Mortgage Lenders' Diversity Policies and Mortgage Lending to Minorities*

Ivy Feng
University of Wisconsin-Madison

Devin M. Shanthikumar
University of California Irvine

Dayin Zhang
University of Wisconsin-Madison

August 30, 2024

Abstract

Research suggests that minorities continue to face lower mortgage application approval rates, and, if approved, higher interest rates. At the same time, research suggests that disparities between minority and white borrowers have narrowed in recent years. We examine the role of diversity policies in addressing mortgage lending disparities, using both within-lender analyses and an event study design. We find that diversity policies significantly reduce race-related gaps in borrowing costs, captured by effective interest rate spreads. However, they drive larger gaps in approval rates. Additional analyses provide insights into the mechanisms through which diversity policies affect loan costs and approval rates. The increase in application completion rates and the reduction in loan costs, both driven by the front office, are in part driven by better matching of borrower and loan officer race. The reduction in approval rates is in part driven by an increase in higher-risk loan applications from minority borrowers. However, the increase in risk does not fully explain the approval rate effect, suggesting an overreaction from the back office – in which the back office increases approval standards for minorities. Examination of ex post loan performance is consistent with an overreaction, with a significant decrease in ex post defaults and an increase in prepayment from minority borrowers. Together, our results suggest that diversity policies in part address race-related disparities in lending. However, the policies also induce wider loan approval gaps. We discuss possible explanations.

Keywords: Mortgage lending, Race, Disparity, Diversity, Equity, Inclusion, DEI, Diversity Policy, Banks
JEL Codes: G21, G28, J15, L85, M14

---

* We thank Jonathan Becker, Sahil Chekuri, Milan Nguyen, Jinzhou Xu, Heejin Yoon, and Qixiang Zhao for their excellent research assistance. We also thank Neil Bhutta, Scott Frame, Justin Contat, and Karen Pence; as well as the audience members at the Federal Reserve Bank of Philadelphia, the UC Irvine Center for Liberation, Anti-Racism, and Belonging (C-LAB), Santa Clara University, University of Illinois Chicago, University of Wisconsin Madison, the 2024 Pre-WFA Summer Real Estate Research Symposium, the 2024 AREUEA National Conference, the 2024 FSU-UF Critical Issues in Real Estate Symposium, the 2024 American Accounting Association Annual Meeting, the 2024 University of Washington Fostering Inclusion Workshop, and the 2023 Financial Management Association Annual Meeting New Ideas Session for helpful feedback. We thank C-LAB for a grant to support data collection and coding.
Ivy Feng, ivy.feng@wisc.edu; Devin M. Shanthikumar, dshanthi@uci.edu; Dayin Zhang, dayin.zhang@wisc.edu.

I. Introduction

Mortgages play a critical role in Americans' home purchases. As of 2022, residential mortgage debt in the U.S. totaled $11.92 trillion. However, there is a long history of racial disparities in mortgage lending in the United States (Munnell, Tootell, Browne, and McEneaney 1996). While evidence suggests that these gaps have narrowed over time (e.g., Bhutta and Hizmo 2021; Bhutta, Hizmo and Ringo 2024), several studies find that minorities continue to face lower approval rates, and, if approved, higher interest rates (e.g., Ambrose, Conklin and Lopez 2021; Bartlett, Morse, Stanton, and Wallace 2022). At the same time, mortgage lenders have increasingly adopted diversity-related policies in recent decades. Broadly speaking, it is unclear whether and how diversity policies address race-related outcome gaps. These policies can be a form of window dressing in which lenders state a policy publicly for public relations or legal reasons. Conversely, policies can overshoot and include controversial features, such as quotas, raising concerns about lower standards for minorities and reverse discrimination against majority-group members. Policies that overshoot, or raise concerns about overshooting, can create a stigma against minority individuals and cause backlash. A third possibility is that these policies are effective in addressing race-related outcome gaps. We examine these possibilities by investigating how mortgage lenders' diversity policies affect 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 and loan pricing data, as well as more detailed borrower-related data. This allows us to examine the effects of diversity policies on both the intensive margin (loan costs such as interest rate) and the extensive margin (approval rate), while controlling for a host of borrower and loan characteristics. We also utilize a longer 2010-2021 period to conduct an event study around the initial adoption of a diversity policy to strengthen causal inferences. 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.

We utilize a rich set of fixed effects to control for other factors which might affect mortgage outcomes, including lender, year, borrower-related, loan-related, and county fixed effects. Our 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 focus on the incremental effects of diversity policies on race-related outcome gaps at a given lender.

Focusing first on borrowing costs, we find that diversity policies reduce race-related gaps in such costs. We focus on effective interest rate spreads, which combine interest rates and closing costs. Inferences are similar examining individual components of borrowing costs, including contract interest rates and discount-point-adjusted rates. The overall reduction in the average minority borrowing cost gap is roughly 3 to 4 basis points, depending on the exact specification. While loan costs decrease for all borrowers, the reduction is larger for minority borrowers, therefore narrowing race-related gaps. More specifically, the black-white interest rate gap shrinks from 7.4 to 3.4 basis points.

To strengthen the causal inference between diversity policy adoption and the examined outcomes, we perform an event study using the initial adoption of a diversity policy at 12 lenders with clear policy adoption dates between 2010 and 2021. For this analysis, we use an indicator for large rate spreads (above 150 basis points), a loan cost measure for which we have data over the extended time period (Larson 2024). We find that the higher likelihood of having a high-spread loan for minority borrowers relative to white borrowers declines after the diversity policy is adopted. This suggests a causal relation between diversity policies and the reduction in loan costs.

Focusing on mortgage approvals and originations, we find an opposing effect: diversity lenders have *lower* approval rates for minority borrowers. Although diversity policies appear to partially narrow differences in application completion rates, with Black borrowers increasing application completions at diversity-policy lenders relative to other mortgage lenders, this effect is more than offset by the lower approval rates. Specifically, the black-white approval rate gap is widened by 3.34 percentage points after the diversity policy is adopted.

Event study analysis suggests a causal relation between diversity policy adoption and these outcomes. Following diversity policy adoption, we find an incremental increase in application completion rates, but a decrease in approval rates. Together, the combined effect leads to a reduction in origination rates for minority borrowers relative to white borrowers. These results are consistent with the fixed effects model, and point more strongly to a causal relation.

We explore potential mechanisms behind the differential impact of diversity policies on different phases of the lending process. The borrowing cost, including both interest rates and closing costs, is part of the mortgage lending process heavily influenced by the "front office," e.g., loan officers at a bank branch location who work directly with borrowers. Prior research has shown that race alignment between minority borrowers and minority loan officers leads to smaller racial gaps in mortgage lending outcomes (Ambrose, Conklin, and Lopez 2021; Frame, Huang, Jiang, Lee, Liu, Mayer, and Sunderam 2024). We posit that diversity policies may increase the extent to which lenders match borrower and loan officer race. Consistent with this, we find that lenders with diversity policies tend to hire more minority loan officers and achieve better race alignment between minority borrowers and minority loan officers.

Approvals are decided by the back office based on assessed application risks. We aim to shed some light on the decision-making process that leads to the widened approval rate gap. Since we cannot directly observe or fully replicate the back office's risk assessment process, we use a machine learning approach to predict each mortgage applicant's default risk based on a comprehensive set of observable risk characteristics. This predicted default risk allows us to estimate the impact of diversity policy adoption on application riskiness and to analyze approval rates conditional on that riskiness.

We find that the average riskiness of minority applications increases after policy adoption, largely driven by an increase in applications with very high risk. Examining applicant income, we find that there is a 3-4% decrease in minority applicant income relative to the local median. Using our more comprehensive measure of predicted default risk, we find that there is a 0.5-1.3% increase in predicted default risk for minority borrowers relative to White borrowers. This shift suggests that the back office is encountering more high-risk minority applicants after policy adoption, at least in part explaining the observed decline in approval rates for minority applicants.

However, we find that changes in application riskiness do not fully explain the widened approval rate gap between minority and white borrowers. In particular, the widened approval gap between white and minority applicants persists even after controlling for changes in predicted default risk, and occurs within similar-risk buckets. To further examine whether the decrease in approval rates for minority applicants is warranted, we examine ex-post loan performance. We find a significant decrease in delinquencies for minority borrowers at lenders with diversity policies, driven by black and Hispanic borrowers. While we cannot examine the quality of denied mortgages, the decrease in ex-post defaults is consistent with increasing standards for minority loan approvals. These results suggest that the marginal minority application which is denied by lenders with a diversity policy in place is similar to, or higher quality than, those denied by lenders without such a policy.

Together, these results suggest an overreaction to diversity policies – in which the back-office anticipates and observes an increase in the riskiness of minority applications due to the diversity policy, but overreacts. Consistent with this possibility, an examination of lender-reported loan denial reasons supports both aspects: Denial reasons related to applicant risk metrics, such as debt-to-income ratio and credit history, increase for minority borrowers. However, there is also an increase in citing "other" as a denial reason, suggesting increased denials which do not specifically pertain to typical risk factors.

Taken together, our results provide evidence of the effects of lenders' diversity policies on race-related gaps in mortgage lending. We find evidence that lenders' diversity policies reduce the race-related gap in loan costs (the intensive margin) but increase the gap in loan approvals and originations (the extensive margin), controlling for a host of borrower and loan characteristics. Additional analyses that focus on the mechanisms for these effects suggest that diversity policies have a differential impact on the front office, which works with borrowers in completing applications, setting loan-specific interest rates, providing information, etc., versus the back office, which makes approval decisions based on the risk assessment of the completed applications.

We acknowledge two limitations to our study. First, diversity policy adoption is inherently endogenous. As such, the diversity policies in our data can best be viewed as an indicator for the chosen/stated approach of the company. Our empirical design allows us to draw inferences for the causal effects of these efforts. However, we do not claim that externally mandated diversity policies would have the same effects. Our results are of significant importance despite this constraint, as diversity policies are expected to remain discretionary going forward. Our results can inform lenders as they make decisions about their policies, and as they attempt to implement policies and inform investors and borrowers regarding the effects of these stated policies in practice. Second, there is a lack of direct visibility into the back-office process to fully elucidate the mechanisms behind the overreaction that occurs there. Several potential drivers exist – psychological biases and misperceptions; resistance to or backlash towards diversity policies; poor internal communication regarding the policy; differential training at the front and back office; and limited resources at the back office, which may hinder back office ability to carefully analyze the increasing number of completed minority applications. It is likely that our findings are due to a combination of these factors. Examining these factors will likely require a different research design, such as in-depth case studies and the use of internal lender data. We leave it to future research to shed more light on the exact mechanisms. Our research provides evidence of an overreaction at the back office, and points to the importance of such research going forward.

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, Tootell, Browne, and McEneaney 1996; Ambrose, Conklin, and Lopez 2021; Bhutta and Hizmo 2021; Bartlett, Morse, Stanton, Wallace 2022; An, Bushman, Kleymenova, and Tomy 2023; Frame, Huang, Jiang, Lee, Liu, Mayer, and Sunderam 2024) and other financial services (e.g., Morse and Pence 2020; Begley and Purnanandam 2021; Erel and Liebersohn 2022; Butler, Mayer, and Weston 2023; Ambrose, Conklin, Coulson, Diop, and Lopez 2023). Our study is one of the first, to our knowledge, to examine how lenders can address such disparities, and in particular, is the first to examine the effect of diversity policies on mortgage lending outcomes.

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. We also demonstrate the importance of considering effects holistically – an improvement in one part of the business (e.g., higher application completion rates, and lower interest rates requested) – can spill over to drive a converse effect in another part of the business (e.g., lower approval rates).

More broadly, our paper contributes to the nascent literature on the effectiveness of diversity policies. While a significant body of research has established the existence of different forms of race- and other characteristic-related biases, there is still little understanding of what actions can address such biases (e.g., Paluck, Porat, Clark, and Green 2020; Devine and Ash 2022). 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.

Finally, our paper can shed some light on a fundamental question of whether diversity policies shift the distribution of limited resources, or whether they drive an increase in resources. In theory, alleviating inefficiencies in the utilization of minority human capital and the acquisition of potential minority customers can "grow the pie." However, it is also possible that diversity policies will simply redistribute resources away from majority-group members. Our results contribute to this discussion. The main effect of diversity policies in our sample indicates a reduction in loan costs and an increase in application completion rates for all borrowers, suggesting improved support at the front office regardless of borrower race. We find mixed evidence for approval rates, suggesting that backlash effects, such as a more cautious approach at the back office, can spill over to hurt majority group members, though minority applicants are more strongly affected. The results are consistent with diversity policies affecting majority group members in the same direction as minority members –i.e., there can be a growing (or shrinking) of the pie – rather than necessitating reallocation.

II. 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/why they might affect mortgage lending outcomes.

II.1 Diversity Policy Adoption

A large body of research has shown that race can impact economic outcomes, even controlling for other factors. A notable example is in hiring. Field experiments show that companies are less likely to contact or interview a job applicant with a Black-sounding name than an applicant with an otherwise identical resume, but with a White-sounding name, even as recently as 2020 (Bertrand and Mullainathan 2004; Kline, Rose and Walters 2022). Recent research suggests that investors are also subject to race-related biases (e.g., Dougal, Gao, Mayew, and Parsons 2019; Fairlie, Robb, and Robinson 2022). Together, this research suggests that race-related biases, whether conscious or unconscious, can create economic inefficiencies, affecting the utilization of human capital and the allocation of financial capital.

Over the late 20th and early 21st centuries, the share of the United States population identifying as a racial or ethnic minority group has increased significantly, highlighting the growing economic importance of addressing race-related frictions in the economy. As of the 1980 US Census, 79.6% of the US population identified as White, non-Hispanic.[1] In 2010, the first year in our sample, 63.7% of the population identified as White, non-Hispanic. By 2020, that number had dropped to 57.8%.[2] Due to lower birth rates, an aging population, higher immigration, and an increase in the mixed-race population, this trend is expected to continue, and the percentage is expected to dip below 50% around 2045-2050.[3]

Diversity policies have arisen as a common response to the increasing diversity of the US 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, with significant variation in the timing of adoption. 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 2010, 43% of the 67 public lenders in our data had an identifiable diversity policy. By 2022, 88% 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 for 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.

---

[1] https://www2.census.gov/prod2/decennial/documents/1980/1980censusofpopu8011u_bw.pdf

[2] https://www.census.gov/library/visualizations/interactive/racial-and-ethnic-diversity-in-the-united-states-2010-and-2020-census.html, accessed June 2024.

[3] https://www.census.gov/data/tables/2023/demo/popproj/2023-summary-tables.html, accessed June 2024; https://www.brookings.edu/articles/new-census-data-shows-the-nation-is-diversifying-even-faster-than-predicted/

II.2 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.

We hand collect and hand code components of 105 diversity policies for lenders in our sample, to better understand lender diversity policies. Motivated by sociological research (Kalev, Dobbin and Kelly 2006), we examine whether policies include (a) diversity training, and (b) the establishment of an individual or team responsible for diversity efforts.[4] We include an additional dimension, given our focus on customer-focused mortgage lending outcomes: (c) discussion of customer diversity.

Kalev, Dobbin and Kelly (2006) find that diversity training is the least effective approach to increasing minority representation among management, suggesting that it has minimal effects on hiring and promotion. However, it is plausible that diversity training could improve mortgage lending outcomes for minorities. In particular, the loan application process is almost always assisted by loan officers. Loan officers play an important role in helping borrowers complete loan applications, providing necessary documentation, and determining appropriate interest rates and closing costs. 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, 78% include some form of diversity or anti-discrimination training.

---

[4] The Kalev, Dobbin and Kelly (2006) framework includes a third dimension – mentoring and social connection, based upon their internal survey data, which they find to have intermediate value in driving management diversity. We find that it is difficult to code this dimension using publicly available data, given that it is more subjective and varied. Thus, we exclude it from our discussions. Additional details are available upon request.

Evidence suggests that establishing responsibility for diversity initiatives has the strongest impact on managerial diversity (Kalev, Dobbin and Kelly 2006), creating both a direct effect and strengthening the effects of other diversity efforts. Lenders frequently establish such responsibility: 81% of the policies in our data include the appointment of a Chief Diversity Officer or a Diversity Council. This practice likely results in an increase in loan officer diversity, which can have a positive effect on minority borrowers, as indicated by prior studies that minority borrowers obtain better mortgage outcomes when working with minority loan officers (Ambrose, Conklin, and Lopez 2021; Frame, Huang, Jiang, Lee, Liu, Mayer, and Sunderam 2024).

While diversity policies often focus internally, they can also include aspects which relate to customers. We find that 79% of the policies we code discuss customer diversity. Some of these policies include specific goals for increasing lending to minority borrowers, while others describe increasing demographic diversity among potential customers as a motivation for adopting and implementing a diversity policy. This focus on customer diversity could improve lending outcomes for minority borrowers – in particular by increasing the number of loans made to minority borrowers and decreasing the interest rate premiums on these loans relative to loans with similar risk profiles for majority borrowers.

While the arguments above suggest that diversity policies should improve lending outcomes for minority borrowers, these arguments rely on the assumption that such policies are genuine, and that implementation is effective. 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, Vitanza, Wang and Zhu (2022) find that banks with high ESG ratings, including high Social ratings, issue fewer mortgages in higher-poverty areas, rejecting more applications in those areas. While

Basu, Vitanza, Wang and Zhu (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.

At the other extreme, there are concerns that some diversity policies have gone too far, focusing on specific diversity targets rather than the more general elimination of discrimination.[5] While the intention of implementing the diversity policies might be to counter the higher bar set for minority groups, the bar can be lowered too much, such that majority group members now face the risk of 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 suggests that diversity policies often create concerns of reverse discrimination, i.e., a lower bar for minorities, particularly among majority-group members (Dover, Major and Kaiser 2016). Such concerns about reverse discrimination can lead to worse outcomes for minorities. For example, 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). In the setting of mortgage lending, if lenders believe that lower-quality minority applicants are being encouraged to apply for loans due to the diversity policy, these lenders may

[5] In 2023, the Supreme Court ruled that using race in deciding college admissions is unconstitutional. The majority opinion lays out the reasoning and specific conerns with race-based admissions. Additional legal challenges to race-based programs are in progress, and several states have already made race-based hiring and contracting illegal. 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.

be more careful and stringent in their treatment of such applicants. This can lead to more negative outcomes for minority applicants. As such, we do not make directional predictions.

III. 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 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.

III.1 Diversity Policy Data

We obtain 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, Vitanza, Wang and Zhu (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 (hereafter as D&I)

rating. Refinitiv's D&I score captures firms' performance across four dimensions, which they call pillars: diversity, inclusion, people development, and controversies. Some of these pillars, such as people development, relate more to general human capital practices, and are not diversity-focused.

Underlying the diversity pillar, which is most strongly related to our intended research question, are scores for the following eight measures: (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.

Based on discussions with several Refinitiv representatives and data scientists, we learned that Refinitiv uses a large collection of publicly available sources to collect ESG information and determine if a firm has a diversity policy.[6] 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.

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

[6] 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).

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.[7]

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 the accuracy of the diversity policy indicators provided by Refinitiv.

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 years. Thus, while Refinitiv is generally quite accurate, hand collection appears to be important for event date accuracy.[8]

It is worth repeating that Refinitiv only identifies lenders as having a diversity policy if the lenders make information about their policies public in some way. For lenders identified as not having a diversity policy, it is possible that they have internal policies in place. Thus, our study examines the effects of *public* diversity policies.

---

[7] 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.

[8] The two adoption date corrections are for Prime Lending and First National Bank of Pennsylvania. Refinitiv data indicates the adoption years for these two lenders to be 2018 and 2016, respectively. We found earlier adoption dates for both, 2016 and 2015, respectively, utilizing the Wayback Machine Internet Archive (http://web.archive.org/).

III.2 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. HMDA provides insights into both loan origination outcomes and specific reasons for denials within the reported mortgage applications, which is a primary focus of our paper. Furthermore, it discloses racial and ethnic backgrounds of borrowers, enabling us to compare mortgage origination 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 variations in 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 loan costs (intensive margin) and approval rates (extensive margin).[9]

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. More importantly, the new HMDA data includes mortgage interest rates, their associated origination fees, and the APR spreads. The newly added information allows us to analyze potential variations in mortgage costs across different racial groups, with more extensive controls for borrower and loan attributes. We rely on HMDA panel data from 2018 through 2021 for the majority of our analyses. In particular, we use this sample to examine the

[9] We constrain our sample to begin in 2010 to minimize the influence from potential confounding factors correlated with the 2008 financial crisis. In the long panel, we measure loan costs using the share of high-spread mortgages, since loan cost information is only available for mortgages with rate spreads above 150 basis points.

impact of diversity policies on racial disparities in both loan cost (intensive margin) and approval decisions (extensive margin), also with an expanded set of control variables.

We construct our sample following prior research (Frame, Huang, Jiang, Lee, Liu, Mayer, and Sunderam 2024; Bhutta, Hizmo, and Ringo 2024; Bartlett, Morse, Stanton, and Wallace 2022). Specifically, our analysis centers on first-lien, 30-year, fixed-rate mortgages for the purchase of owner-occupied single-family homes. Concentrating on one type of mortgage contract mitigates potential selection issues stemming from diverse contracts, especially since 30-year fixed-rate mortgages are predominant in the U.S. In addition, we focus on purchase mortgages to further mitigate selection concerns caused by existing borrower-lender relationships, since most refinancing transactions tend to retain the initial lender. Finally, we exclude entries where the applicant/borrower's race is not specified, which accounts for 28.0% of the applications.

III.3 Loan Performance Data

In additional analyses, we incorporate loan performance data from the two government-sponsored enterprises (GSEs): Fannie Mae and Freddie Mac. These two entities jointly guarantee around 70% of the mortgages in the U.S. and make performance data for securitized mortgages available to the public.[10] Their datasets include the borrowers' credit scores (FICO) at mortgage originations, which are one of the most important risk factors determining the loan costs and approval decisions. The GSE performance data also reports the mortgage performance metrics, particularly flagging loans that have been prepaid or delinquent after originations.

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

---

[10] See data on Fannie Mae & Freddie Mac (GSEs) from National Association of Realtors (https://www.nar.realtor/fannie-mae-freddie-mac-gses).

rate, LTV, and DTI etc. 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. Whenever possible, we test our hypotheses in both the short HMDA and the short HMDA-GSE matched panels. The latter provides better inference, since we can include credit scores as a control variable to make the borrowers of different races more comparable. However, we cannot use the short HMDA-GSE matched panel for the approval rate analysis, since the GSE performance data only include mortgages that are approved and originated.

III.4 Sample Mortgage Lenders: Merging Refinitiv with HMDA Data

We focus on mid-to-large size mortgage lenders with a national market share above 0.1% during 2018-2021. One hundred thirty-eight mortgage lenders qualify for this criterion, with an aggregate market share is 67.1%. For public lenders, we search for their diversity policy information on Refinitiv. For lenders that are private, 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. As we discuss in Section II, we are less likely to be able to determine whether such firms have a diversity policy. To make sure that the policy changes we observe are not due to merger and acquisition activity, we also exclude lenders that were acquired during the sample period. Our final sample includes 44 mortgage lenders, with aggregate market share of 25.5%.

III.5 Difference-in-Differences Estimation Framework

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

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

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}) include both the interest rates associated with the loan (intensive margin) and the decisions surrounding loan approval (extensive margin). For the loan approval decisions, we include application completion and approval. In these cases, Equation (1) represents a linear probability model for these outcomes.

Our main independent variables include lagged diversity policy dummy (DEI_{jt-1}) and its interactions with minority borrower race groups ($\mathbb{M}$). In our main specification, we focus on racial and ethnic minority borrowers, i.e., those who are non-White, and break them into three groups: $R_i \in \mathbb{M} = \{Black, Hispanic, Other\ Minority\}$. 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 avoid partial implementation of a diversity policy if the policy was adopted in the middle of the year. Our primary coefficients of interest are the interaction coefficients between the racial groups and the policy dummy (i.e., β_Rs). These coefficients capture the differences in racial disparities for each specific minority borrower category for lenders with a diversity policy, relative to those without one.

Following Frame et al. (2022), we include control variables (X_{ijt}) such as log (loan amount), LTV bins, DTI bins, score bins,[11] an indicator for conforming loans, an indicator for joint applications, centile bins of the applicant income-to-MSA median income ratio, ten-year bins of applicant age, loan type indicators, and property counties. In addition, we flexibly control for lender-race fixed effects ($\theta_{j\times R(i)}$) 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.

III.6 Event Study

A crucial assumption that the Difference-in-Differences model relies on is the parallel trends between the treated and control groups. To visualize the dynamics of the diversity policy effect, and test the parallel trend assumption, we conduct an event study analysis with a staggered Difference-in-Differences design at the lender level. We take the following event study regression specification:

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

where $DEI_{jt,\tau}$ 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 the estimated causal treatment effects when using staggered-rollout designs with two-way fixed-effects (e.g., De Chaisemartin

[11] FICO scores are only included for regressions on the short HMDA-GSE matched sample. The FICO score bins are 40-wide windows moving in both directions from 620, which is the rule-of-thumb division between prime and non-prime borrowers used by the industry.

and d'Haultfoeuille 2024, De Chaisemartin and d'Haultfoeuille 2020, Goodman-Bacon 2021, Callaway and Sant'Anna 2021, Borusyak, Jaravel, and Spiess 2021). Several papers have presented estimators to address these issues. In this paper, we adopt the approach proposed by Gardner (2022), which utilizes a two-stage estimation technique. Under this approach, we first estimate both sets of fixed effects (lender and year) from untreated units. This method ensures that increasing treatment effects over time do not inappropriately affect cross-sectional averages, and that time fixed effects late in our sample do not heavily rely on outcomes at treated lenders. After removing problematic variations, 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. Most importantly, it allows for analytical inference, which is advantageous for our analysis of prices, drawing from mortgage microdata with tens of millions of observations.

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, conforming loan indicator, and ten-year bins of applicant age.

IV. Results

IV.1 Mortgage Costs

Table 3 presents the results of estimating Equation (1) to evaluate the impact of diversity policies on racial disparities in loan costs (intensive margin).

IV.1.1 Reduced Racial Gap in Effective Interest Rate Spreads

Panel A focuses on the rate spread variable, which equals the spread between the Annual Percentage Rate (APR) and a survey-based estimate of APRs currently offered on prime mortgage loans of a comparable type (Larson 2024). We believe this measure best captures loan costs for the following two reasons. First, mortgage costs are affected by both interest rate and discount points: the borrowers can choose to buy discount points (upfront costs) to reduce their contract interest rates (on-going costs). APR represents the annual cost of funds by incorporating both upfront and on-going loan costs, which reveals the effective borrowing cost of the mortgage. Second, the rate spreads exclude the time-varying prime rates at the lock-in date, which are mainly driven by monetary policies and macroeconomic conditions. This mitigates the shortcoming of our low-frequency time fixed effects at the year level. While we think the rate spread measure is a better measure for our setting, our results are robust using other measures, including the contract interest rate. Details are reported in the Online Appendix.

Panel A presents estimation results. Columns (1) through (4) present results for the full short HMDA panel (full data for years 2018-2021), and columns (5) through (8) present results for the short HMDA panel merged with GSE data. Including GSE data allows us to control for borrower FICO scores, however, it reduces the sample as it requires that mortgages (1) are securitized by either Fannie Mae or Freddie Mac and (2) have a unique match in the GSE performance data. For both samples, we leverage the detailed information disclosed by the new HMDA data and control for a rich set of borrower and mortgage characteristics to rule out risk-driven racial disparities. Importantly, we are able to include Loan-to-value (LTV) bin and Debt-to-income (DTI) bin fixed effects in both samples, and FICO bin fixed effects in the HMDA-GSE matched sample.

Columns (1) and (2) include year and lender fixed effects. Consistent with prior findings, minority borrowers in general incur higher loan costs compared with white borrowers of similar characteristics, as indicated by the positive significant coefficients on *Minority Borrower* in column (1). Column (2) breaks the minority borrowers into Black, Hispanic and other minority racial groups. The coefficient on each category indicates that without any diversity policy interventions the average effective interest rates for Black borrowers and Hispanic borrowers are 10.6 and 6.6 basis points higher than that for the white borrowers.

Our coefficients of interest are the coefficients on the race-diversity policy interaction terms (*X Borrower # Diversity Policy*$_{-1}$), which capture the effects of diversity policies on racial disparities in loan costs. Column (1) shows that the effective rate spread falls for all borrowers after the lenders adopt a diversity policy. The decrease is 3.5 basis points larger for minority borrowers, resulting in a decrease in race-related disparities in interest rates between minority and white borrowers. Column (2) shows that the black-white racial gap in effective interest rates shrinks by 3.3 basis points from a baseline of 10.6 basis points; and the Hispanic-white racial gap shrinks by 2.6 basis points from a baseline of 6.6 basis points. Columns (5) and (6) estimate the results using the HMDA-GSE matched sample, where we can control for the credit scores. The results are very similar when using these additional controls for the borrowers' credit history.

Columns (3)-(4) and (7)-(8) apply our preferred specification in Equation (1) and control for lender-race fixed effects. This approach provides more flexibility and controls for (time-invariant) lender heterogeneities in serving borrowers of different races. In other words, if lenders who tend to have smaller race-related gaps adopt diversity policies, we are controlling for that normal tendency. With our preferred specification, and the full set of controls in the HMDA-GSE matched sample, we estimate that the diversity policy reduces the average minority-white interest rate gap by 4.1 basis points. Specifically, the black-white rate gap shrinks by 4 basis points, and the Hispanic-white rate gap shrinks by 8 basis points. For a loan of $300,000, this reduced gap translates into an annual reduction of difference in interest expenses of $120 ($240) for a Black (Hispanic) borrower relative to a comparable white borrower.

IV.1.2 Share of High-Spread Mortgages

Panel B of Table 3 presents the estimation results for an alternative measure of loan costs—an indicator for high-spread mortgages. We define a mortgage as high-spread if the rate spread is above 150 basis points (Larson 2024). This measure is important for the event study analysis which we conduct. Prior to 2018, the only measure of interest rates included in the HMDA data were rate spreads, which were only disclosed if they exceeded 150 basis points. Thus, high-spread mortgages serve as the only available loan cost proxy for analysis including years prior to 2018. For completeness, we report results of estimating Equation (1) with this alternative dependent variable. A positive coefficient on the race-diversity policy interaction terms (*X Borrower # Diversity* $Policy_{-1}$) indicates that it is more likely for borrowers in the given group to get a mortgage with high spreads.

Similar to the pattern of effective rate spreads, we observe racial disparities in the likelihood of a high-spread mortgage, without any diversity policy. As captured by the coefficients on each specific minority borrower category in columns (2) and (6), Black and Hispanic borrowers are more likely to end up with high-spread mortgages than the white borrowers that choose the same product. This racial gap shrinks significantly for both Black and Hispanic borrowers after diversity policies are adopted, consistent across all model specifications.

IV.1.3 Event Study on the Likelihood of a High-Spread Mortgage

While the above results present a cohesive set of results around the effect of diversity policies on race-related gaps in mortgage costs, such findings are based on a crucial assumption that the treated group (minority borrowers) and control group (white borrowers) share parallel trends before the adoption of the diversity policies. To visualize the dynamics of the diversity policy effect, and to test the parallel trend assumption, we conduct an event study analysis with a staggered Difference-in-Differences design at the lender level. We define the event as a lender's adoption of a diversity policy and employ a two-stage estimation technique proposed by Gardner (2022). To include a broader range of events, we extend the sample period to be between 2010 and 2021, yielding a total of 12 policy adoption events, for which we have a clear adoption year, during the expanded timeframe.

While the long HMDA panel expands the horizon around the diversity policy adoption events, it suffers from more data limitations compared with the short panel DID regressions. First, the HMDA data prior to 2018 only disclose sparse information on mortgage costs: Interest rate and closing costs are not available, and the rate spread is only available for 5%-7% of the mortgage that are high-spread. Therefore, we can only carry out an event study exploiting an indicator for high-spread mortgages, capturing changes in the share of a given race/ethnicity group's mortgages which are defined as high-spread mortgages. Second, HMDA data prior to 2018 contain fewer borrowers or mortgage characteristics, so we cannot control for LTV, DTI, conforming loan and borrower age in the event study regressions. Third, due to the lack of overlapping information with the GSE performance data, we cannot fuzzy merge the prior-2018 HMDA data with the GSE performance data, therefore limiting our abilities to control for credit scores.

With these caveats in mind, we conduct an event study analysis on high-spread mortgages by estimating Equation (2) with the Gardner estimator. Figure 2 presents results. We observe no significant difference in the high-spread mortgage share between white and minority borrowers prior to the introduction of the diversity policies, with no clear trend in the difference. The lack of difference prior to the diversity policy seems to be at odds with the results in Table 3, Panel B, which show a disparity in the likelihood of a high-spread mortgage. However, this difference in results may be due to the lack of controls for borrower and loan risk. Importantly, the lack in a trend prior to the adoption of a diversity policy supports the parallel trend assumption we rely on in our Difference-in-Differences research design. Consistent with the findings in Panel B of Table 3, we observe a change in the minority-white gap in high-spread mortgage likelihood after lenders implement diversity policies. The relative drop in high-cost likelihood for the minority borrowers is significant during the first two years of diversity policy adoption, but reverts to zero after that. The magnitude of the high-spread mortgage share reduction is similar to the finding in Table 3.

Overall, the event study results allow us to strengthen inferences and suggest a causal effect of diversity policy adoption on reducing racial disparities in mortgage costs. The evidence is consistent with the policies being effective in achieving DEI-related goals, at least for the first two years after adoption.

IV.2 Mortgage Approval

Table 4 presents the result of estimating Equation (1) for approval decisions (extensive margin). Columns (1)-(4) 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 (5)-(8) presents results for whether the loan is approved, conditional on application completion, where LTV and DTI are controlled for.

IV.2.1 Reduced Racial Gap in Application Completion Rates

Consistent with prior research, we find lower completion and approval rates for Black borrowers, absent diversity policies. The coefficient on *Black Borrower* is negative and statistically significant in both completion and approval rates. However, Column (4) shows that diversity policies improve completion rates across all borrower groups. 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*$_{-1}$, which results in a reduced black-white completion gap of 1.86 percentage points.

We repeat the event study analysis for application completion and present the result in Figure 3. Consistent with the findings in Table 4, 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 year after the policy adoption, with a 2-percentage-point improvement in closing completion gaps between minority and majority borrowers. The diversity policy effect seems to drop from year 4 onwards.

IV.2.2 Increased Racial Gap in Application Approval Rates

Columns (5) through (8) of Table 4 present results for application approval rates. Columns (5) and (6) indicate that there is inconsistency in approval rate gaps without a diversity policy: Black and non-Black non-Hispanic minority borrowers (primarily Asian) face lower approval rates, however Hispanic borrowers experience higher approval rates. A potentially surprising finding is that diversity policies seem to be associated with a further decrease in approval rates for Black and other minority borrowers. Specifically, we find significantly negative coefficients on the interaction term between *Minority Borrow* and *Diversity Policy*$_{-1}$ in Column (7), indicating a widening of the racial gap in approval rates between minority and white borrowers. The effect is particularly strong for Black borrowers and is significant for other minority borrowers. As indicated by the coefficient on the interaction term between *Black Borrower* and *Diversity Policy*$_{-1}$ in Column (8), the approval rate racial gap increases by as much as 3.34 percentage points, which outpaces the closing completion rate gap and results in an overall decrease in the mortgage originations.

Figure 4 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 2 through 4. Four years into the policy implementation, the difference in approval rates between minority and white applicants widens by 5.5 percentage points.

Figure 5 investigates overall mortgage originations rates, which measure the share of mortgage applications that end up being originated. Both application completion and approval are necessary conditions for mortgage origination. We document a decrease in origination rate for minority borrowers compared with white borrowers after the adoption of diversity policies, which is mainly driven by the increased racial gap in mortgage approval rates.

V. Mechanisms Analysis for the Effects of Diversity Policies

The evidence presented in Section IV suggests a differential impact of diversity policies on different phases of the lending process. On one hand, minority borrowers at diversity lenders experience enhanced completion rates and reduced loan costs. Both completion rates and loan costs are part of the mortgage lending process that is heavily influenced by the "front office," e.g., loan officers at a bank branch location who work with borrowers. Therefore, a lender's diversity policy appears to benefit minority borrowers through the channel of the front office. On the other hand, almost all minority groups at the diversity lenders experience worse loan approval rates, which is likely due to more stringent approval decisions from the back office. To shed more light on specific mechanisms through which diversity policies affect front office and back office decisions, we conduct several additional analyses.

V.1 Front Office: Race Matching between Borrowers and Loan Officers at the Front Office

Both Frame et al. (2022) and Ambrose et al. (2021) have demonstrated that minority borrowers tend to achieve better outcomes when assisted by minority loan officers. One avenue through which diversity policies may have an influence in the mortgage process is by fostering a more diverse pool of loan officers and improving the alignment of race and ethnicity between loan officers and borrowers. Since one important goal of most diversity policies is to eliminate any racial barriers in the hiring process, such policies are likely to increase minority representation among loan officers. We find that after adopting diversity policies, lenders in our sample increased minority representation among loan officers by 1.03 percentage points, from 19.97% to 21%. In addition, if lenders are more aware of the potential benefits of race alignment, existing minority loan officers might focus more on minority borrowers. We examine whether diversity policies induce an increase in borrower-loan-officer race alignment.

While our data includes race information for borrowers, it does not include loan officer race. We identify loan officer race in the following way: First, we obtain the loan officer license ID by merging the originated HMDA mortgages with CoreLogic mortgage data. The CoreLogic

Mortgage data reports the Nationwide Multistate Licensing System (NMLS) identification number for the loan officer for the originated mortgages. This ID number uniquely identifies loan officers across time and employers. Following prior literature, we merge HMDA with CoreLogic based on lender name, loan amount, and property census tract. We only keep observations with one-to-one matches based on those dimensions. Second, we retrieve the loan officer names and work locations from the NMLS registry dataset based on their NMLS IDs. Finally, we obtained the loan officers' race from InfoUSA Residential Historical Dataset. InfoUSA tracks almost all households in the U.S. and provides home addresses, individual names, races, and other demographic information. We merge our sample with InfoUSA based on loan officers' names and work locations. We apply two criteria to locate loan officers: (1) name match (including first names and last names); (2) geolocation match (i.e., home address within 100 miles of the work location). Upon completing these three steps, we successfully identify the race of loan officers for 25% of the originated mortgages.

Table 5 reports results. Column (1) shows that minority borrowers are 3.7% more likely to be matched with minority loan officers compared with white borrowers after diversity policies are adopted. Columns (2)-(4) break down the match rate by race. We find an improved match rate between borrowers and loan officers for each respective minority group at diversity lenders. Specifically, the match rate for Black borrower-Black loan officer is increased by 3.5%. The match rates for Hispanic borrower-Hispanic loan officer increases by 5.2%. And the match rate for other minority group borrower-other loan officer increases by 3.6%. Columns (5)-(8) repeat the race match analysis in the HMDA-GSE matched the sample, and the results are similar.

V.2 Back Office

While the above analyses provide insights into the mechanism through which diversity policies affect front office, which subsequently impact the enhanced completion rates and reduced loan costs, it does not explain the widened gap in approval rate between minority and white borrowers. Approvals are decided by the back office. In the subsequent analyses, we try to shed some light on the back office's decision process that leads to this outcome.

V.2.1 Methodology: A Machine Learning Approach for Predicted Default Risk

The back office needs to assess default risk and determine if a given loan application should be approved conditional on the assessed risk. In an ideal analysis, we would be able to fully model the back office's risk assessment using all relevant risk factors. Since we cannot fully replicate the back office's risk assessment, we rely instead on a machine learning approach. In particular, we use a machine-learning-based model to predict each mortgage applicant's default risk based on a comprehensive set of observable risk characteristics. We train a random forest model using the default outcomes and 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 complete 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.[12] In the Online Appendix, we demonstrate the model's accuracy in closely tracking realized delinquency outcomes. Full details of the random forest model are also provided in the Online Appendix. In

[12] We apply the model only to completed applications, since DTI and LTV are missing in most of the incomplete applications.

the subsequent subsections, we use this risk assessment to estimate the impact of diversity policy adoption on applicant riskiness and to analyze approval rates conditional on applicant riskiness.

V.2.2 Increase in Mortgage Applicants' Riskiness Following Diversity Policy Adoption

The implementation of a diversity policy may increase the number of risky minority applications reaching the back office, potentially widening the approval gap even if approval standards remain steady. To explore this possibility, we analyze the risk profiles of mortgage applications processed by the back office. We begin by analyzing the predicted default risk for mortgage applications arriving at the back office, without conditioning on diversity policies. Panel A of Figure 6 shows that, consistent with common perceptions, minority applicants exhibit higher predicted default risks compared to white applicants, particularly among those in the higher-risk tail.

We then examine whether distributions of the predicted default risk for minority and white applicants change following the adoption of diversity policies. Figure 6 Panel B shows the distribution of applicant default risk for white and minority applicants before and after diversity policy adoption, for lenders that adopt policies during our sample period. The riskiness of minority applicants increases after policy adoption, with a particularly strong increase in the highest predicted default risk range.

We further examine whether there is a shift in application riskiness in a regression model, controlling for other loan characteristics, as well as lender and lender*race fixed effects. The results reported in Table 6 are consistent with the inferences from Figure 6, Panel B. Columns (1) through (4) focus on changes in income as a specific dimension of risk, while columns (5) and (6) assess shifts in overall predicted default risk. The results suggest a relative increase in minority applicant riskiness after diversity policy adoption. The estimated effect sizes indicate a 3-4%

decrease in applicant income relative to the applicant's local (MSA) median and a 0.5-1.3% increase in predicted default risk for minority applicants. This evidence indicates that, after diversity policy adoption, the back office is encountering more minority applicants with elevated risk profiles. Thus, it is likely that a shift in application riskiness at least in part explains the decrease in approval rates for minority applicants.

V.2.3 Widened Approval Rate Gap Accounting for Changes in Applicant Risk

In this section, we further examine whether the shift in applicant riskiness fully explains the widened approval rate gap following diversity policy adoption. In panel A of Figure 7, we present approval rates by race across different predicted default risk levels, unconditional on diversity policies. As expected, the approval rate declines as predicted default risk increases for all applicants, reinforcing the validity of our random forest model. However, the approval rate for minority borrowers is consistently lower than that of white borrowers, even within the same default risk level, indicating racial disparities in approval decisions. This gap in approval rates is more pronounced in higher-risk categories, suggesting that an increase in risky minority applications could lower approval rates through two mechanisms: an increase in high-risk applications that are generally less likely to be approved (regardless of race) and an amplified race-related approval rate gap among high-risk applications.

An additional potential mechanism, which would either augment or counteract the risk shift discussed above, is that the approval rates themselves shift for minority applicants, holding risk levels constant. An increase would be consistent with the lender taking specific actions to achieve DEI lending goals. A decrease would be consistent with a backlash effect – in which the stigma of diversity policies causes the back office to perceive that minority applicants are even higher-risk and/or lower-quality than they are, due to the diversity policy. Panel B of Figure 7 presents approval rates by race across different predicted default risk levels, both before and after diversity policy adoption. Similar to the patterns observed in Panel A, approval rates decrease as predicted default risk increases, and minority applicants consistently have lower approval rates. More importantly, the approval rate gap between white and minority applicants widens following the policy adoption, even after controlling for predicted default risks. This is consistent with a backlash/stigma effect, in which back office employees overreact to the diversity policy.

To examine the extent to which application riskiness explains the widening approval gap, and whether the gap persists after controlling for predicted default risk, we estimate an augmented version of Equation (1). In particular, we repeat the difference-in-differences analysis in Table 4, which assesses the impact of lenders' diversity policies on the approval rate gap between white and minority applicants, adding fixed effects for bins of predicted default risk. The results are presented in Columns (1) and (2) of Table 7. We find that the widened approval gap between minority and white applicants persists even after accounting for changes in minority applicants' risk profiles following diversity policy adoption. Specifically, the gap in approval rates increases by 1.3% without risk controls and persists at 0.94% after controlling for the predicted default risks. Therefore, the shift in applicant riskiness explains 27.7% of the changes in the approval rate gap. In the subsample analysis in column (3) through (10) of Table 7, we consistently observe a widened disparity in approval rates between minority and white applicants after the adoption of diversity policies, across all predicted default risk buckets.

The collective evidence above suggests that the increase in approval rate disparity cannot be fully explained by changes in predicted default risk, giving rise to the question of whether the lower approval rates for minority applicants after diversity policy adoption are warranted. To gain further insights into that, we examine ex-post loan performance outcomes. Panel A of Table 8 report results for the effect of a diversity policy on mortgage default within 2 years after loan origination.[13] We use a standard indicator of mortgage default, which equals one if the borrower misses payments for 2 consecutive months. The results indicate a significant reduction in default rates for Black borrowers (by 1.3 percentage points) after the lenders adopt the diversity policy. This finding suggests 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. In other words, this suggests that the decrease in approval rates, particularly for minority applicants, is not warranted by subsequent 2-year default rates.

While we cannot examine the quality of denied mortgages, the decrease in ex-post defaults provides additional support that the decrease in minority loan approvals cannot be entirely explained by actual risks.

V.2.4 Discussion

Ultimately, the results reported above are puzzling from a fully rational perspective. Why would the back office deny more applications if not for increased risk? To better understand the reasons behind higher denials in the back office, we examine lender-reported loan denial reasons in Table 9. We find consistent support for both increased applicant risk and increased denials not explained by risks. Denial reasons related to applicant risk, such as debt-to-income ratio and credit history, increase for minority borrowers after policy adoption. However, there is also a notable rise in the use of "other" as a denial reason, indicating an increase in denials which do not specifically

[13] We also examine the effect of the diversity policy on mortgage prepayment within 2 years after originations in Panel B. We observed an increased rate of prepayment after the implementation of diversity policies, which is not surprising because prepayment tends to negatively correlate with default.

pertain to typical risk factors. Consistent with findings of higher completions at the front office, denial reasons related to incomplete information decline.

Taken together, our results reveal the complexity of the effects that diversity policies have on mortgage lending. While front offices actively work to attract and support minority applicants after policy adoption, they pass more minority applicants with higher predicted default risks to the back office. In response, back-office risk management practices tighten approval standards, leading to a widened approval rate gap between minority and white applicants. However, this effect persists even after accounting for predicted default risks, suggesting a backlash/stigma effect where the perceived riskiness is even higher than the actual riskiness, driving approval rates to drop beyond what actual risk levels justify. This underscores the complex interactions among different segments of a business, the differential effects policies can have at different points in the business process, and the importance for considering all portions of a business when designing and implementing diversity policies. For example, better communication between the front and back office, training for the back office, and time/resources for the back office to more carefully and thoughtfully process higher-risk applications, could all potentially alleviate the backlash effect we observe.

VI. Conclusion

In this paper, we examine the impact of mortgage lenders' diversity policies on racial disparities in mortgage lending outcomes. We utilize rich fixed effects specifications and an event study approach to strengthen causal inferences. Our results suggest that diversity policies reduce race-related gaps in borrowing costs measured by effective interest rate spreads. While loan costs decrease for all borrowers, the reduction is largest for minority borrowers, therefore narrowing race-related gaps. However, we find an opposing effect when focusing on mortgage approvals and originations: lenders with diversity policies have lower approval and origination rates for minority borrowers. Even though diversity policies appear to partially narrow differences in application completion rates, this effect is more than offset by the lower approval rates, resulting in an incremental decrease in origination rates for minority borrowers.

The results collectively point to a differential effect of diversity policies on the front office, in charge of application completions and loan costs, and the back office, in charge of approvals. Additional analyses address possible mechanisms, shedding additional light on front- and back-office effects. In particular, we find that diversity policies increase the alignment of racial backgrounds between loan officers and borrowers at the front office, which prior evidence suggests will improve loan outcomes for minorities.

Focusing on the back office, we find an increase in the riskiness of minority applications following diversity policy adoption, using both standard measures (e.g., applicant income) and a machine learning model for predicted default risk. This increase in risky minority applications partially explains the drop in approval rates for minority applicants. However, we find that the widened approval gap persists after controlling for changes in riskiness, suggesting the decrease in minority loan approvals cannot be entirely explained by actual risks. This is further supported by examination of the ex-post loan performance.

Overall, the evidence suggests that the back office overreacts to the introduction of a diversity policy, increasing lending standards for minority applicants. This is consistent with the policy creating a stigma, in which the back office perceives minority applications completed under a diversity policy to be even lower quality. Such implicit biases will be exacerbated if the back office lacks time and resources to carefully evaluate the increased volume of completed applications (Bertrand, Chugh and Mullainathan 2005). Our results suggest that lenders who want to narrow approval rate gaps should pay close attention to the training of, communication with, and resourcing of, the back office.

It is also important to note that our results indicate that diversity policies do not induce a zero-sum game in lending. By addressing inefficiencies in the lending process, lenders appear to generate better outcomes for *all* borrowers. Moreover, the diversity policies benefit lenders as well. Following the diversity policy adoption, the total number of completed applications increases by 4.65%. The increase in completed applications leads to a 1.96% increase in loan volume, which, in turn, enhances lenders' profitability by approximately 1.1%. Our results contribute to the growing discussion of whether diversity policies shift the distribution of limited resources away from majority-group members, or whether such policies result in an increase in resources (i.e., "grow the pie").

Our paper presents the first large-sample analysis of the effects of diversity policies on mortgage lending. 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. But it is important to consider potential overreaction, stigmas, and backlash effects when designing and implementing such policies. Finally, careful analyses of diversity policy effects can provide insight into how to improve such policies. It should not be assumed that all policies do what they claim.

References

Ambrose, B. W., Conklin, J., Coulson, N. E., Diop, M., & Lopez, L. A. (2023). Do Appraiser and Borrower Race Affect Mortgage Collateral Valuation? *Working paper*.

Ambrose, B. W., Conklin, J. N., & Lopez, L. A. (2021). Does borrower and broker race affect the cost of mortgage credit?. *The Review of Financial Studies*, *34*(2), 790-826.

An, B., Bushman, R., Kleymenova, A., & Tomy, R. E. (2024). Bank Supervision and Organizational Capital: The Case of Minority Lending. *Journal of Accounting Research*, 62(2), 505-549.

Bartlett, R., Morse, A., Stanton, R., & Wallace, N. (2022). Consumer-lending discrimination in the FinTech era. *Journal of Financial Economics*, *143*(1), 30-56.

Baker, A. C., Larcker, D. F., McClure, C. G., Saraph, D., & Watts, E. M. (2024). Diversity washing. *Journal of Accounting Research, forthcoming*.

Basu, S., Vitanza, J., Wang, W., & Zhu, X. R. (2022). Walking the walk? Bank ESG disclosures and home mortgage lending. *Review of Accounting Studies*, *27*(3), 779-821.

Begley, T. A., & Purnanandam, A. (2021). Color and credit: Race, regulation, and the quality of financial services. *Journal of Financial Economics, 141*(1), 48-65.

Bertrand, M., & Mullainathan, S. (2004). Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination. *American Economic Review, 94*(4), 991-1013.

Bertrand, M., D. Chugh, and S. Mullainathan. (2005) Implicit discrimination. *American Economic Review, 95*(2): 94-98.

Bhutta, N., & Hizmo, A. (2021). Do minorities pay more for mortgages? *Review of Financial Studies,* 34: 763-789.

Bhutta, N., Hizmo, A., & Ringo, D. (2024). How much does racial bias affect mortgage lending? Evidence from human and algorithmic credit decisions. *Working paper*.

Borusyak, K., Jaravel, X., & Spiess, J. (2021). Revisiting event study designs: Robust and efficient estimation. *Review of Economic Studies, rdae007.*

Butler, A. W., Mayer, E. J., & Weston, J. P. (2023). Racial disparities in the auto loan market. *The Review of Financial Studies, 36*(1), 1-41.

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200-230.

Chen, T.-P., & Smith, R. A. (2023). No One Is Happy About Diversity Efforts at Work. *The Wall Street Journal*. Available at https://www.wsj.com/articles/diversity-workplace-affirmative-action-dei-3646683b

De Chaisemartin, C., & d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, *110*(9), 2964-2996.

De Chaisemartin, C., & d'Haultfoeuille, X. (2024). Difference-in-differences estimators of intertemporal treatment effects. *Review of Economics and Statistics, 1-45.*

Devine, P. G., & T. L. Ash. (2022). Diversity training goals, limitations, and promise: A review of the multidisciplinary literature. *Annual Review of Psychology* 73: 403-429.

Dougal, C., Gao, P., Mayew, W. J., & Parsons, C. A. (2019). What's in a (school) name? Racial discrimination in higher education bond markets. *Journal of Financial Economics, 134*(3), 570-590.

Dover, T. L., Major, B., & Kaiser, C. R. (2016). Diversity policies rarely make companies fairer, and they feel threatening to white men. *Harvard Business Review*. Available at: https://hbr.org/2016/01/diversity-policies-dont-help-women-or-minorities-and-they-make-white-men-feel-threatened.

Erel, I., & Liebersohn, J. (2022). Can FinTech reduce disparities in access to finance? Evidence from the Paycheck Protection Program. *Journal of Financial Economics, 146*(1), 90-118.

Fairlie, R., Robb, A., & Robinson, D. T. (2022). Black and white: Access to capital among minority-owned start-ups. *Management Science, 68*(4), 2377-2400.

Frame, S. Huang, R., Jiang, E., Lee, Y., Liu, W., Mayer, E., & Sunderam, A. (2024). The Impact of Minority Representation at Mortgage Lenders. *Journal of Finance, forthcoming.*

Gardner, J. (2022). Two-stage differences in differences. *Working paper*.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254-277.

Heilman, M. E., Block, C. J., & Lucas, J. A. (1992). Presumed incompetent? Stigmatization and affirmative action efforts. *Journal of Applied Psychology, 77*(4), 536-544.

Heilman, M. E., Block, C. J., & Stathatos, P. (1997). The affirmative action stigma of incompetence: Effects of performance information ambiguity. *The Academy of Management Journal, 40*(3), 603-625.

Kalev, A., Dobbin, F., & Kelly, E. (2006). Best practices or best guesses? Assessing the efficacy of corporate affirmative action and diversity policies. *American Sociological Review, 71*(4), 589-617.

Kline, P., Rose, E. K., & Walters, C. R. (2022). Systemic discrimination among large U.S. employers. *Quarterly Journal of Economics, 127*(4), 1963-2035.

Larson, B. (2024). Internal controls and consumer protection: Evidence from retail mortgage lending. *Working paper*, Arizona State University.

Monea, N. (2024). Next on the chopping block: The litigation campaign against race-conscious policies beyond affirmative action in university admissions. *Boston University Public Interest Journal 33:1.*

Morse, A., & Pence, K. (2021). Technological innovation and discrimination in household finance. In D. Drasch, J. Hess, & A. Richman (Eds.), *The Palgrave Handbook of Technological Finance* (pp. 783-808). Springer International Publishing.

Munnell, A. H., Tootell, G. M., Browne, L. E., & McEneaney, J. (1996). Mortgage lending in Boston: Interpreting HMDA data. *The American Economic Review*, 25-53.

Paluck, E. L., Porat, R., Clark, C. S., & Green, D. P. (2020). Prejudice reduction: Progress and challenges. *Annual Review of Psychology* 72: 533-560.

Thomas, J., Yao, W., Zhang, F., & Zhu, W. (2022). Meet, beat, and pollute. *Review of Accounting Studies*, 27(3), 1038-1078.

Table 1 Description of the Variables

Application Outcomes	Source	Definition
Completed	HMDA	Indicator equal to one if the application is completed and submitted for decision
Approved (given completed)	HMDA	Indicator equal to one if the loan is originated or the application is approved but not accepted, given the application is completed
Originated	HMDA	Indicator equal to one if the loan is originated, given the application is completed
Interest Rate (%)	HMDA	The interest rate for the approved mortgage as a percentage of the outstanding loan amount. Only available post-2018.
Rate Spread (%)	HMDA	The spread between the Annual Percentage Rate (APR) and a survey-based estimate of APRs currently offered on prime mortgage loans of a comparable type. Prior to 2018, rate spreads are defined differently, as the spread between the interest rate and the prime rate, and are only disclosed if they exceeded 150 basis points.
Default (within 2 years)	Loan Performance	Indicator equal to one if the borrower fails to make payments or misses the deadlines for two consecutive months.
Prepaid (within 2 years)	Loan Performance	Indicator equal to one if the borrower makes payments before the deadlines
Denial – X (reason)	HMDA	Indicator equal to one if the applicant is denied and the principal reason for denial is X, as reported by the lender. The possible categories (X) are: debt-to-income ratio; employment history; credit history; collateral; insufficient cash (e.g., for down payment and closing costs); unverifiable information; credit application incomplete; mortgage insurance denied; other
Key Independent Variables		
Minority Borrower	HMDA	Indicator equal to one if the borrower is a racial/ethnic minority
Black Borrower	HMDA	Indicator equal to one if the race of the borrower is Black
Hispanic Borrower	HMDA	Indicator equal to one if the ethnicity of the borrower is Hispanic or Latino
Other Minority Borrower	HMDA	Indicator equal to one if the borrower is a racial/ethnic minority, but not Black, Hispanic or Latino
Diversity Policy$_{-1}$	Refinitiv	Indicator equal to one if the lender has a diversity policy in the past calendar year
Control Variables		
log(Loan Amount)	HMDA	The amount of the covered loan in dollars, controlled for with log(Loan Amount)
Income Ratio (Relative to MSA Median Income)	HMDA	The ratio of the applicant gross annual income and the local MSA median income, controlled for with percentile of income ratio.
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.
Joint Application	HMDA	Indicator equal to one if there are multiple people on the application
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 - FSA/RHS	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)
Credit Score	Loan Performance	FICO Score, controlled for with 40-point bins ranging from 580 to 820, and with bins less than 580 and higher than 820
Combined Loan-to-Value	HMDA	Loan-to-Value ratio, controlled for with bins
Debt-to-Income	HMDA	Debt-to-Income ratio, controlled for with bins

Table 2 Summary Statistics

	Mean	S.D.	P1	P25	P50	P75	P99	Obs.
Application Outcomes								
Completed	0.83	0.38	0.00	1.00	1.00	1.00	1.00	2,397,799
Approved (given completed)	0.90	0.30	0.00	1.00	1.00	1.00	1.00	1,976,734
Originated	0.73	0.45	0.00	0.00	1.00	1.00	1.00	2,397,799
Delinquent (within 2 years)	0.03	0.16	0.00	0.00	0.00	0.00	1.00	318,042
Prepaid (within 2 years)	0.40	0.49	0.00	0.00	0.00	1.00	1.00	318,042
Denial - Debt-to-income ratio	0.47	0.50	0.00	0.00	0.00	1.00	1.00	200,969
Denial - Employment history	0.06	0.24	0.00	0.00	0.00	0.00	1.00	200,969
Denial - Credit history	0.23	0.42	0.00	0.00	0.00	0.00	1.00	200,969
Denial - Collateral	0.15	0.36	0.00	0.00	0.00	0.00	1.00	200,969
Denial - Insufficient cash	0.14	0.34	0.00	0.00	0.00	0.00	1.00	200,969
Denial - Unverifiable information	0.10	0.30	0.00	0.00	0.00	0.00	1.00	200,969
Denial - Credit application incomplete	0.06	0.24	0.00	0.00	0.00	0.00	1.00	200,969
Denial - Mortgage insurance denied	0.00	0.05	0.00	0.00	0.00	0.00	0.00	200,969
Denial - Other	0.16	0.37	0.00	0.00	0.00	0.00	1.00	200,969
Key Independent Variables								
Minority Borrower	0.34	0.48	0.00	0.00	0.00	1.00	1.00	2,397,799
- Black Borrower	0.10	0.30	0.00	0.00	0.00	0.00	1.00	2,397,799
- Hispanic Borrower	0.13	0.34	0.00	0.00	0.00	0.00	1.00	2,397,799
- Other Minority Borrower	0.11	0.32	0.00	0.00	0.00	0.00	1.00	2,397,799
Diversity Policy$_{-1}$	0.90	0.30	0.00	1.00	1.00	1.00	1.00	2,397,799
Control Variables								
log(Loan Amount)	12.54	0.66	10.92	12.13	12.53	12.91	14.28	2,397,799
Conforming Loan	0.90	0.29	0.00	1.00	1.00	1.00	1.00	2,397,799
Borrower Age - less than 25	0.05	0.22	0.00	0.00	0.00	0.00	1.00	2,397,799
Borrower Age - 25-34	0.32	0.47	0.00	0.00	0.00	1.00	1.00	2,397,799
Borrower Age - 35-44	0.27	0.45	0.00	0.00	0.00	1.00	1.00	2,397,799
Borrower Age - 45-54	0.17	0.37	0.00	0.00	0.00	0.00	1.00	2,397,799
Borrower Age - 55-64	0.11	0.31	0.00	0.00	0.00	0.00	1.00	2,397,799
Borrower Age - 65-74	0.06	0.24	0.00	0.00	0.00	0.00	1.00	2,397,799
Borrower Age - greater than 74	0.02	0.13	0.00	0.00	0.00	0.00	1.00	2,397,799
Joint Application	0.45	0.50	0.00	0.00	0.00	1.00	1.00	2,397,799
Loan Type - Conventional	0.76	0.43	0.00	1.00	1.00	1.00	1.00	2,397,799
Loan Type - FHA	0.15	0.35	0.00	0.00	0.00	0.00	1.00	2,397,799
Loan Type - VA	0.08	0.27	0.00	0.00	0.00	0.00	1.00	2,397,799
Loan Type - FSA/RHS	0.02	0.13	0.00	0.00	0.00	0.00	1.00	2,397,799
Credit Score	760	248	635	724	764	791	817	317,617
Combined Loan-to-Value	80.66	16.27	27.00	75.00	80.00	95.00	97.00	318,042
Debt-to-Income	35.28	9.45	12.00	29.00	36.00	43.00	50.00	318,041

Table 3 The Effect of Diversity Policy on Loan Cost

The table reports regression results for mortgage costs with Equation (1). The observations are all the originated mortgages in the short panel HMDA data (2018-2021), as well as the ones that can be matched with Fannie Mae and Freddie Mac Performance Data. Panel A reports results on rate spreads, and Panel B reports results on the share of high spread mortgages. The description of the variables is 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: The Effect of Diversity Policy on Rate Spread

	Rate Spread = APR – Prime Rate (%)							
	Full HMDA Sample				HMDA matched with GSE Performance Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority Borrower # Diversity Policy$_{-1}$	-0.035***		-0.033***		-0.036***		-0.041***	
	(-5.95)		(-4.12)		(-5.64)		(-5.28)	
Black Borrower # Diversity Policy$_{-1}$		-0.033***		-0.020*		-0.037***		-0.040***
		(-4.72)		(-1.85)		(-5.05)		(-3.66)
Hispanic Borrower # Diversity Policy$_{-1}$		-0.026***		-0.064***		-0.051***		-0.080***
		(-2.84)		(-5.38)		(-5.25)		(-7.36)
Other Minority # Diversity Policy$_{-1}$		-0.014**		0.001		-0.007		0.008
		(-2.54)		(0.10)		(-1.06)		(0.80)
Diversity Policy$_{-1}$	-0.055***	-0.059***	-0.059***	-0.059***	-0.048***	-0.049***	-0.049***	-0.049***
	(-8.05)	(-8.42)	(-8.40)	(-8.41)	(-8.52)	(-8.68)	(-8.71)	(-8.70)
Minority Borrower	0.058***				0.038***			
	(8.51)				(5.69)			
Black Borrower		0.106***				0.074***		
		(13.95)				(9.63)		
Hispanic Borrower		0.066***				0.063***		
		(6.36)				(5.96)		
Other Minority Borrower		-0.014***				-0.020***		
		(-2.70)				(-3.21)		
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
FICO Bin FE					x	x	x	x
Conforming	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x
Income 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
Year FE	x	x	x	x	x	x	x	x
Property County FE	x	x	x	x	x	x	x	x
Lender FE	x	x			x	x		
Lender*Race FE			x	x			x	x
Dependent Var. Mean	0.32	0.32	0.32	0.32	0.28	0.28	0.28	0.28
R^2	0.60	0.61	0.61	0.61	0.53	0.53	0.54	0.54
Obs.	1,650,855	1,650,855	1,650,855	1,650,855	869,686	869,686	869,686	869,686

Panel B: The Effect of Diversity Policy on High Spread Mortgage Probability

	High Spread Mortgage [Prob(Rate Spread>150 bps) in %]							
	Full HMDA Sample				HMDA matched with GSE Performance Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority Borrower # Diversity Policy$_{-1}$	-3.89***		-5.05***		-2.10***		-3.67***	
	(-7.63)		(-7.21)		(-4.82)		(-5.24)	
Black Borrower # Diversity Policy$_{-1}$		-4.90***		-4.30***		-2.91***		-4.40***
		(-8.72)		(-4.64)		(-5.35)		(-4.35)
Hispanic Borrower # Diversity Policy$_{-1}$		-5.67***		-9.09***		-3.43***		-6.79***
		(-7.30)		(-9.80)		(-4.95)		(-6.49)
Other Minority # Diversity Policy$_{-1}$		1.20***		1.23**		0.23		0.79*
		(3.45)		(2.25)		(0.87)		(1.75)
Diversity Policy$_{-1}$	-2.40***	-2.40***	-2.17***	-2.17***	-1.11***	-1.11***	-0.78***	-0.78***
	(-9.12)	(-9.28)	(-8.78)	(-8.78)	(-3.99)	(-4.01)	(-3.19)	(-3.19)
Minority Borrower	4.26***				2.40***			
	(8.14)				(5.53)			
Black Borrower		5.89***				3.42***		
		(9.72)				(5.93)		
Hispanic Borrower		5.67***				3.47***		
		(6.84)				(4.69)		
Other Minority Borrower		-0.86**				0.25		
		(-2.52)				(1.00)		
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
FICO Bin FE					x	x	x	x
Conforming	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x
Income 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
Year FE	x	x	x	x	x	x	x	x
Property County FE	x	x	x	x	x	x	x	x
Lender FE	x	x			x	x		
Lender*Race FE			x	x			x	x
Dependent Var. Mean	4.35	4.35	4.35	4.35	1.79	1.79	1.79	1.79
R^2	0.21	0.21	0.22	0.22	0.14	0.14	0.14	0.14
Obs.	1,650,855	1,650,855	1,650,855	1,650,855	869,686	869,686	869,686	869,686

Table 4 The Effect of Diversity Policy on Approval Decisions

The table reports regression results for mortgage application completion and approval with Equation (1). The observations are from the short panel HMDA data (2018-2021). The description of the variables is 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 %)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority Borrower # Diversity Policy$_{-1}$	-0.03		1.09***		-3.58***		-1.49***	
	(-0.10)		(3.09)		(-14.31)		(-4.09)	
Black Borrower # Diversity Policy$_{-1}$		1.88***		1.86***		-4.99***		-3.34***
		(4.97)		(3.44)		(-15.96)		(-6.42)
Hispanic Borrower # Diversity Policy$_{-1}$		-0.27		0.60		-3.84***		0.05
		(-0.76)		(1.15)		(-9.16)		(0.10)
Other Minority # Diversity Policy$_{-1}$		-1.13**		0.47		-1.52***		-0.76*
		(-2.04)		(0.72)		(-5.78)		(-1.95)
Diversity Policy$_{-1}$	3.12***	2.95***	2.75***	2.74***	0.23	0.32	-0.53***	-0.53***
	(12.13)	(11.55)	(10.88)	(10.87)	(1.08)	(1.54)	(-3.53)	(-3.52)
Minority Borrower	-2.69***				-0.07			
	(-9.49)				(-0.27)			
Black Borrower		-3.82***				-0.75***		
		(-10.91)				(-2.62)		
Hispanic Borrower		-1.07***				0.89**		
		(-3.21)				(2.21)		
Other Minority Borrower		-3.56***				-1.23***		
		(-6.62)				(-5.27)		
log(Loan Amount)	x	x	x	x	x	x	x	x
LTV Bin FE					x	x	x	x
DTI Bin FE					x	x	x	x
FICO Bin FE								
Conforming	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x
Income 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
Year FE	x	x	x	x	x	x	x	x
Property County FE	x	x	x	x	x	x	x	x
Lender FE	x	x			x	x		
Lender*Race FE			x	x			x	x
Dependent Var. Mean	82.40	82.40	82.40	82.40	89.62	89.62	89.62	89.62
R^2	0.02	0.02	0.02	0.02	0.28	0.28	0.28	0.28
Obs.	2,289,776	2,289,776	2,289,775	2,289,775	1,883,680	1,883,680	1,883,680	1,883,680

Table 5 The Effect of Diversity Policy on Loan Officer-Borrower Race Match

The table reports regression results for the race match between loan officers and borrowers with Equation (1). The observations are from the short panel HMDA data (2018-2021), matched with loan officer information from CoreLogic and NMLS. The description of the variables is 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.

	Full HMDA Sample Loan Officer is				HMDA matched with GSE Performance Sample Loan Officer is			
	Minority	Black	Hispanic	Asian	Minority	Black	Hispanic	Asian
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority Borrower # Diversity Policy$_{-1}$	3.65***				3.72**			
	(3.15)				(2.55)			
Black Borrower # Diversity Policy$_{-1}$		3.45***	-0.60	-1.10**		4.12***	-1.44	-0.84
		(2.71)	(-0.72)	(-2.47)		(2.74)	(-0.86)	(-1.56)
Hispanic Borrower # Diversity Policy$_{-1}$		0.30	5.15***	-0.30		-0.18	5.16**	0.21
		(0.86)	(2.59)	(-0.83)		(-0.40)	(2.14)	(0.52)
Other Minority # Diversity Policy$_{-1}$		1.62**	-1.49	3.59***		0.23	-1.93	4.22**
		(2.23)	(-0.95)	(2.66)		(0.34)	(-0.86)	(2.38)
Diversity Policy$_{-1}$	-0.80	-0.38	-0.42	-0.00	-0.14	-0.28	-0.36	0.42
	(-1.38)	(-1.55)	(-1.15)	(-0.00)	(-0.21)	(-1.09)	(-0.80)	(0.94)
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
FICO Bin FE					x	x	x	x
Conforming	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x
Income 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
Year FE	x	x	x	x	x	x	x	x
Property County FE	x	x	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x	x	x
Dependent Var. Mean	19.63	2.27	10.07	7.14	17.98	1.98	10.25	5.63
R^2	0.20	0.08	0.16	0.22	0.21	0.07	0.18	0.20
Obs.	394,472	394,472	394,472	394,472	215,460	215,460	215,460	215,460

Table 6 The Effect of Diversity Policy on Riskiness of Mortgage Applicants

The table reports regression results of Equation (1) for the income level and high-debt share of the mortgage applicants. The observations are all the originated mortgages in the short panel HMDA data (2018-2021). The description of the variables is 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.

	Applicant Income (Relative to MSA Median, in %)				Predicted Default Probability (%)	
	Applications		Completed Applications		Completed Applications	
	(1)	(2)	(3)	(4)	(5)	(6)
Minority Borrower # Diversity Policy$_{-1}$	-2.55**		-2.80***		0.69***	
	(-2.12)		(-3.38)		(8.69)	
Black Borrower # Diversity Policy$_{-1}$		-2.68*		-3.01**		1.31***
		(-1.78)		(-2.49)		(11.47)
Hispanic Borrower # Diversity Policy$_{-1}$		-4.03***		-4.06***		0.51***
		(-3.26)		(-4.31)		(4.54)
Other Minority # Diversity Policy$_{-1}$		0.55		0.09		-0.21*
		(0.32)		(0.07)		(-1.79)
Diversity Policy$_{-1}$	-2.72	-2.72	-2.25	-2.25	0.32***	0.32***
	(-1.37)	(-1.37)	(-1.38)	(-1.38)	(6.63)	(6.62)
log(Loan Amount)	x	x	x	x		
LTV Bin FE						
DTI Bin FE						
FICO Bin FE						
Conforming	x	x	x	x		
Joint Application	x	x	x	x		
Income Percentile FE						
Borrower Age Bin FE	x	x	x	x		
Loan Type FE	x	x	x	x		
Year FE	x	x	x	x	x	x
Property County FE	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x
Dependent Var. Mean	132.53	132.53	129.68	129.68	4.75	4.75
R^2	0.03	0.03	0.02	0.02	0.30	0.30
Obs.	2,289,775	2,289,775	1,886,803	1,886,803	1,883,680	1,883,680

Table 7 The Effect of Diversity Policy on Approval Decisions by Predicted Default Risk Levels

The table reports regression results for mortgage application approval with Equation (1), after accounting for predicted default risk. The observations are all the originated mortgages in the short panel HMDA data (2018-2021). Column (1) and (2) control for the default risk bin fixed effects predicted by the random forest model. The default risk bins are set at 1% intervals, ranging from 0% to 15%, with all risks above 15% grouped into a combined bin. Column (3)-(10) reports regression results for mortgage application approval with Equation (1) across different the default risk buckets. The description of the variables is 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.

	Approved (Given Completed, in %)		Approved (Given Completed, in %)							
			Default Risk 0-5%		Default Risk 5-10%		Default Risk 10-15%		Default Risk >15%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Minority Borrower # Diversity Policy$_{-1}$	-0.94**		-1.14***		-1.34**		-1.04		-2.07**	
	(-2.54)		(-2.66)		(-2.31)		(-1.44)		(-2.00)	
Black Borrower # Diversity Policy$_{-1}$		-1.89***		-2.80***		-3.52***		-2.87***		-4.22***
		(-3.43)		(-3.67)		(-4.51)		(-2.99)		(-3.12)
Hispanic Borrower # Diversity Policy$_{-1}$		0.44		-0.59		1.04		1.08		0.80
		(0.96)		(-0.99)		(1.33)		(1.10)		(0.61)
Other Minority # Diversity Policy$_{-1}$		-1.73***		-0.01		-1.60		-2.09		-3.62
		(-3.67)		(-0.03)		(-1.62)		(-1.24)		(-1.34)
Diversity Policy$_{-1}$	-0.42***	-0.41***	-0.21	-0.21	-1.31***	-1.31***	-1.89***	-1.88***	-2.86***	-2.84***
	(-2.74)	(-2.74)	(-1.30)	(-1.29)	(-4.23)	(-4.22)	(-3.50)	(-3.49)	(-3.43)	(-3.41)
RF-Predicted Default Risk Bin FE	x	x								
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
FICO Bin FE										
Conforming			x	x	x	x	x	x	x	x
Joint Application			x	x	x	x	x	x	x	x
Income 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
Year FE	x	x	x	x	x	x	x	x	x	x
Property County FE			x	x	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x	x	x	x	x
Dependent Var. Mean	89.62	89.62	92.85	92.85	85.46	85.46	80.55	80.55	79.96	79.96
R^2	0.05	0.05	0.27	0.27	0.29	0.29	0.32	0.32	0.31	0.31
Obs.	1,883,744	1,883,744	1,250,167	1,250,167	361,215	361,215	170,240	170,240	101,008	101,008

Table 8 The Effect of Diversity Policy on Ex post Mortgage Performance

The table reports regression results for mortgage default and prepayment after originations with Equation (1). The observations are all the originated mortgages in the short panel HMDA data (2018-2021) that can be matched with Fannie Mae and Freddie Mac Performance Data. Panel A reports results on default outcomes within 2 years of loan origination. Panel B reports results on prepayments. The description of the variables is 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: The Effect of Diversity Policy on Mortgage Default Rate

	Default (within 2 years, in %)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority Borrower # Diversity Policy$_{-1}$	-1.133***		-1.094***		-1.072***		-0.943***	
	(-3.56)		(-3.45)		(-3.39)		(-3.02)	
Black Borrower # Diversity Policy$_{-1}$		-1.402**		-1.360**		-1.330**		-1.076
		(-2.11)		(-2.04)		(-1.99)		(-1.64)
Hispanic Borrower # Diversity Policy$_{-1}$		-1.251**		-1.131**		-1.133**		-0.994**
		(-2.48)		(-2.25)		(-2.26)		(-2.02)
Other Minority # Diversity Policy$_{-1}$		-0.768		-0.831*		-0.787		-0.770
		(-1.54)		(-1.70)		(-1.60)		(-1.59)
Diversity Policy$_{-1}$	-0.050	-0.050	-0.035	-0.035	-0.020	-0.020	-0.075	-0.075
	(-0.39)	(-0.38)	(-0.27)	(-0.27)	(-0.16)	(-0.16)	(-0.58)	(-0.58)
log(Loan Amount)	x	x	x	x	x	x	x	x
LTV Bin FE			x	x	x	x	x	x
DTI Bin FE					x	x	x	x
FICO Bin FE							x	x
Conforming	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x
Income 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
Year FE	x	x	x	x	x	x	x	x
Property County FE	x	x	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x	x	x
Dependent Var. Mean	2.93	2.93	2.93	2.93	2.93	2.93	2.93	2.93
R^2	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.04
Obs.	871,014	871,014	871,014	871,014	871,014	871,014	869,686	869,686

Panel B: The Effect of Diversity Policy on Mortgage Prepayment Rate

	Prepayment (within 2 years, in %)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority Borrower # Diversity Policy$_{-1}$	4.099***		3.990***		3.980***		3.863***	
	(5.20)		(5.20)		(5.19)		(5.07)	
Black Borrower # Diversity Policy$_{-1}$		7.783***		7.665***		7.651***		7.423***
		(6.74)		(6.81)		(6.79)		(6.56)
Hispanic Borrower # Diversity Policy$_{-1}$		4.364***		4.132***		4.097***		3.990***
		(4.25)		(4.11)		(4.07)		(3.99)
Other Minority # Diversity Policy$_{-1}$		0.761		0.812		0.835		0.793
		(0.60)		(0.65)		(0.67)		(0.63)
Diversity Policy$_{-1}$	-1.330***	-1.331***	-1.358***	-1.359***	-1.352***	-1.353***	-1.297***	-1.298***
	(-2.72)	(-2.72)	(-2.78)	(-2.78)	(-2.76)	(-2.77)	(-2.66)	(-2.66)
log(Loan Amount)	x	x	x	x	x	x	x	x
LTV Bin FE			x	x	x	x	x	x
DTI Bin FE					x	x	x	x
FICO Bin FE							x	x
Conforming	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x
Income 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
Year FE	x	x	x	x	x	x	x	x
Property County FE	x	x	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x	x	x
Dependent Var. Mean	26.10	26.10	26.10	26.10	26.10	26.10	26.10	26.10
R^2	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16
Obs.	871,014	871,014	871,014	871,014	871,014	871,014	869,686	869,686

Table 9 The Effect of Diversity Policy on Denial Reasons

The table reports regression results for reasons of mortgage application denials with Equation (1). The observations are all the denied mortgage applications in the short panel HMDA data (2018-2021). The description of the variables is 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.

	Denial Probability by Reasons								
	Debt-to-income ratio	Employment history	Credit history	Collateral	Insufficient cash	Unverifiable information	Credit application incomplete	Mortgage insurance denied	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Black Borrower # Diversity Policy$_{-1}$	2.00***	0.23**	2.06***	-0.19	0.05	0.02	-0.04	-0.00	0.48***
	(6.71)	(2.18)	(6.14)	(-1.30)	(0.33)	(0.20)	(-0.72)	(-0.26)	(2.79)
Hispanic Borrower # Diversity Policy$_{-1}$	0.51*	-0.13	0.55**	-0.55**	-0.22**	-0.49*	-0.08	0.01*	0.26**
	(1.96)	(-1.24)	(2.12)	(-2.20)	(-2.17)	(-1.77)	(-1.49)	(1.81)	(2.16)
Other Minority # Diversity Policy$_{-1}$	0.49**	0.20	0.42**	0.11	0.05	0.10	-0.14**	-0.00	0.01
	(2.04)	(1.53)	(2.12)	(0.76)	(0.36)	(0.74)	(-2.25)	(-0.64)	(0.05)
Diversity Policy$_{-1}$	0.23***	0.02	0.44***	-0.05	0.16***	0.00	-0.18***	0.01	-0.08
	(2.77)	(0.54)	(5.95)	(-0.75)	(3.79)	(0.03)	(-5.59)	(1.61)	(-1.33)
log(Loan Amount)	x	x	x	x	x	x	x	x	x
LTV Bin FE	x	x	x	x	x	x	x	x	x
DTI Bin FE	x	x	x	x	x	x	x	x	x
FICO Bin FE									
Conforming	x	x	x	x	x	x	x	x	x
Joint Application	x	x	x	x	x	x	x	x	x
Income 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
Year FE	x	x	x	x	x	x	x	x	x
Property County FE	x	x	x	x	x	x	x	x	x
Lender*Race FE	x	x	x	x	x	x	x	x	x
Dependent Var. Mean	4.89	0.61	2.44	1.55	1.41	0.99	0.55	0.02	1.67
R^2	0.49	0.05	0.04	0.05	0.03	0.03	0.02	0.01	0.03
Obs.	1,883,680	1,883,680	1,883,680	1,883,680	1,883,680	1,883,680	1,883,680	1,883,680	1,883,680

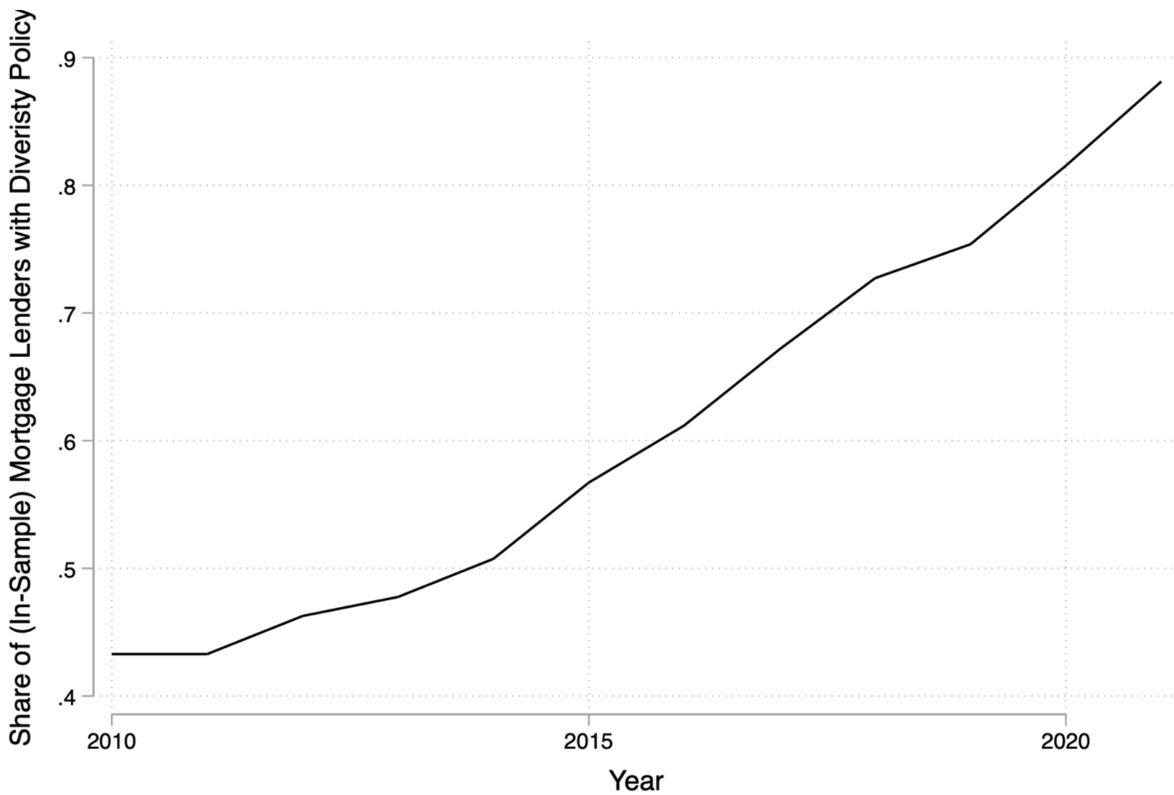


Figure 1 Share of Mortgage Lenders with a Diversity Policy

The 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 sample period 2010 through 2021.

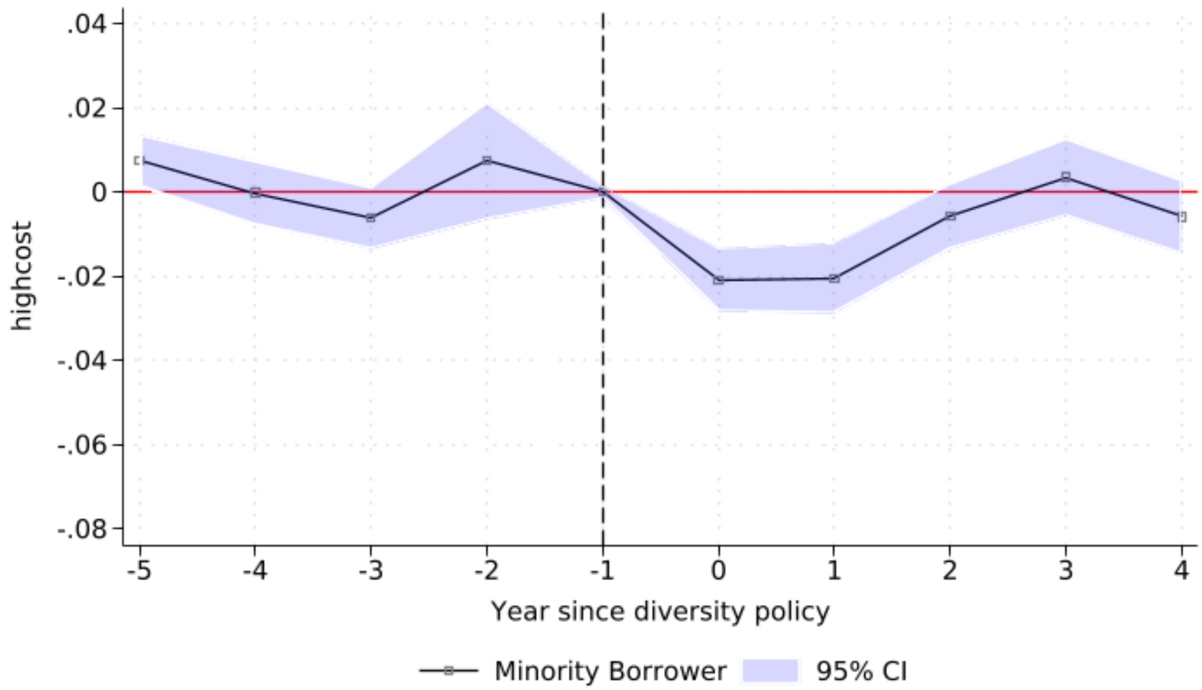


Figure 2 Event Study on Minority Borrowers' High Spread Share (2010-2021 Sample)

The figure plots the event study of the impact of the diversity policy on minority borrowers' probability of High-Cost Mortgage. 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 description of the variables is 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.

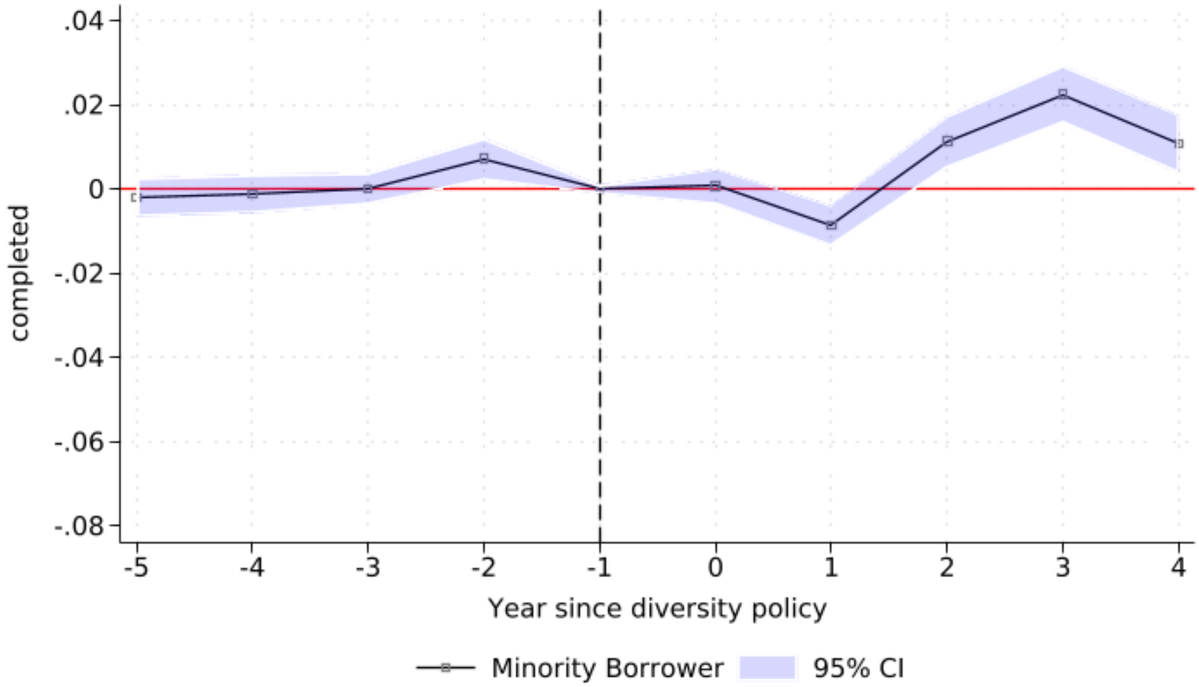


Figure 3 Event Study on Minority Borrowers' Application Completion Rate (2010-2021 Sample)

The 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 description of the variables is 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.

Panel A Disparity between Minority and White Borrowers

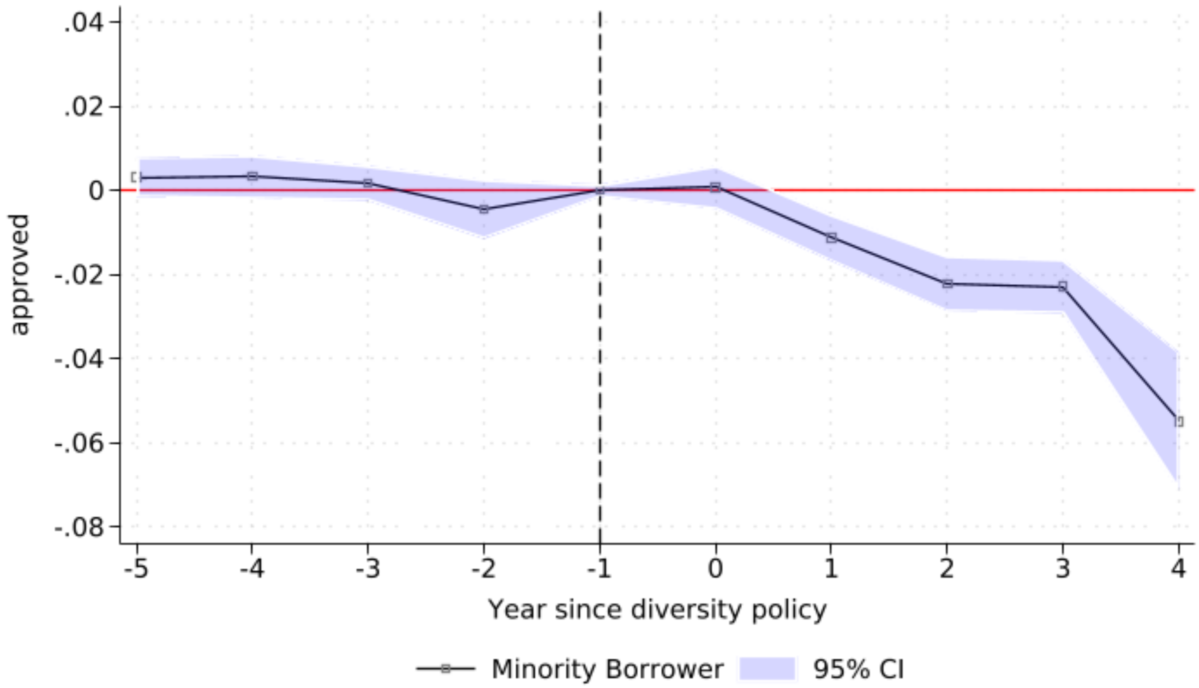


Figure 4 Event Study on Minority Borrowers' Approval Rate (2010-2021 Sample)

The 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 description of the variables is 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.

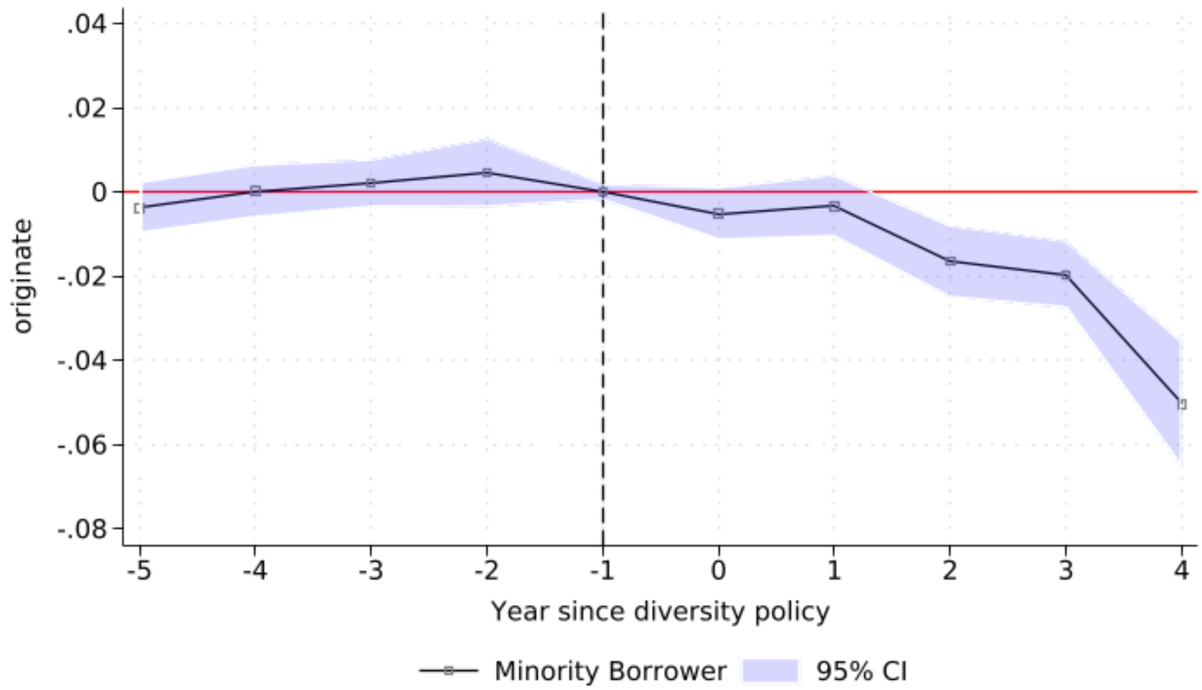
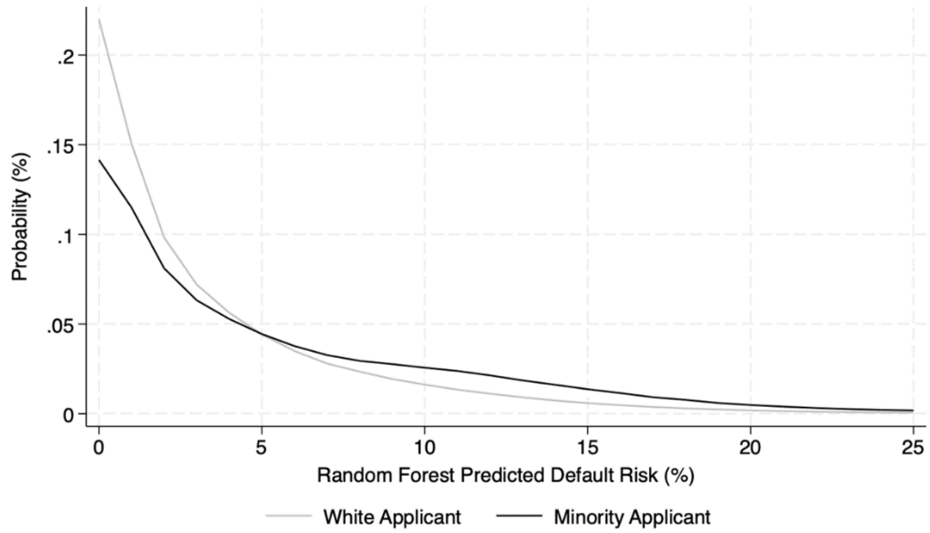
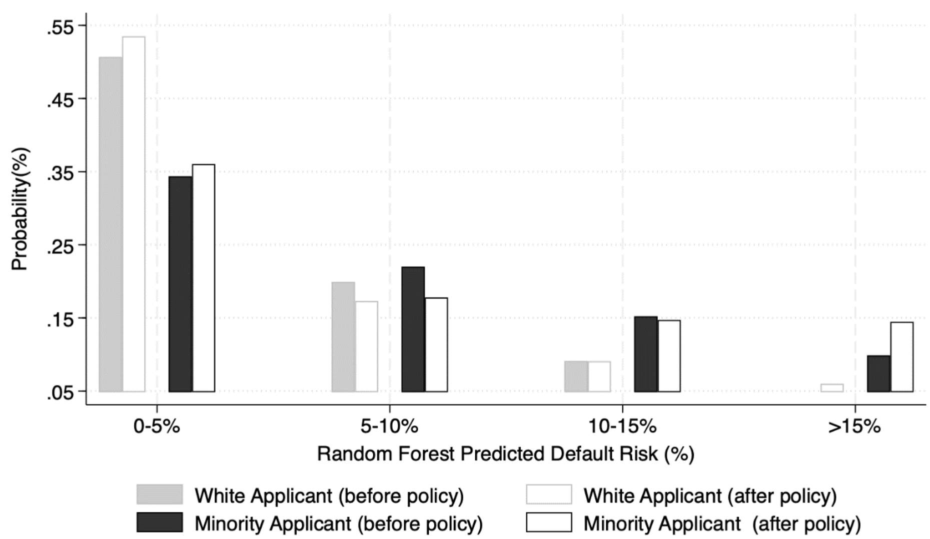


Figure 5 Event Study on Minority Borrowers' Origination Rate (2010-2021 Sample)

The 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 description of the variables is 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.



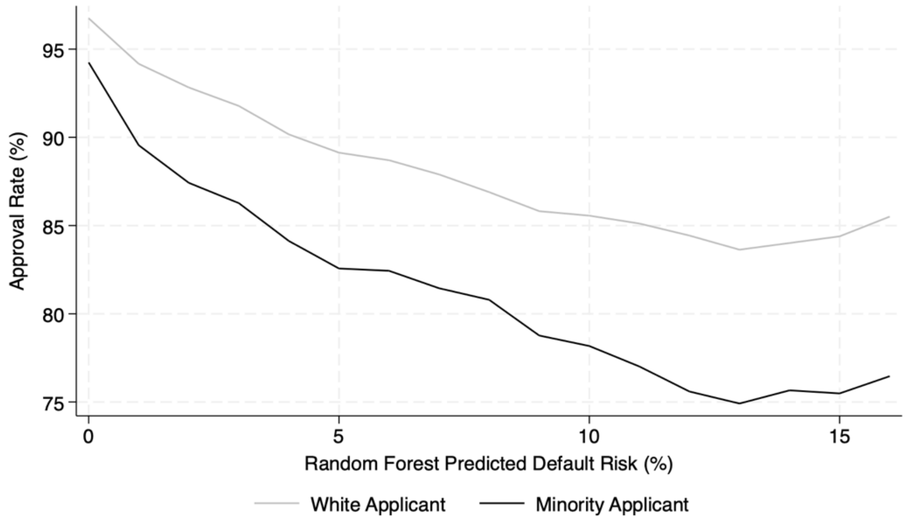
Panel A: Distribution of Predicted Default Risk by Race



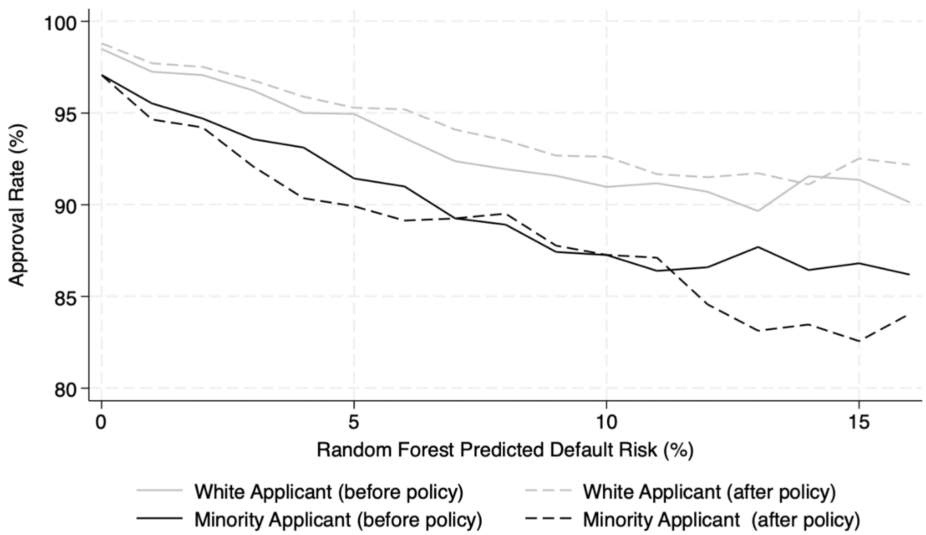
Panel B: Distribution of Predicted Default Risk by Race Prior to and After Diversity Policy Adoption

Figure 6 Mortgage Applicant Default Risk by Race

Panel A plots the distribution of predicted default risk for minority and white applicants, for the full short panel HMDA data (2018-2021). Panel B 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. We focus only on the completed applications, since DTI and LTV are missing in most of the incomplete applications.



Panel A: Mortgage Approval Rate by Race and Default Risk



Panel B: Mortgage Approval Rate by Race and Default Risk Prior to and After Diversity Policy Adoption

Figure 7 Mortgage Approval Rate by Race and Default Risk

Panel A plots the approval rates by predicted default risk for the minority and white applicants, for the full short panel HMDA data (2018-2021). Panel B plots the approval rates by predicted default risk for the 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. We focus only on the completed applications, since DTI and LTV are missing in most of the incomplete applications.

Appendix A: Examples of Mortgage Lenders' Diversity Policy Statements

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

2021 Environmental, Social & Governance Report

CADENCE Bank

HUMAN CAPITAL

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)

10

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.

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.

> 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.

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