, 3, and 5, and is validated on fold 4, and so on, until each fold has served as the validation fold. This is a robust technique for estimating the model's performance by reducing the risk of overfitting and ensuring the results generalize well to unseen data.

II.2 Hyperparameter Tuning

One crucial hyperparameter that we have to calibrate to improve the performance of the model is the minimum leaf size, which refers to the smallest number of data points allowed in a leaf (terminal node) of a decision tree. It controls the complexity of the trees, where smaller leaf sizes lead to deeper, more detailed trees capable of capturing fine-grained patterns in the data. This can reduce bias but increases variance, as the model becomes more prone to overfitting and sensitive to noise in the training data. Larger leaf sizes, on the other hand, produce simpler trees that generalize better by reducing variance but may introduce bias by missing subtle patterns. Tuning the minimum leaf size is critical for balancing the bias-variance tradeoff and optimizing the model's performance.

Figure S1 shows the result of hyperparameter tuning for the minimum leaf size hyperparameter. Extremely low minimum leaf sizes tend to result in extreme overfitting, while even slightly larger leaf sizes perform much better. The out-of-sample R^2 stabilizes for a choice of minimum leaf size above 15. Therefore, we set the minimum leaf size of our model to be 15.

II.3 Model Fit

The random forest model fits the data well, achieving an out-of-sample R^2 of 5.16%, which is approximately 1.5 times higher than that of a linear regression model using the same set of controls. This result suggests that the random forest model effectively captures nonlinear relationships and interactions, thereby making better use of the limited borrower information available.

Because the model-predicted credit risk is going to be used as an input into additional regression exercises, it is important to verify that the model-predicted default probabilities closely track realized default rates. This is in some sense more important than a high R^2. Since we do not believe that lenders can perfectly predict which loans will be delinquent, it is more important to have a measure that represents their expectation of likely default probability. Figure S2 shows the relationship between the model predicted default probability and realized default outcomes for the observations where default outcomes are known. Realized default rates closely track the model predicted probabilities, suggesting that the constructed measure of credit risk is a reasonable one.

I.4 Random Forest Model Predicted Default Risk

We use the estimated random forest model to predict default risk for all completed mortgage applications in our dataset, including both approved and denied cases. To mitigate overfitting, all predictions are generated out of sample via five-fold cross-validation. Specifically, for applications within the estimation sample, where ex post default outcomes are observed, we train the random forest on the four folds that exclude the observation's fold and then predict on the held-out fold. For applications outside the estimation sample (e.g., denied loans), we obtain predictions by averaging the outputs from the five random forest models (one from each fold-exclusion), as these observations not used in training.

Figure S3 presents the distribution of predicted default risks for mortgage applications across different racial groups. The analysis is restricted to completed applications, as key variables like debt-to-income (DTI) and loan-to-value (LTV) ratios are unavailable for incomplete applications. Gray bars represent White applicants, black bars represent Black applicants, navy bars represent Hispanic applicants, and red bars represent other minority applicants. The figure reveals distinct differences in the distribution of predicted default risks among racial groups. Specifically, minority applicants – particularly Black and Hispanic individuals – exhibit significantly higher predicted default risks compared to White applicants, as shown by the fatter tails in their respective distributions. These patterns align with broader societal and economic perceptions, where minority groups often face higher financial vulnerabilities and access to credit.

The random forest model helps identify the most relevant dimensions of an application's risk profile, effectively focusing on key factors that contribute to default risk. By reducing the dimensionality of the data, the model simplifies the analysis, enabling us to conduct and visualize the results in a more straightforward and comprehensible manner.

III. The Effect of Diversity Policy on Home Equity and Cash-out Refinance Loans

III.1 Home Equity Loans

To investigate whether the stigma effect of diversity policies extends to other mortgage product markets, we replicate our main analysis using home equity loan products.

Our initial step involves examining home equity loan applications reported in HMDA from 2018 to 2021. To ensure the analysis is comparable to the main analysis on purchase mortgages, we restrict the sample to residential, single-family, non-reverse home equity loan applications. Additionally, we exclude applications for home equity loans with interest-only or other non-amortizing features, as these products may differ significantly in risk profile and structure. As in the main analysis, we retain only those applications that were directly submitted to lenders, to capture the direct impact of lender diversity policies on application outcomes in the context of home equity loans.

In this analysis, we include mortgage applications with the full range of loan terms, as there is no dominant choice among borrowers. Additionally, we retain applications for loans collateralized by non-owner-occupied properties and those pledged with a second lien. To account for these heterogeneities, we control for loan term (in 5-year bins), occupancy type, and lien type using fixed effects in the regression analysis.

Table S1 provides a summary of the characteristics of home equity loan applications. In general, the loan sizes are much smaller compared to purchase mortgages. Applicants for home equity loans tend to be wealthier and older, with a median loan term of 15 years. Additionally, 38% of these loans are secured as second liens. Notably, the approval rate for home equity loans is significantly lower than that of purchase mortgages, with nearly half of the applications being rejected. This highlights the riskier nature of home equity loan products and the greater discretion lenders have in deciding whether to approve these applications.

Table S2 presents our estimation of the effect of diversity policies on lending outcomes for home equity loans. In addition to including fixed effects for loan term (in 5-year bins), occupancy type, and lien type, one key difference from the main analysis in Table 3 is that we are limited to controlling for lender fixed effects rather than lender-race fixed effects. This limitation arises because lenders adopting diversity policies during the sample period hold a very small share of the home equity loan market, particularly among minority applicants. As a result, incorporating lender-race fixed effects would nearly absorb all the variation in the independent variables, leaving little scope for meaningful estimation. Consequently, we rely on a less flexible regression specification to ensure the analysis remains feasible and interpretable.

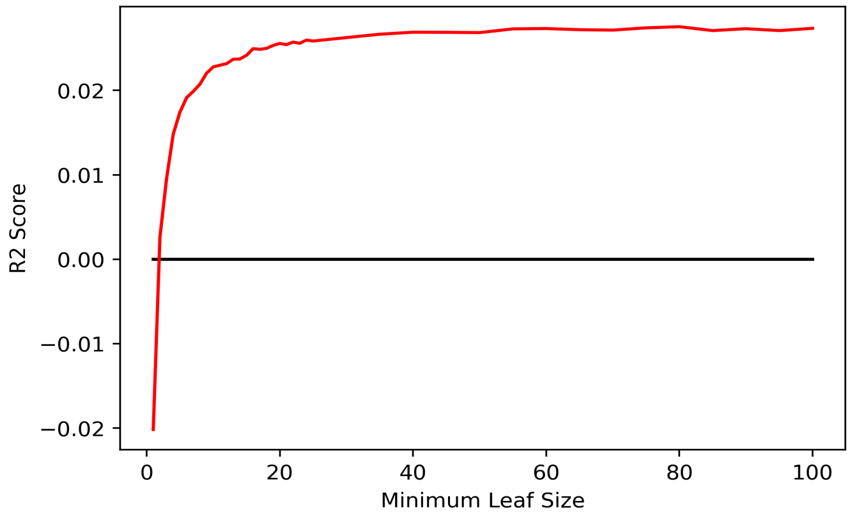
Consistent with the findings from the purchase mortgage analysis, lenders' diversity policies appear to reduce racial disparities at the application completion stage. However, these policies exacerbate racial disparities at the approval and origination stages, where minority applicants face greater disadvantages. Notably, the magnitude of this effect is approximately three times larger compared to the results observed in the purchase mortgage market, highlighting the pronounced impact of diversity policies on home equity loan outcomes.

III.2 Cash-out Refinances

Conklin, Gerardi, and Lambie-Hanson (2024) also examine two other forms of home equity credit: home equity lines of credit (HELOCs) and cash-out refinances. Our setting is not suitable for studying HELOCs, as the lenders adopting diversity policies during our sample period had only negligible applications for this credit product. However, we are able to analyze cash-out refinances. Using the same filters applied to home equity loans, we compile a sample of 1,382,415 cash-out refinance applications.

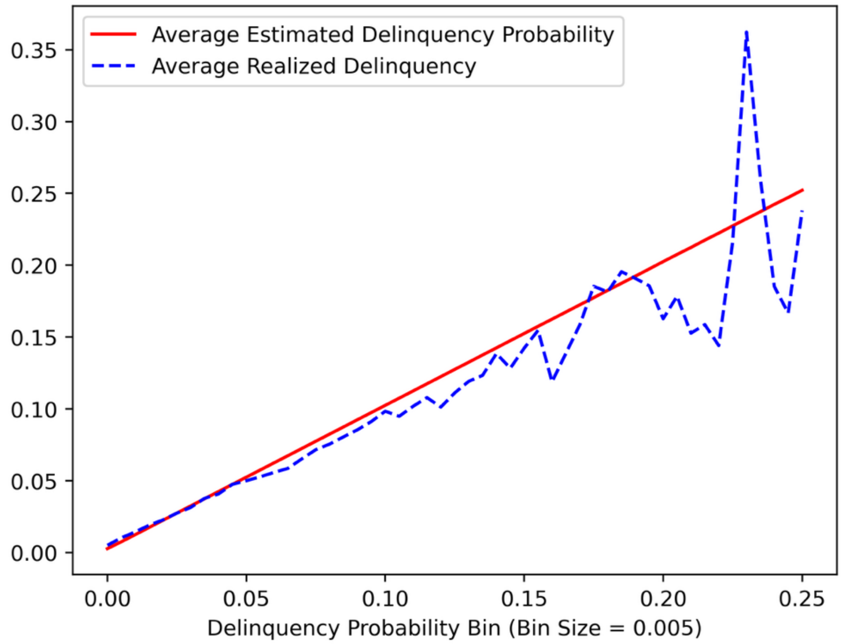
Table S3 summarizes the characteristics of these applications, and Table S4 presents the results of our estimation of the effect of diversity policies on lending outcomes for cash-out refinances. The findings are largely consistent with those for home equity loans, showing that lenders' diversity policies exacerbate racial disparities at the approval and origination stages. This alignment underscores the persistent challenges in achieving equity across various mortgage product markets.

Figure S1. Hyperparameter Tuning: Minimum Leaf Size



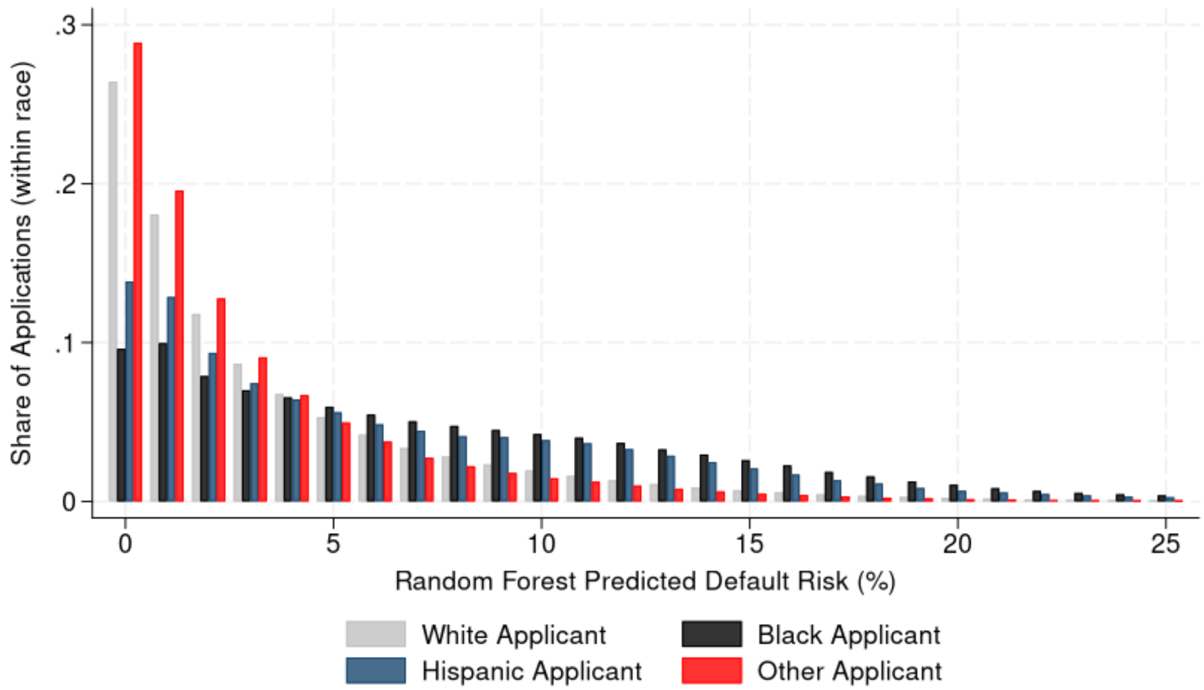
This figure illustrates the out-of-sample R^2 of the random forest model used to predict loan default across different minimum leaf size values. Each random forest consists of 500 trees. The R^2 represents the proportion of variation in realized mortgage defaults explained by the estimated random forest model within the estimation sample. The predicted default probability is calculated as the average output of the random forest models trained on the four folds excluding the fold containing the target mortgage.

Figure S2. Predicted vs. Actual Default Probabilities



This figure displays the predicted default probability plotted against the realized default rate, within the estimation sample. The x-axis represents predicted default probabilities grouped into bins of width 0.005, while the y-axis shows the corresponding fraction of delinquent loans in each bin, depicted in blue.

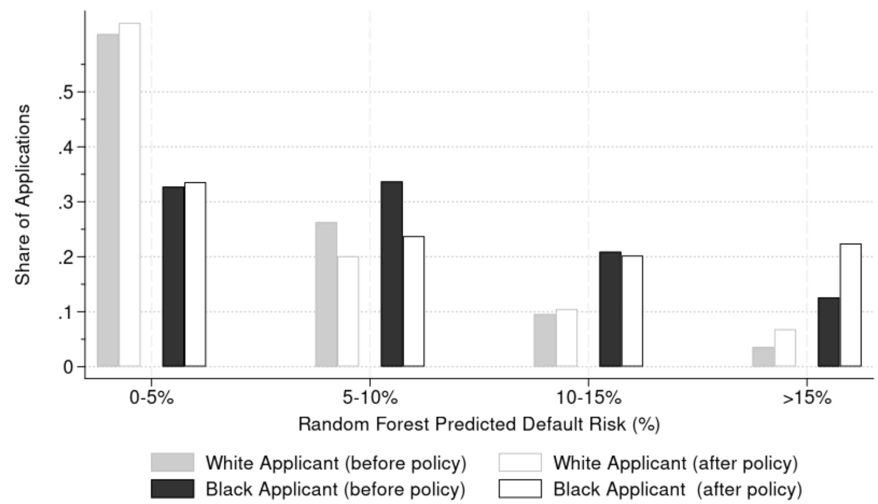
Figure S3 Distribution of Applicant Riskiness by Race



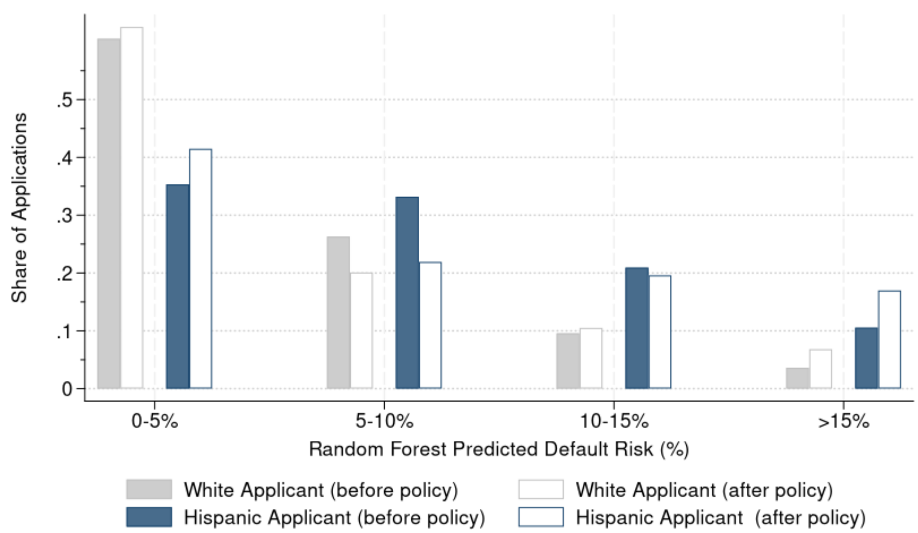
This figure shows the distributions of predicted default probabilities for applicants of different races. The default risk is predicted by the random forest model using the observed characteristics in the data. The sample includes completed applications, as DTI and LTV are missing for the incomplete applications. Default risk bins are set at 1% intervals, ranging from 0% to 25%, with risks above 25% truncated. Gray bars represent White applicants, black bars represent Black applicants, navy bars represent Hispanic applicants, and red bars represent other minority applicants.

Figure S4 Applicant Default Risk Distribution by Race (Hispanic and Other Minorites)

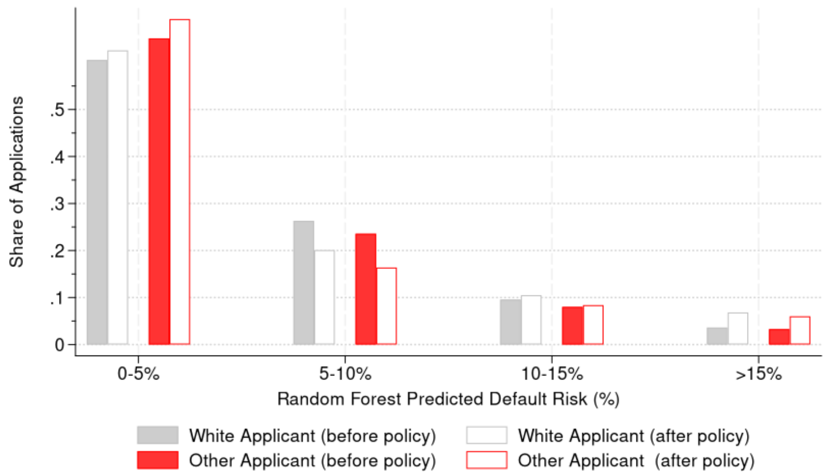
Panel A Mortgage Applicant Default Risk (White vs Black)



Panel B Mortgage Applicant Default Risk (White vs Hispanic)



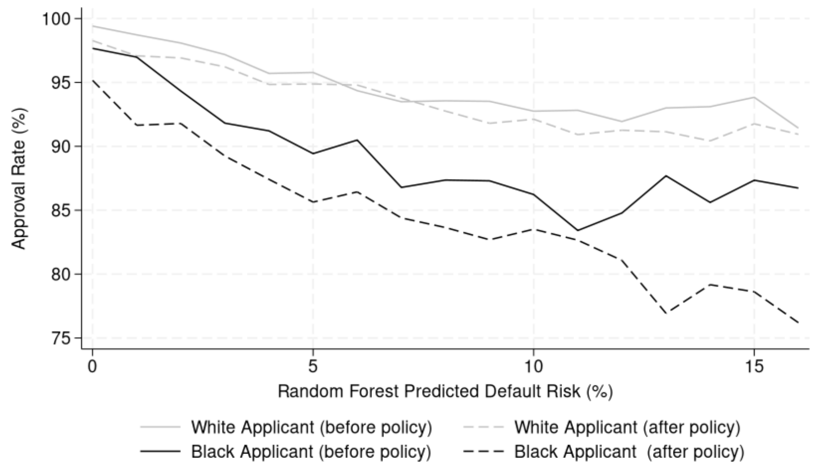
Panel C Mortgage Applicant Default Risk (White vs Other Minorities)



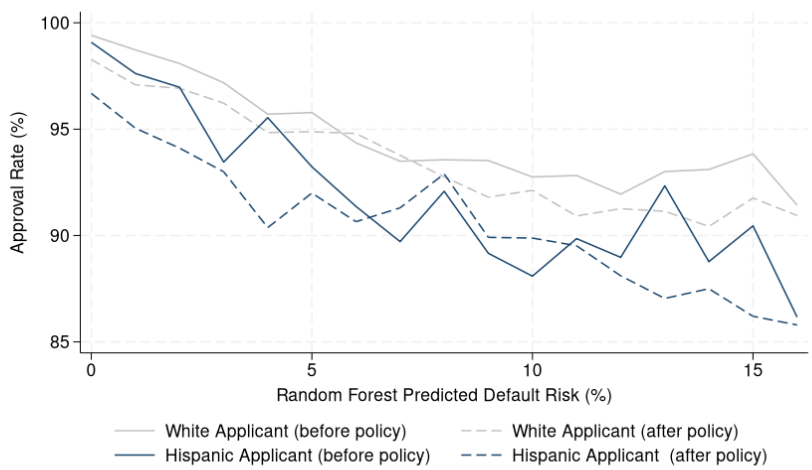
This figure displays the distribution of predicted default risk for Black, Hispanic, other minorities, and White applicants before and after the adoption of diversity policies by lenders within the sample period. Default risk is predicted using a random forest model based on observed applicant characteristics in the data. The sample includes only completed applications, as DTI and LTV data are missing for incomplete ones.

Figure S5 Approval Rate by Race and Default Risk (Hispanic and Other Minorites)

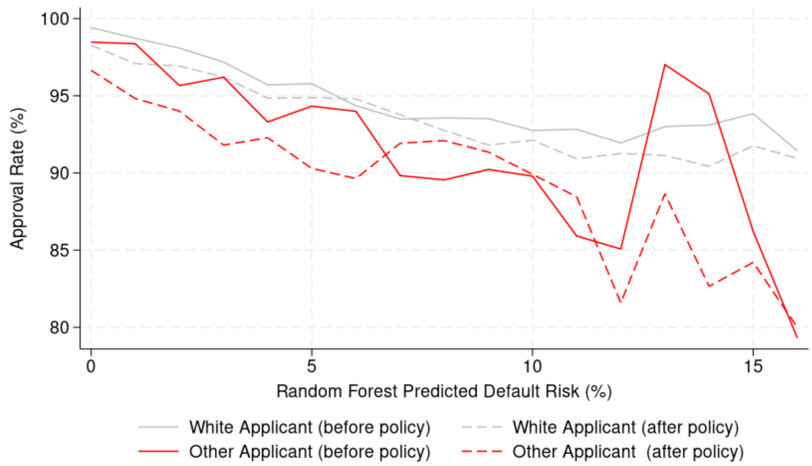
Panel A Application Approval Rate by Default Risk (White vs Black)



Panel B Application Approval Rate by Default Risk (White vs Hispanic)



Panel C Application Approval Rate by Default Risk (White vs Other Minorities)



This figure plots the approval rates by predicted default risk for Black, Hispanic, other minorities, and White applicants prior to and after diversity policy adoption, for lenders that adopt policies during our sample period. The default risk is predicted by the random forest model using the observed characteristics in the data. The sample includes completed applications, as DTI and LTV are missing for the incomplete applications.

Table S1 Summary Statistics of Home Equity Loan Applications

The table shows the summary statistics of the home equity loan applications used in Table S3.

	Mean	S.D.	P1	P25	P50	P75	P99	Obs.
Application and Performance Outcomes								
Completion	81.16	39.11	0	100	100	100	100	347,511
Approval (given completion)	50.45	50.00	0	0	100	100	100	282,028
Origination	38.32	48.62	0	0	0	100	100	347,511
Key Independent Variables								
Diversity Policy$_{-1}$	0.98	0.14	0	1	1	1	1	347,511
Minority Borrower	0.26	0.44	0	0	0	1	1	347,511
- Black Borrower	0.07	0.26	0	0	0	0	1	347,511
- Hispanic Borrower	0.11	0.31	0	0	0	0	1	347,511
- Other Minority Borrower	0.07	0.26	0	0	0	0	1	347,511
Borrower and Mortgage Characteristics								
Loan Amount ($K)	154.4	335.4	15	35	65	155	1,355	347,511
Income Ratio	1.99	14.74	0.00	0.74	1.20	1.93	13.61	347,511
Joint Application	0.40	0.49	0	0	0	1	1	347,511
Conforming Loan	0.96	0.20	0	1	1	1	1	347,511
Borrower Age - less than 25	0.01	0.09	0	0	0	0	0	347,511
Borrower Age - 25-34	0.10	0.30	0	0	0	0	1	347,511
Borrower Age - 35-44	0.20	0.40	0	0	0	0	1	347,511
Borrower Age - 45-54	0.24	0.43	0	0	0	0	1	347,511
Borrower Age - 55-64	0.24	0.43	0	0	0	0	1	347,511
Borrower Age - 65-74	0.15	0.36	0	0	0	0	1	347,511
Borrower Age - greater than 74	0.06	0.24	0	0	0	0	1	347,511
Loan Type - Conventional	0.98	0.13	0	1	1	1	1	347,511
Combined Loan-to-Value (%) (LTV)	58.8	25.0	3	10	15	30	30	250,907
Debt-to-Income (%) (DTI)	34.9	15.5	10	20	37	47	60	270,794
Loan term (in years)	18.42	8.80	639.0	726.0	763.0	790.0	817.0	863,996
Occupancy Type - Owner Occupied	0.91	0.29	0	1	1	1	1	347,511
Occupancy Type - Second Home	0.04	0.20	0	0	0	0	1	347,511
Occupancy Type - Investment Home	0.05	0.22	0	0	0	0	1	347,511
Second Lien	0.04	0.20	0	0	0	0	1	347,511

Table S2 The Effect of Diversity Policy on Lending Outcomes in Home Equity Loans

This table reports regression results for mortgage lending outcomes from estimating Equation (1) for home equity loans. The observations are from HMDA data (2018-2021). The variables are defined in Table I. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. *, **, *** indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

	Completion (in %)		Approval (Given Completed, in %)		Origination (in %)	
	(1)	(2)	(3)	(4)	(5)	(6)
Black Borrower # Diversity Policy$_{-1}$	6.13**		-10.81***		-7.40***	
	(2.07)		(-2.98)		(-2.83)	
Hispanic Borrower # Diversity Policy$_{-1}$	2.31		-7.68***		-5.21***	
	(1.15)		(-3.44)		(-2.89)	
Other Minority Borrower # Diversity Policy$_{-1}$	0.58		-4.55***		-3.59***	
	(0.29)		(-2.73)		(-2.85)	
Minority # Diversity Policy$_{-1}$		2.56*		-7.30***		-5.13***
		(1.88)		(-5.28)		(-4.55)
Black Borrower	-5.12*		1.60		-0.45	
	(-1.74)		(0.44)		(-0.17)	
Hispanic Borrower	-3.73*		1.56		-0.03	
	(-1.93)		(0.69)		(-0.02)	
Other Minority Borrower	-3.96*		-0.11		-1.02	
	(-1.94)		(-0.07)		(-0.81)	
Minority		-4.05***		0.86		-0.53
		(-3.02)		(0.63)		(-0.47)
Diversity Policy$_{-1}$	-9.77***	-9.63***	-3.79*	-3.88*	-4.43**	-4.48**
	(-4.22)	(-4.22)	(-1.68)	(-1.72)	(-2.39)	(-2.43)
log(Loan Amount)	x	x	x	x	x	x
LTV Bin FE			x	x	x	x
DTI Bin FE			x	x	x	x
Conforming	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x
Income Percentile FE	x	x	x	x	x	x
Borrower Age Bin FE	x	x	x	x	x	x
Loan Type FE	x	x	x	x	x	x
Occupancy Type FE	x	x	x	x	x	x
Lien Type FE	x	x	x	x	x	x
Loan Term 5-year Bin FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
Property Tract FE	x	x	x	x	x	x
Lender FE	x	x	x	x	x	x
Dependent Var. Mean	81.22	81.22	50.63	50.63	38.48	38.48
R^2	0.23	0.23	0.51	0.51	0.53	0.53
Obs.	337,361	337,361	270,192	270,192	337,361	337,361

Table S3 Summary Statistics of Cash-out Refinance Applications

The table shows the summary statistics of the cash-out refinance loan applications used in Table S5.

	Mean	S.D.	P1	P25	P50	P75	P99	Obs.
Application and Performance Outcomes								
Completion	76.01	42.70	0	100	100	100	100	1,382,415
Approval (given completion)	76.71	42.27	0	100	100	100	100	1,050,831
Origination	56.51	49.57	0	0	0	100	100	1,382,415
Key Independent Variables								
Diversity Policy$_{-1}$	0.84	0.36	0	1	1	1	1	1,382,415
Minority Borrower	0.28	0.45	0	0	0	1	1	1,382,415
- Black Borrower	0.07	0.26	0	0	0	0	1	1,382,415
- Hispanic Borrower	0.12	0.33	0	0	0	0	1	1,382,415
- Other Minority Borrower	0.08	0.28	0	0	0	0	1	1,382,415
Borrower and Mortgage Characteristics								
Loan Amount ($K)	281.3	1,164	45	135	205	325	1,315	1,382,415
Income Ratio	1.74	12.05	0.23	0.81	1.25	1.93	8.73	1,382,415
Joint Application	0.47	0.50	0	0	0	1	1	1,382,415
Conforming Loan	0.94	0.25	0	1	1	1	1	1,382,415
Borrower Age - less than 25	0.00	0.04	0	0	0	0	0	1,382,415
Borrower Age - 25-34	0.06	0.24	0	0	0	0	1	1,382,415
Borrower Age - 35-44	0.19	0.39	0	0	0	0	1	1,382,415
Borrower Age - 45-54	0.28	0.45	0	0	0	1	1	1,382,415
Borrower Age - 55-64	0.25	0.43	0	0	0	1	1	1,382,415
Borrower Age - 65-74	0.16	0.36	0	0	0	0	1	1,382,415
Borrower Age - greater than 74	0.06	0.24	0	0	0	0	1	1,382,415
Loan Type - Conventional	0.93	0.26	0	1	1	1	1	1,382,415
Combined Loan-to-Value (%) (LTV)	62.93	17.16	18	52	66	76	98	1,038,811
Debt-to-Income (%) (DTI)	34.03	13.02	10	20	37	43	60	1,042,663
Loan term (in years)	25.46	6.84	10	20	30	30	31	863,996
Occupancy Type - Owner Occupied	0.95	0.22	0	1	1	1	1	1,382,415
Occupancy Type - Second Home	0.02	0.13	0	0	0	0	1	1,382,415
Occupancy Type - Investment Home	0.03	0.18	0	0	0	0	1	1,382,415
Second Lien	0.02	0.15	0	0	0	0	1	1,382,415

Table S4 The Effect of Diversity Policy on Lending Outcomes in Cash-out Refinance

This table reports regression results for mortgage lending outcomes from estimating Equation (1) for cash-out finance loans. The observations are from HMDA data (2018-2021). The variables are defined in Table I. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. ∗, ∗∗, ∗∗∗ indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

	Completion (in %)		Approval (Given Completed, in %)		Origination (in %)	
	(1)	(2)	(3)	(4)	(5)	(6)
Black Borrower # Diversity Policy$_{-1}$	-5.23***		-3.25***		-3.36***	
	(-13.40)		(-6.46)		(-10.87)	
Hispanic Borrower # Diversity Policy$_{-1}$	-1.04**		-2.00***		-2.16***	
	(-2.51)		(-4.50)		(-8.31)	
Other Minority Borrower # Diversity Policy$_{-1}$	2.59***		1.07**		-0.63**	
	(4.40)		(2.09)		(-1.99)	
Minority # Diversity Policy$_{-1}$		-1.30***		-1.40***		-2.01***
		(-4.10)		(-4.24)		(-9.37)
Black Borrower	2.71***		-4.10***		-2.76***	
	(7.12)		(-8.05)		(-9.42)	
Hispanic Borrower	-3.47***		-3.52***		-2.44***	
	(-8.38)		(-7.69)		(-10.00)	
Other Minority Borrower	-7.46***		-4.98***		-2.98***	
	(-14.33)		(-11.24)		(-11.99)	
Minority		-2.96***		-3.99***		-2.61***
		(-10.29)		(-11.67)		(-14.01)
Diversity Policy$_{-1}$	5.06***	5.09***	-2.07***	-2.11***	0.05	0.02
	(3.72)	(3.72)	(-5.01)	(-5.11)	(0.10)	(0.05)
log(Loan Amount)	x	x	x	x	x	x
LTV Bin FE			x	x	x	x
DTI Bin FE			x	x	x	x
Conforming	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x
Income Percentile FE	x	x	x	x	x	x
Borrower Age Bin FE	x	x	x	x	x	x
Loan Type FE	x	x	x	x	x	x
Occupancy Type FE	x	x	x	x	x	x
Lien Type FE	x	x	x	x	x	x
Loan Term 5-year Bin FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
Property Tract FE	x	x	x	x	x	x
Lender FE	x	x	x	x	x	x
Dependent Var. Mean	76.03	76.03	76.78	76.78	56.55	56.55
R^2	0.12	0.12	0.44	0.44	0.64	0.64
Obs.	1,379,107	1,379,107	1,046,430	1,046,430	1,379,107	1,379,107

Table S5 Robustness: The Effect of Diversity Policy on Lending Outcomes If Keeping Lenders with M&As

This table reports regression results for mortgage lending outcomes from estimating Equation (1). The observations are from the short panel HMDA data (2018-2021). The variables are defined in Table 1. Different from Table 3, we keep the 8 lenders that have M&As in the sample period. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. *, **, *** indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

	Completion (in %)			Approval (Given Completed, in %)			Origination (in %)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Black Borrower # Diversity Policy-1	1.79***	1.80***		-5.34***	-3.07***		-3.93***	-2.65***	
	(3.77)	(2.97)		(-14.95)	(-5.21)		(-12.71)	(-5.54)	
Hispanic Borrower # Diversity Policy-1	0.06	0.02		-3.56***	-0.03		-2.64***	-0.04	
	(0.12)	(0.04)		(-8.68)	(-0.07)		(-7.19)	(-0.09)	
Other Minority Borrower # Diversity Policy-1	0.30	0.59		-1.79***	-0.91**		-0.94***	-0.53	
	(0.53)	(0.93)		(-5.59)	(-2.33)		(-2.68)	(-1.37)	
Minority Borrower # Diversity Policy-1			0.79**			-1.32***			-1.10***
			(2.09)			(-3.75)			(-3.71)
Diversity Policy-1	3.00***	2.97***	2.97***	0.25	-0.66***	-0.66***	-0.20	-0.81***	-0.81***
	(11.24)	(11.26)	(11.25)	(1.18)	(-4.00)	(-3.99)	(-1.04)	(-4.73)	(-4.72)
Black Borrower	-3.45***			0.36			-0.39		
	(-7.45)			(1.03)			(-1.31)		
Hispanic Borrower	-1.60***			0.63*			0.12		
	(-3.38)			(1.76)			(0.39)		
Other Minority Borrower	-4.47***			-0.81***			-1.36***		
	(-7.84)			(-2.71)			(-4.22)		
log(Loan Amount)	x	x	x	x	x	x	x	x	x
LTV Bin FE				x	x	x	x	x	x
DTI Bin FE				x	x	x	x	x	x
Conforming Loan	x	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x	x
Income Ratio Percentile FE	x	x	x	x	x	x	x	x	x
Borrower Age Bin FE	x	x	x	x	x	x	x	x	x
Loan Type FE	x	x	x	x	x	x	x	x	x
Property Tract FE	x	x	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x	x	x
Lender FE	x			x			x		
Lender*Race FE		x	x		x	x		x	x
Dependent Var. Mean	82.30	82.30	82.30	89.29	89.29	89.29	71.81	71.81	71.81
R^2	0.05	0.05	0.05	0.32	0.32	0.32	0.67	0.67	0.67
Obs.	2,148,819	2,148,818	2,148,818	1,767,285	1,767,284	1,767,284	2,148,819	2,148,818	2,148,818

Table S6 First Stage Regressions for the Alternative Shareholder Diversity Initiative IV

This table reports regression results for the first stage regressions for the shareholder diversity initiative and its interactions with races. Panel A, B and C report the first stage results for the completion, approval and origination, respectively. The observations are from the short panel HMDA data (2018-2021). The variables are defined in Table 1. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. ∗, ∗∗, ∗∗∗ indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

Panel A: First stage for Completion Regression

	Diversity Policy$_{-1}$ (1)	Black # Diversity Policy$_{-1}$ (2)	Hispanic # Diversity Policy$_{-1}$ (3)	Other Minority # Diversity Policy$_{-1}$ (4)
Shareholder Diversity Iniative$_{-2}$	0.77***	-0.02***	-0.06***	-0.01***
	(23.25)	(-7.95)	(-4.78)	(-4.85)
Black # Shareholder Diversity Iniative$_{-2}$	-0.00	0.96***	0.00	0.00
	(-0.29)	(102.65)	(0.79)	(0.76)
Hispanic # Shareholder Diversity Iniative$_{-2}$	0.01***	0.00**	0.98***	-0.00***
	(3.85)	(2.79)	(214.71)	(-2.97)
Other Minority # Shareholder Diversity Iniative$_{-2}$	0.01***	0.00***	0.00**	0.99***
	(3.32)	(3.00)	(2.82)	(206.85)
log(Loan Amount)	x	x	x	x
LTV Bin FE				
DTI Bin FE				
Conforming Loan	x	x	x	x
Joint Application	x	x	x	x
Income Ratio Percentile FE	x	x	x	x
Borrower Age Bin FE	x	x	x	x
Loan Type FE	x	x	x	x
Property Tract FE	x	x	x	x
Year FE	x	x	x	x
Lender*Race FE	x	x	x	x
First Stage: Kleibergen-Paap rk F			134.4	
First Stage: Anderson-Rubin p-val			0	
Obs.	495,741	495,741	495,741	495,741

Panel B: First stage for Approval Regression

	Diversity Policy$_{-1}$ (1)	Black # Diversity Policy$_{-1}$ (2)	Hispanic # Diversity Policy$_{-1}$ (3)	Other Minority # Diversity Policy$_{-1}$ (4)
Shareholder Diversity Iniative$_{-2}$	0.78***	-0.01***	-0.06***	-0.01***
	(24.77)	(-7.65)	(-4.80)	(-4.73)
Black # Shareholder Diversity Iniative$_{-2}$	0.00	0.97***	0.00	0.00*
	(0.78)	(131.77)	(1.53)	(1.66)
Hispanic # Shareholder Diversity Iniative$_{-2}$	0.01***	-0.00**	0.99***	-0.00**
	(4.07)	(2.78)	(269.01)	(-2.53)
Other Minority # Shareholder Diversity Iniative$_{-2}$	0.01***	-0.00***	-0.00	0.99***
	(3.30)	(2.98)	(-0.67)	(261.66)
log(Loan Amount)	x	x	x	x
LTV Bin FE	x	x	x	x
DTI Bin FE	x	x	x	x
Conforming Loan	x	x	x	x
Joint Application	x	x	x	x
Income Ratio Percentile FE	x	x	x	x
Borrower Age Bin FE	x	x	x	x
Loan Type FE	x	x	x	x
Property Tract FE	x	x	x	x
Year FE	x	x	x	x
Lender*Race FE	x	x	x	x
First Stage: Kleibergen-Paap rk F			153.8	
First Stage: Anderson-Rubin p-val			0	
Obs.	412,495	412,495	412,495	412,495

Panel C: First stage for Orgination Regression

	Diversity Policy$_{-1}$ (1)	Black # Diversity Policy$_{-1}$ (2)	Hispanic # Diversity Policy$_{-1}$ (3)	Other Minority # Diversity Policy$_{-1}$ (4)
Shareholder Diversity Iniative$_{-2}$	0.77***	-0.02***	-0.06***	-0.01***
	(23.25)	(-7.95)	(-4.78)	(-4.85)
Black # Shareholder Diversity Iniative$_{-2}$	-0.00	0.96***	0.00	0.00
	(-0.29)	(102.65)	(0.79)	(0.76)
Hispanic # Shareholder Diversity Iniative$_{-2}$	0.01***	0.00**	0.98***	-0.00***
	(3.85)	(2.79)	(214.71)	(-2.97)
Other Minority # Shareholder Diversity Iniative$_{-2}$	0.01***	0.00***	0.00**	0.99***
	(3.32)	(3.00)	(2.82)	(206.85)
log(Loan Amount)	x	x	x	x
LTV Bin FE	x	x	x	x
DTI Bin FE	x	x	x	x
Conforming Loan	x	x	x	x
Joint Application	x	x	x	x
Income Ratio Percentile FE	x	x	x	x
Borrower Age Bin FE	x	x	x	x
Loan Type FE	x	x	x	x
Property Tract FE	x	x	x	x
Year FE	x	x	x	x
Lender*Race FE	x	x	x	x
First Stage: Kleibergen-Paap rk F			134.4	
First Stage: Anderson-Rubin p-val			0	
Obs.	495,741	495,741	495,741	495,741

Table S7 Alternative IV Regression: The Effect of Diversity Policy on Lending Outcomes

This table reports IV regression results for mortgage lending outcomes. The instrumental variables are increases in shareholder diversity initiatives, and its interactions with borrower race or minority indicators. The first stage results are reported in Table S6. The observations are from the short panel HMDA data (2018-2021). The variables are defined in Table I. The standard errors are clustered at the county level. *t*-stats are shown in parentheses. *, **, *** indicates the observed coefficient is statistically significant at the 90%, 95%, and 99% confidence intervals, respectively.

	Completion (in %)		Approval (Given Completed, in %)		Origination (in %)	
	(1)	(2)	(3)	(4)	(5)	(6)
Black # $\widehat{\text{Diversity Policy}}_{-1}$	-0.11*		-3.33***		-2.99***	
	(-1.72)		(-6.27)		(-6.32)	
Hispanic # $\widehat{\text{Diversity Policy}}_{-1}$	0.01		-1.01***		-1.05**	
	(0.20)		(-2.74)		(-2.55)	
Other Minority $\widehat{\text{\# Diversity Policy}}_{-1}$	0.04		-1.07***		-0.81*	
	(0.65)		(-2.59)		(-1.84)	
Minority # $\widehat{\text{Diversity Policy}}_{-1}$		-0.03		-1.95***		-1.78***
		(-0.80)		(-6.23)		(-6.21)
$\widehat{\text{Diversity Policy}}_{-1}$	-0.29***	-0.30***	-0.17	-0.22	-0.88***	-0.93***
	(-9.25)	(-9.22)	(-0.52)	(-0.67)	(-2.63)	(-2.72)
log(Loan Amount)	x	x	x	x	x	x
LTV Bin FE			x	x	x	x
DTI Bin FE			x	x	x	x
Conforming Loan	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x
Income Ratio Percentile FE	x	x	x	x	x	x
Borrower Age Bin FE	x	x	x	x	x	x
Loan Type FE	x	x	x	x	x	x
Property Tract FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x
Dependent Var. Mean	83.80	83.80	93.72	93.72	76.27	76.27
First Stage: Kleibergen-Paap rk F	134.4	273	153.8	311.3	134.4	273
First Stage: Anderson-Rubin p-val	0	0	0	0	0	0
Obs.	495,741	495,741	412,495	412,495	495,741	495,741