Does the Disclosure of Consumer Complaints Reduce Racial Disparities in the Mortgage Lending Market?*

Xiang Li†

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Abstract

The Consumer Financial Protection Bureau (CFPB) publicly disclosed consumer complaint narratives in 2015. Utilizing a difference-in-differences design, I discover that, following disclosure, CFPB-supervised banks whose complaint narratives are disclosed are less prone to discriminate against minority borrowers in the mortgage lending market, thereby reducing racial disparities in interest rates, default rates, and rejection rates. My findings reveal that disclosure saves $102 million for minority borrowers in interest rate payments and assists over 14,000 minority households in obtaining loans yearly. Furthermore, other stakeholders, such as peer banks and stock market investors, facilitate the disclosure's effects on reducing discrimination.

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†Finance Department, Carroll School of Management, Boston College, Chestnut Hill, MA 02467, Email: xiang.li.5@bc.edu.

1 Introduction

Disclosure has emerged as a crucial and prevalent strategy for addressing disparities and promoting diversity, equity, and inclusion (DEI). As of 2023, all companies listed on the NASDAQ exchange are required to disclose their board diversity statistics.[1] In 2020, 24% of S&P 500 companies disclosed board diversity information. By mid-2021, this number had increased to 59%, reflecting a semi-annual growth rate of 146% (Tonello (2020)). In the sphere of education, all public schools are obligated to disclose students' diversity statistics.[2] Academic journals, spearheaded by the largest academic publishing house, Elsevier, adopt a similar approach to foster DEI through disclosure. By the end of 2021, 772 journals (43% of journals) owned by Elsevier disclosed gender diversity information regarding their editorial boards, marking an annual increase of over 40% since the disclosure initiative began in February 2021.[3] While abundant studies probe the influence of disclosure on enhancing DEI in non-financial markets,[4] investigations into its potential role in reducing disparities within financial markets are notably scant. To address this gap, my study examines the potential of mandatory disclosure of consumer complaints against banks by the Consumer Financial Protection Bureau (CFPB) to alleviate racial discrepancies in the financial market.

The CFPB plays a crucial role in advocating for consumer rights and fostering fairness in the financial markets. Since its inception in 2011, it has been receiving complaints about financial institutions. On June 25, 2015, it took a further step by publicly disclosing complaint narratives and financial institutions' responses (CFPB (2015)). This transparency initiative aims to promote a comprehensive analysis of complaint data,

[1] For more details about this policy, see here.

[2] The Civil Rights Data Collection (CRDC), mandated by the U.S. Department of Education, requires all public schools and certain private schools to collect and report student statistical data, including information on race, gender, and more. The purpose of publicly releasing this data is to monitor and ensure compliance with federal anti-discrimination laws in public schools. For detailed requirements, refer to the following link: https://www2.ed.gov/about/offices/list/ocr/frontpage/faq/crdc.html.

[3] Elsevier is the largest publishing house in the academic publishing industry, with over 3,000 academic journals. For more information about Elsevier's disclosure of editorial board diversity, see the following link: https://www.elsevier.com/connect/inclusion-diversity-board-report.

[4] For example, Raghunandan and Rajgopal (2021) find that the UK's 2017 mandatory gender pay gap disclosure has modest effects on gender pay disparity. Pan, Pikulina, Siegel, and Wang (2022) reveal negative equity market responses to the first-time CEO-worker pay ratio disclosures in the U.S. in 2018. Bennedsen, Simintzi, Tsoutsoura, and Wolfenzon (2022) analyze the effect of a 2006 Danish law on pay transparency, finding it reduced the gender pay gap by slowing male wage growth without affecting firm profitability.

facilitating a productive discourse between consumers and financial institutions. Despite the implementation of various measures, little empirical evidence exists supporting its effectiveness in protecting minority consumers or mitigating racial bias in lending markets. This study aims to address these critical questions: Does the disclosure of complaint narratives against a bank lead to a reduction in discrimination against minority borrowers? Moreover, do minority borrowers tend to avoid banks with a significant number of discriminatory complaints?

However, the answers to the aforementioned questions remain uncertain. On one side, there is a possibility that stringent government oversight, combined with banks' reputation costs and fear of facing substantial litigation risks,[5] could potentially motivate banks to decrease discriminatory treatment in light of the CFPB's release of complaint narratives. Moreover, the CFPB's disclosure enables minority consumers to compare loan options thoroughly, empowering them to avoid banks with a history of discriminatory complaints. Additionally, in areas where certain banks have a significant number of discriminatory complaints, their competitors, aware of the disclosed narratives by the CFPB, might be drawn to enter that underserved market for a bigger slice of the pie (Dou, Hung, She, and Wang (2023)). Lastly, the capital markets could use these narratives to steer clear of investments in banks with a high volume of discrimination complaints, given such banks may be exposed to both ethical and litigation risks (Pan et al. (2022)).

On the other side, skepticism remains regarding the extent to which consumers incorporate this data into their decision-making, as they may have limited exploration of the market (Woodward and Hall (2012)) might obstruct them from incorporating this data into their decision-making. Furthermore, the choices of minority consumers could be limited if only a few banks dominate the local financial market (Li (2023); Stanton, Walden, and Wallace (2014)). The disclosure activities could also have the potential to increase administrative workload and raise concerns about consumer privacy, which could lead to resistance. Therefore, the influence of disclosure on racial disparities in the lending market is, in the end, a subject for empirical examination.

[5]Between 2012 and 2022, the CFPB imposed an approximate total of $66 million in fines on 21 banks for illegal discrimination against applicants, predominantly minorities. Moreover, these banks were mandated to contribute over $51 million towards loan subsidy programs. These programs, intended to lessen the loan burden of minority groups, may comprise measures such as reductions in interest rates, assistance with closing costs, and support for down payments.

The CFPB discloses consumer complaint narratives covering a variety of financial products, such as credit cards, mortgages, auto loans, and student loans. My research primarily concentrates on the mortgage market for two key reasons. First, discrimination against minority consumers in the mortgage market has been consistently observed in both real court cases and academic studies. Despite the enactment of anti-discrimination laws, such as the Fair Housing Act of 1968 in the United States, it is evident that discriminatory practices persist in the housing and finance sectors. Notable instances include allegations made by the U.S. Department of Justice against several major mortgage lenders for violating fair lending principles during the housing boom, which led to settlements exceeding \$500 million.[6] Moreover, academic scholars consistently find evidence of unequal loan pricing, indicating the enduring existence of discriminatory behavior in the mortgage sector (Ambrose, Conklin, and Lopez (2021); Bartlett, Morse, Stanton, and Wallace (2022); Cheng, Lin, and Liu (2015); Ghent, Hernandez-Murillo, and Owyang (2014); Woodward and Hall (2012)). In particular, Bartlett et al. (2022) pinpoint discrepancies in interest rates between minority and white borrowers, with these disparities costing minority borrowers an excess of \$450 million annually.

Second, the mortgage market is the most significant but opaque consumer financial market. As of 2023, mortgages account for 70.6% of consumer debt in the United States, with approximately 83.4 million homeowners bearing a mortgage, and the collective mortgage debt reaches \$11.92 trillion.[7] However, minority consumers frequently face challenges due to a lack of sufficient knowledge about the quality and details of mortgage products and services. For minority consumers, gaining knowledge through experience is often an uphill battle since decisions such as choosing a mortgage are infrequent (Campbell, Jackson, Madrian, and Tufano (2011); Lusardi and Mitchell (2011); Murphy (2005)). Moreover, conversations about personal finance are often avoided due to societal conventions, and financial advisors can sometimes provide biased advice to serve their own interests (Guiso, Pozzi, Tsoy, Gambacorta, and Mistrulli (2022)). Even when pertinent information is provided, compared with white consumers, minority consumers may encounter challenges in understanding it due to processing biases, lack of attention, and financial illiteracy (Gurun, Matvos, and Seru

[6] Regarding the three most substantial settlements, Bank of America reached a settlement of \$335 million in 2011, followed by Wells Fargo's settlement of \$175 million in 2012, and JPMorgan Chase's settlement of \$55 million in 2017.

[7] For more details, see: https://www.lendingtree.com/home/mortgage/u-s-mortgage-market-statistics/

(2016); Keys, Pope, and Pope (2016)). Given these two motivations, it becomes imperative to investigate whether disclosure can reduce racial disparities in the mortgage lending market and to understand the underlying mechanism.

Empirically studying this question involves addressing two crucial challenges: accurately identifying discrimination while mitigating concerns related to omitted variables and identifying exogenous variation in the disclosure at the bank level. To address the first issue, following Bartlett et al. (2022), I use information from the government-sponsored enterprises (GSEs) to construct an 8×9 matrix known as the Loan-Level Price Adjustments (LLPAs), an essential tool for adjusting credit-risk pricing based on credit score and Loan-to-Value (LTV) ratios. Consequently, during empirical investigations, the inclusion of this grid allows for the identification of any discernable differences in interest rates within the grid that can not be attributed to varying credit risks that could imply potential discriminatory practices.

Regarding the source of exogenous variation, I utilize a disclosure policy implemented by the CFPB. Since June 2015, consumer complaint narratives have been made accessible to the public, but only for banks with total assets exceeding $10 billion. This policy shift serves as an exogenous shock, enabling the observation of varied bank behaviors post-disclosure. Taking into account the potential impact of bank size on the outcomes of interest, my sample primarily focuses on banks with total assets of less than $100 billion as of the first quarter of 2015. Using this sample, I employ a difference in differences method to study shifts in lending behavior and service outcomes for minority borrowers in the mortgage market. Particular emphasis is placed on banks close to the asset threshold during both the pre and post-June 2015 periods.

Additionally, in my model, I consider bank $\times$ similar borrower fixed effects and bank $\times$ year and month fixed effects. By controlling for bank $\times$ similar borrower fixed effects, I can analyze changes pre and post-disclosure for borrowers with similar characteristics within the same racial group at the same bank. Meanwhile, controlling for bank $\times$ year and month fixed effects absorbs any unobservable time-varying shocks at the bank level that could potentially influence lending practices and service outcomes.

Through the utilization of the pricing grid from LLPAs within the HMDA-GSE merged dataset, I discover that following the disclosure of complaint narratives, the excess interest rates applied to minority borrowers compared with white borrowers decline by around 2.55 basis points. This decrease mitigates nearly 87% of the racial disparities in interest rates, which originally stand at 2.7 basis points. These findings suggest that the enactment of the disclosure policy succeeds in saving minority borrowers in the mortgage market an average of $102 million each year. Moreover, the ability to reduce racial disparities takes effect immediately after the disclosure and exhibits a persistent influence. Through further discussion, I demonstrate that the disclosure has a more pronounced effect on mitigating racial disparities among banks that engage in discriminatory practices. The disciplinary impacts of disclosure intensify when lenders' discriminatory treatments receive increased social attention or when the litigation risks associated with discrimination are high.

In addition, I use the "outcome test" approach (Becker, 1957, 1993) to isolate racial bias from omitted variable bias or statistical discrimination by investigating the effects of disclosure on the default rate of minority borrowers.[8] If racial bias exists, marginal minority borrowers may exhibit a lower default rate compared to marginal White borrowers because minorities are held to unfairly high standards by banks. My findings substantiate the presence of this hypothesis, and further reveal that compared to consumers from control lenders, the unfair lower default rate manifested by minority consumers almost disappears following disclosure. The racial discrepancies I observe through the outcome test could originate from banks imposing stricter approval criteria on consumers. By analyzing the rejection rate in the HMDA origination dataset, my findings are consistent with the results obtained from the default rate analysis. Minority borrowers are more likely to face loan rejections, implying that banks use higher standards to screen loan applications from minority borrowers. After disclosure, the higher rejection rates faced by minorities, standing at 7.7 percentage points concerning loan accessibility, decrease by 1.6 percentage points. This highlights that each year, the disclosure policy aids over 14,000 minority applicants in securing mortgage loans by lessening the unjust accessibility standards imposed upon them.

In terms of the mechanisms that render the disclosure policy so effective, I discuss the responses of different stakeholders to provide more clues on the impact pathways. I find that peer banks may make decisions to enter local markets by drawing insights from the disclosed weaknesses in their competitors' operations, particularly in areas where customer service

[8] Lenders engage in statistical discrimination when they utilize race as a substitute for facets of creditworthiness that cannot be observed, with the aim of maximizing profits. In this study, I designate the term "statistical discrimination" to signify decisions that maximize profits. Conversely, I employ the term "racial bias" to denote lending decisions that are biased, whether motivated by particular preferences or founded on incorrect beliefs. A more detailed description is provided in Section 5.

is deficient and discriminatory treatments are prevalent. Simultaneously, the market may interpret the unveiling of the disclosure policy as an adverse shock that provokes significant reactions. Considering potential litigation risks, investors may view the future performance of banks engaged in discriminatory practices with skepticism. Additionally, in line with the emphasis on Socially Responsible Investing (SRI), investors may show a reluctance toward racial inequality. By evaluating the market reaction subsequent to the disclosure policy using an event study method, I find that banks supervised by the CFPB exhibit lower market reactions, characterized by a relative decrease in Cumulative Abnormal Returns (CAR), with the downward revision of firm value being more severe among banks engaged in discriminatory practices.

Finally, I survey the status of financial consumer protection organizations in the main developed countries and find that, aside from the CFPB in the United States, nearly no financial regulatory agencies in other countries choose to disclose consumer complaint information publicly. My research shows that public exposure to customer complaints can mitigate discriminatory and unfair practices in the financial system through multiple avenues. From this perspective, these findings may provide practical insights for real-world financial practices. Other countries can look to this disclosure policy as a reference point in crafting their strategies for handling and publicizing consumer complaints. The adoption of such disclosure policies may have considerable promise in promoting DEI at a global level.

Notably, to further aid minority borrowers in the United States in mitigating potential risks in mortgage lending, I develop an online inquiry system that permits the public to directly and transparently access information regarding discriminatory practices of banks at different location levels.

The remainder of the paper is organized as follows. Section 2 describes the related background, existing research, and contributions of my research. Section 3 introduces the datasets used and the results of summary statistics. Section 4 reports the main analysis of the paper, the impact of disclosure on racial disparities in loan interest rates. Section 5 reports the outcome test for default rates. Section 6 reports the impact on rejection rates. Section 7 presents the reactions of various stakeholders to the disclosure policy. Section 8 concludes.

2 Background and Literature Review

2.1 Background of Complaints Disclosure

Established by the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, the CFPB has the mandate of safeguarding consumers in the financial sector and promoting fairness and competition in consumer financial markets. Initially, it started accepting consumer complaints regarding credit cards in July 2011 and later expanded its scope to encompass complaints about mortgages, bank accounts, credit reporting, and other financial products and services. After a pilot phase in 2012 and 2013, the CFPB gradually began to release information related to consumer complaints to the public.[9] On June 25, 2015, the CFPB publicly released the narratives of consumer complaints. The complaint database exclusively records complaints against banks supervised by the CFPB, particularly those with total assets surpassing \$10 billion. Complaints concerning depository institutions holding less than \$10 billion in assets are directed to the relevant safety and soundness regulators and are not included in the database.

In fact, before deciding to make complaint narratives public, the CFPB solicited comments on the issue. They received 137 distinct responses from consumer groups, trade organizations, businesses, and individuals, along with 30,000 identical letters from individuals. Banks and their associations object to the disclosure of these narratives, arguing that releasing "unverified" consumer narratives could unfairly damage companies' reputations. In response, the CFPB addressed these objections by (i) confirming business relationships between the banks and complainants to prevent fraud, and (ii) making banks' responses to complaints public, allowing banks to contest the complaints.

In contrast, the inclusion of narratives received support from consumer advocates, civil rights groups, and proponents of open governance, who highlighted three key benefits: (i) empowering consumers with timely and relevant information to make informed decisions before purchase, thereby promoting customer-oriented businesses, and uncovering unfair or deceptive practices post-purchase; (ii) aiding the Bureau and other stakeholders in identifying

[9]On March 28, 2013, the CFPB disclosed complaints about mortgages and other products. Since then, the public has been able to download information related to the financial product type involved in the complaint, the submitting consumer's ZIP Code, the submission date, the name of the implicated bank, and the bank's brief response.

harmful trends before they escalate into widespread damage; and (iii) encouraging greater use of the database as a practical tool serves to promote a cycle of accumulating data on consumer experiences in the financial sector. These benefits align with the CFPB's original intentions for this measure (CFPB (2015)). Nevertheless, supporters also raised concerns regarding potential privacy issues for consumers who provide complaint narratives. To address these concerns, the CFPB committed to anonymizing identifiable information and disclosing only limited zip code data.

In this study, a significant focus is placed on complaints related to discrimination. By employing textual analysis to analyze complaint narratives, it is revealed that there is a relatively consistent range of 700-900 discrimination-related complaints in the mortgage market reported annually, as depicted in panel A of Figure 1. Additionally, panel B of Figure 1 demonstrates that discrimination-related complaints consistently make up 5-7% of all mortgage market complaint narratives each year. This stable proportion highlights the persistent issue of discrimination. Given the smaller fraction of minority consumers in the lending market,[10] the 5-7% representation is particularly significant, thereby emphasizing the severity of discrimination problems.

[Insert Figure 1 about here]

Table 1 presents a consumer complaint example concerning "Applying for a mortgage or refinancing an existing mortgage," sourced from CFPB's public dissemination. The components included are "Date received", "Product", "Consumer complaint narrative", "Company", and "Company response to consumer", and others. Although personal data being de-identified in complaint narratives, claims of racial discrimination become more evident, especially through statements like "I believe that I am being discriminated against because I disclosed my race as XXXX".[11] The company's reply to this particular situation is categorized as "closed with monetary relief," and the company does not dispute the complaint. These indicators suggest potential misconduct by the bank towards this consumer. Undoubtedly, thanks to the presence of the CFPB's complaint system, the aggrieved party received compensation for the unfair treatment.

[Insert Table 1 about here]

[10]In the HMDA dataset spanning from 2011 to 2019, used in this study, loan applications from minority consumers make up 12.24% of total applications. However, this proportion diminishes to 11.55% when considering loans that receive approval.

[11]The race information is erased by the CFPB to protect consumer privacy.

2.2 Literature Review and Contribution

My research contributes to the extant literature on CFPB oversight, which currently presents varying viewpoints on the effectiveness of the CFPB. Supporters highlight its success in curbing deceptive and predatory practices within credit markets, Fuster, Plosser, and Vickery (2021) emphasize its role in reducing lending and potentially preventing foreclosures, and DeFusco, Johnson, and Mondragon (2020) underscore the significant impact of the Ability-to-Repay and Qualified Mortgage Rule, implemented by the CFPB, in restraining high-leverage mortgages - an action that potentially mitigates instability within the financial system.[12] In contrast, critics argue that the CFPB's oversight increases regulation and compliance costs, heightens legal liabilities, and subsequently, reduces the supply of consumer credit (U.S. Chamber of Commerce (2018); Neugebauer and Williams (2015); Fuster et al. (2021); DeFusco et al. (2020)). Unlike these research perspectives, my paper, adopts a DEI lens to investigate the CFPB's contribution to addressing discrimination in the financial market, thereby substantiating its positive influence on advancing DEI.

Among the various oversight strategies implemented by the CFPB, the distinctive and vital practice of consumer complaint disclosure has received limited research attention.[13] Previous studies like Dou and Roh (2023) evaluating the impact of disclosing total complaint counts on mortgage applications reveal a notable reduction in applications submitted to banks with a history of complaints after the disclosure. Dou et al. (2023) examine how unregulated competitor banks react to complaint disclosures compared to CFPB-regulated institutions. They observe an increase in mortgage approvals in areas with a high number of complaints, indicating that banks effectively learn from the operational shortcomings of their counterparts. This study diverges from previous research that primarily focuses on the release of total complaint counts. Instead, it specifically concentrates on the disclosure of complaint narratives. Through these narrative disclosures which offer more comprehensive information than mere complaint numbers, a deeper understanding of banking behaviors, particularly regarding misconduct, becomes possible. This enables a more thorough investigation into

[12]For more details, please refer to prepared remarks of CFPB director Richard Cordray at the LendIt USA Conference. This is the related link: https://www.consumerfinance.gov/about-us/newsroom/prepared-remarks-cfpb-director-richard-cordray-lendit-usa-conference/.

[13]I catalog 27 developed nations worldwide, of which 13 have financial regulatory agencies that establish dedicated channels for receiving consumer feedback. However, only the United States, through the CFPB, makes consumer complaints publicly available.

whether such misconduct in the mortgage market is alleviated through the disclosure process.

As the first study examining the consequences of disclosure on DEI within the financial market, my research aligns with the effects of disclosure on DEI observed in other markets. For example, Bennedsen et al. (2022) draw from a 2006 Danish law that compels firms to disclose gender-specific wage data, revealing its impact on the gender wage gap and firm performance. Pan et al. (2022) analyze market reactions to the initial disclosure of CEO-worker pay ratios by U.S. public firms in 2018. They observe unfavorable responses from firms with higher reported ratios, particularly among shareholders who are sensitive to inequality. In addition to analyzing the distinct financial market, my study also expands the potential scope of disclosure policies by considering them from the standpoint of racial inequalities.

Racial discrimination poses a significant barrier to achieving DEI. My study contributes to the existing literature on discrimination in the financial market by demonstrating the potential of disclosure to alleviate such discriminatory practices. While many studies emphasize the unequal treatment of minority consumers in the financial sector, pinpointing instances of discrimination remains a complex challenge for researchers. In previous research, Bartlett et al. (2022) uncover that risk-adjusted Latinx/Black borrowers face higher interest rates in GSE-securitized and FHA-insured loans, accounting for borrowers' creditworthiness. This unjust treatment results in an annual financial burden exceeding $450 million. Building on the foundation of outcome tests (Becker (1957)) - the idea suggesting that marginal minority borrowers, upon acceptance, are anticipated to exhibit lower default rates - Butler, Mayer, and Weston (2023) reveal that despite bearing an extra 70 basis points in interest rates compared to their white counterparts, minority borrowers, under comparable circumstances, display a lower incidence of defaults. Moreover, Li (2023) introduce a textual analysis methodology aimed at identifying instances of discrimination within financial markets.[14] In this study, I demonstrate how disclosure reduces discrimination by incorporating these three distinct methodologies to quantify discrimination. First, inspired by Li (2023), I apply textual analysis to complaints in the mortgage market under CFPB supervision, uncovering instances of racial discrimination. Subsequently, building on Bartlett et al. (2022)'s method of identifying discrimination through the GSE pricing grid, my research indicates that the

[14] Currently, the adoption of textual analysis for scrutinizing discriminatory practices is widely used. As articulated in Hacamo (2022), over 10,000 instances of workplace racial bias are identified through textual analysis of 7 million job reviews on Indeed.com.

narrative disclosure of consumer complaints in the mortgage market results in an estimated annual saving of $100 million for minority individuals. Finally, I examine whether the disclosure of discriminatory practices benefits marginal minority borrowers by rectifying unjust approval standards. My findings affirm this proposition in line with Butler et al. (2023)'s outcome test.

While previous research often addresses discrimination through the lens of market power, my study offers a distinct approach by examining it from the perspective of regulatory policy. Black and Strahan (2001) investigate the impact of bank competition on gender pay gaps among bank officers, uncovering a decrease in male-biased wages and an increase in female managerial positions within a more competitive financial market. Similarly, Li (2023) explores how increased bank competition mitigates discrimination against minority borrowers. In contrast, my study reveals that disclosure serves as an effective regulatory instrument to combat discrimination. This contribution supplements the current research by illustrating how disclosure reduces discrimination through the promotion of intensified competition within the lending sector.

3 Data Description and Summary Statistics

3.1 Data Description

3.1.1 HMDA-GSE Merged Dataset

The main dataset employed in this study is the integrated HMDA-GSE dataset. The Home Mortgage Disclosure Act (HMDA) compliance surveys, which encompass 90% of mortgage originations in the U.S. as reported by Engel and McCoy (2016), serve as the sole data source offering loan-level information regarding the applicant's race and ethnicity. The HMDA data include essential details such as applicant income, race, ethnicity, loan amount, lender name, and the census tract of the property. Complementing this information, the Government-Sponsored Enterprises (GSEs) enhance the dataset by offering precise loan information encompassing factors such as interest rate, default, LTV, credit score, loan product, loan purpose, and loan term. These factors are crucial for discerning the personal characteristics of borrowers.

Due to the absence of an explicit crosswalk between these two datasets, I employ the "fuzzy data matching" methods in accordance with Law and Mislang (2022) to facilitate their integration. The detailed process is elaborated upon in Appendix B. This consolidated dataset comprises all approved loans securitized by the GSEs from 2011 to 2019.[15] Additionally, given the management discrepancies for loans with varying terms in the real market, I implement filtering on this dataset following Bartlett et al. (2022). This filtering is based on variables like credit scores, LTV, and loan amount, with detailed specifics provided in Appendix B. The ultimate outcome is a pooled cross-sectional dataset of loan-bank-years, which I utilize to examine whether the disclosure of consumer complaint narratives affects interest rates and default rates among minority borrowers.

3.1.2 HMDA Origination Dataset

Another crucial dataset employed in this study is the HMDA origination data set. Unlike the HMDA-GSE merged dataset, the original HMDA dataset includes unapproved loans, which offers an opportunity to test the tangible effects of consumer complaint narrative disclosures on the rejection rates of minority borrowers. However, due to the lack of sufficient loan attributes in the HMDA dataset, I adopt a strategy from Bartlett et al. (2022) to minimize potential omitted variable bias. Given that I cannot observe the credit score or LTV of the borrower, I substitute these in my analysis using the median credit score and LTV at the census-tract level, which I calculate using the HMDA-GSE merged data. An in-depth explanation of this process can be found in Appendix B.

3.1.3 CFPB Dataset

Relying on the consumer complaint database from the CFPB, I employ textual analysis methods to identify complaints related to racial discrimination. Further, I pair the annual number of discrimination-related complaints, based on ZIP Codes and bank names from the CFPB's database, with the HMDA-GSE merged dataset and the HMDA origination

[15]Given the profound impact of the COVID-19 pandemic, which has ravaged the globe, including the United States, since 2020, my research excludes samples after 2019 to mitigate the interference from this shock on the financial markets.

dataset.[16] During the merging process, most of the complaints are linked to a singular county. If a ZIP Code spans multiple counties, following Dou and Roh (2023), I match it to the county with the highest population.

3.1.4 Additional Datasets

Beyond the aforementioned primary datasets for analysis, my research employs several other datasets and indicators from varied sources to support the identification of the effects of disclosure.

(i) I retrieve stock market returns for publicly listed banks around June 25, 2015, that is, before and after the disclosure policy came into effect, from Wharton Research Data Services (WRDS), including both market-adjusted cumulative abnormal returns (CAR) and CAR based on the CAPM. Also, WRDS provides financial performance data for these banks for the fourth quarter of 2014, which I use as control variables in the analysis of market reactions.

(ii) Using the Call Reports dataset, I obtain the total assets of each bank in the main dataset for the first quarter of 2015. This indicator assists me in identifying banks affected by disclosure. Additionally, total assets allow for the estimation of causal effects of disclosure, restricting banks of similar size. In this paper, I view banks with total assets between 0 and 10 billion as a control group for treated banks in the 10-100 billion range.[17] Robustness checks confirm that adopting different cutoffs does not significantly impact the estimated results.

(iii) I utilize variables such as branch-level deposits, as reported in the Summary of Deposits (SOD) dataset, to supplement the HMDA origination dataset, and analyze whether the number of applications in local markets at the Zip Code level is affected by the disclosure of discrimination complaints against local banks.

[16] Due to privacy concerns, the narratives of complaints prior to June 25, 2015, are not made public. Therefore, the discrimination-related complaints identified in this study pertain to the period after the implementation of the disclosure policy.

[17] The reasons for dropping big banks are as follows: following the implementation of the Dodd-Frank Act, bank holding companies (BHCs) with assets exceeding $100 billion have become the target of heightened supervision and are subjected to regulatory stress tests under the Comprehensive Capital Analysis and Review (CCAR) framework in 2011. Furthermore, larger banks, compared to smaller banks, may have distinct capital structures or exhibit economies of scale.

3.2 Summary Statistics

Table 2 details the summary statistics for both treated and control banks derived from the primary HMDA-GSE merged dataset. This dataset spans from 2011 to May 2015, a timeline set before the enactment of the CFPB's disclosure policy. The treated group comprises banks with total assets between 10 and 100 billion dollars, while control banks hold assets below 10 billion dollars. The variables presented in this table serve as the basis for examining the impact of the disclosure of consumer complaint narratives on both loan interest rates and default rates.

The proportion of loans filed by minority consumers in treated banks amounts to 0.07, while it stands at 0.08 in the control group, where minority consumers include individuals identified as Black or Hispanic.[18] Regarding interest rates, the average for treated banks, at 4.11%, is slightly lower than the 4.22% in control banks. A similar trend is evident in default rates, with the mean values for LTV ratios and credit scores also showing a close correspondence across treated and control banks. On average, the annual income of these loan borrowers is 107 thousand dollars in the treated group, compared to 100 thousand in the control group. Moreover, the average loan amount in these groups is 239 thousand and 247 thousand dollars, respectively. This table displays comparable characteristics for both treated and control groups across key variables. This similarity in risk attributes prior to the shock suggests that the categorization into treated and control groups in this study is well-founded.

[Insert Table 2 about here]

4 CFPB Disclosure and Racial Gaps in Interest Rates

4.1 Research Design

This paper studies banks' reactions to the disclosure of complaint narratives from three important dimensions during loan application processes: the racial gaps in interest rate,

[18] As for other variables utilized in this study, their definitions can be found in Table AN. Particularly, the final three variables featured in Table 2: Cash-out Refinance, Purchase, and Refinance, represent three distinct categories of loan purpose. To provide meaningful values, individual explanations are given for each category.

default, and rejection. In this section, I mainly focus on the impact of disclosure on racial gaps in interest rates for two reasons. Firstly, the interest rate of loans is paramount to borrowers, and racial disparities in this aspect can result in an annual loss of $450 million for minority borrowers, as indicated by Bartlett et al. (2022). The presence of this unfair treatment also draws significant attention from regulatory bodies.[19] Secondly, the distinctive loan pricing strategy in defaulted guaranteed GSE loans allows me to effectively capture discriminatory behavior within banks.

According to U.S. fair-lending legislation, judicial decisions have established that lenders can base on specific characteristics of borrowers to determine loan prices.[20] This remains legitimate even if these proxy variables result in less favorable outcomes for minorities, given the lender can demonstrate these variables serve a legitimate business necessity. Courts have explicitly established that when a lending practice results in a disparate impact, the onus is on the defendant-lender to prove that any policy, procedure, or practice is clearly associated with the applicant's creditworthiness.[21] In other words, while variations in creditworthiness can justify differing lending outcomes, the act of exploiting higher rates from applicants in financially underserved areas or those with limited shopping tendencies to increase profits is not justifiable.

To discern discrimination without the concerns of omitted variables, I utilize a setting following Bartlett et al. (2022) where all *legitimate business necessity* variables are visible. Within this context, the GSEs establish credit-risk pricing adjustments through a fee that relies solely on the borrower's position within an 8×9 matrix of LTV ratios and credit scores, known as loan-level price adjustments (LLPAs). By paying these LLPA fees, lenders are insured against credit risks. Figure 2 illustrates a typical Fannie Mae LLPA grid for

[19] Senators Elizabeth Warren and Doug Jones express concerns to financial regulators about persistent lender discrimination. This assertion references the recent study by Bartlett et al. (2022), which identifies disparities in interest rates between minority and white borrowers. Their communication can be accessed using this link: https://www.warren.senate.gov/download/2019610-letter-to-regulators-on-fintech-final.

[20] U.S. fair-lending law encompasses both the Fair Housing Act and the Equal Credit Opportunity Act (ECOA), along with all related regulatory implementations and judicial interpretations pertaining to these acts.

[21] For more details, refer to A.B. & S. Auto Service, Inc. v. South Shore Bank of Chicago, 962 F. Supp. 1056 (N.D. Ill. 1997) which states: "[In a disparate impact claim under the ECOA], once the plaintiff has made the prima facie case, the defendant-lender must demonstrate that any policy, procedure, or practice has a manifest relationship to the creditworthiness of the applicant...". Also, see Lewis v. ACB Business Services, Inc., 135 F.3d 389, 406 (6th Cir. 1998) and Miller v. Countrywide Bank, NA, 571 F.Supp.2d 251, 258 (D. Mass 2008) for more insights.

360-month term single-family loans. In the GSE loan sphere, Freddie Mac, another primary entity, also applies a similar pricing model. Consequently, a borrower's interest rate can be partitioned into three parts: a base mortgage rate, credit risk (dictated by the borrower's LTV and credit score), and a residual that reflects strategic lender pricing. The racial disparities that emerge in this strategic lender pricing are the focus of my study, as they reflect potential disparate impacts caused by banks.

Utilizing the HMDA-GSE merged dataset, I am able to empirically examine the change in the difference between the interest rates on minority borrowers and those on white borrowers following the CFPB's disclosure of complaint narratives. The baseline regression model is as follows:

$$\begin{aligned} &InterestRate_{ilt} \\ &\quad = \alpha + \beta_1 Treat_l \times Post_t \times Minority_i + \beta_2 Post_t \times Minority_i \\ &\quad + \beta_3 Treat_l \times Minority_i + \beta_4 Minority_i \\ &\quad + \mu_{Bucket \times LoanPurpose \times YearMonth} + \mu_{Lender \times YearMonth} \\ &\quad + \mu_{BorrowerCharacteristics} + \epsilon_{ilt} \end{aligned} \tag{1}$$

My primary empirical framework employs a triple-difference approach to scrutinize changes in the racial gaps in mortgage interest rates following the disclosure at the mortgage loan level. In Equation (1), i, l, and t index loan applicants, lenders, and time (year-month) respectively. $Treat_l$ classifies lenders into treated and control groups based on whether a lender l is under CFPB supervision in 2015 (i.e., covered by the disclosure policy). In order to avoid identification interference caused by differences in regulatory pressure, capital structures, or economies of scale between large and small banks, the regression sample includes only banks with total assets of less than \$100 billion as of the first quarter of 2015. $Post_t$ equals one if it is in or after June 2015, which is the effective date of the CFPB disclosure policy. $Minority_i$ equals one if the loan applicant i is Black or Latinx. Accordingly, the triple-difference estimation coefficient β_1 signifies the effect of the disclosure on racial gaps in interest rates by estimating the difference between the change in racial gaps in treated lenders relative to control lenders whose complaint narratives are not disclosed to the public.

As stated previously, the pricing grid plays a critical role in eliminating interference from credit risk in my identification. However, the interest rates within the pricing grid may fluctuate with time or loan purposes. Therefore, in Equation (1), my regression model integrates dummy variables for the 8x9 grid levels (referred to as "bucket" in the equation), interacting with the year, month, and the loan's cash-out refinance status. Additionally, my regression model accommodates lender interactions with the year and month, controlling for lender-based differential pricing and temporal variations. Moreover, I control for fixed effects related to a range of loan borrower characteristics, including the loan amount deciles, applicant income deciles, applicant gender, and whether the applicant has a co-applicant, to further control for potential factors that may impact loan pricing. Standard errors are double clustered at the lender and year levels.[22]

4.2 Baseline Results

Table 3 provides the outcomes of my baseline model. Column (1) contains only the first two fixed effects from Equation (1), and in column (2), I incorporate fixed effects for borrower characteristics. Considering lenders may have different pricing strategies (i.e., different markups) when utilizing the pricing grid, I interact the lender fixed effects with the bucket-purpose-time fixed effects in column (3). Furthermore, I construct a similar borrower identifier as an approximation of individual fixed effects.[23] By controlling for this fixed effect, I can directly compare the effects of disclosure on borrowers who share very similar creditworthiness features but with different races, as demonstrated in column (4). In the final column, I include joint lender-similar borrower fixed effects. Controlling for these joint fixed effects allows me to compare behaviors of nearly identical borrowers within the same lender before and after the disclosure policy, thus ensuring that my estimation results are unaffected by the bank-consumer relationship.

[Insert Table 3 about here]

[22] The findings hold steady when I cluster standard errors at the level of the lender, as shown in Table A3 in the Appendix.

[23] The borrower fixed effect under scrutiny results from interplays among the following categorical variables: pricing grid, loan purpose, loan amount deciles, applicant income deciles, applicant gender, and co-applicant status. Leveraging these attributes allows me to segment loan applicants into extremely granular categories, thus identifying borrowers with remarkably similar traits. Given that borrower characteristic fixed effects are absorbed by similar borrower fixed effects due to collinearity, there is no necessity to control borrower characteristics in columns (4) and (5).

Table 3 displays the estimated coefficients on the *Minority* variable, indicating that prior to the disclosure policy, minority borrowers are charged an interest rate that is 2.5-2.9 basis points higher compared to white borrowers. Since the inception of Mortgage Bankers' Association Annual Performance Report in 2008, net production income by year has averaged 55 basis points of principal.[24] Thus, an elevation of 2.7 basis points in the interest rate equates to a 1.88 basis points increase in annual principal repayment, which constitutes 3.4% of the bank's annual net profit.[25] However, this disparity changes after the implementation of the CFPB disclosure policy. The estimated coefficient on the triple-difference term, Treat×Post×Minority, suggests that post-disclosure, the interest rate charged to minority borrowers relative to white borrowers is reduced by 2.3-2.8 basis points, attenuating approximately 87% of the racial gaps. This indicates that the enforcement of the disclosure policy manages to save minority borrowers in the mortgage market an average of $102 million annually, which they previously incurred due to discrimination.[26]

Table 3 also highlights that the model effectively explains between 76% and 82% of the fluctuations in interest rates observed within our sample. The remaining unexplained variance might be attributed to strategic pricing. Further, to validate the applicability of the settings in this study, I replicate the primary results of Bartlett et al. (2022), utilizing GSE loans from my dataset, as shown in Table A4 in the Appendix. I use the same setting as in Table 3 of Bartlett et al. (2022) to estimate the disparity that minority borrowers face in terms of loan interest rates in purchase loans and refinance loans. The sign and magnitude of the coefficients obtained are highly consistent with the estimates of Bartlett et al. (2022),

[24] For more details, see: https://www.mba.org/news-and-research/newsroom/news/2023/04/06/imb-production-profits-falls-to-series-low-in-2022

[25] Consider a mortgage loan where the home price is $200,000 and the down payment is 20%. With an annual interest rate of 4%, an increase to 4.025% would mean an additional annual repayment of approximately $36, representing 2.25 basis points of the principal (80% of $200,000 equals $160,000). The specific numbers used in this example do not drastically alter the final outcome.

[26] According to a report by the Federal Reserve of New York, the market size of housing debt in 2022 is approximately $12.26 trillion. The Survey of Consumer Finance points out that the segment of African-American/Latinx contributors in the mortgage market approximates to about 13.3%. Data from the HMDA indicate that the loan amount processed by banks under the CFPB regulation constitutes 35.75% of the total loan volume post-2015. Back-of-the-envelope calculations suggest that if the interest rate charged to minority borrowers falls by an average of 2.55 basis points following the disclosure, it would result in an annual decrease in their repayment by an amount equivalent to 1.77 basis points of the principal. Consequently, the minority borrowers within the banks regulated by the CFPB in the total housing debt would benefit, resulting in an annual saving of approximately $102 million.

even though I use different matching methods to get the final dataset. This consistency indicates that my results are free of sample selection bias in the matching process.

Another concern that may arise pertains to the potential variation in discount points chosen by minority and white borrowers.[27] This could be the reason for minority borrowers paying significantly higher interest rates relative to non-minority borrowers in Federal Housing Administration (FHA) loans, as suggested by Bhutta and Hizmo (2021).[28] However, this conclusion is contentious as Bartlett et al. (2022) still find discriminatory pricing within FHA loans even after accounting for discount points using a larger sample. In my study, I focus on GSE loans to circumvent this debate, as both Bartlett et al. (2022) and Zhang and Willen (2021) identify the occurrence of discriminatory pricing within the GSE mortgage market. Additionally, I demonstrate the robustness of my results by examining whether significant differences exist in racial gaps in discount points between the treated and control groups. As the HMDA only provides information about discount points after 2018, I utilize the HMDA-GSE merged dataset for 2018-2019 to scrutinize disparities in discount points in the same setting as in Table 3 (adding the interest rate as a control variable). The findings, showcased in Table A5 in the Appendix, reveal no significant divergence in racial gaps in discount points between treated and control lenders. This dispels the concern that the racial gaps might be caused by omitted variables like discount points in baseline results.

Finally, I employ an event study approach to examine the dynamic impacts of disclosure. One significant concern accompanying the triple difference analysis is whether the racial gaps in both treated and control groups follow a parallel trend before the CFPB disclosure. Given that the determination of treated and control groups in this study is based on bank size, the trends of racial gaps may differ among banks of varying sizes.

Figure 3 displays the quarterly coefficient estimates for racial gaps in interest rates within treated lenders, compared to control lenders. I scrutinize results from five quarters prior to the implementation of the disclosure policy (effective in the second quarter of 2015) and ten quarters post-disclosure. Any sample periods beyond this selected range are incorporated

[27]In the mortgage market, borrowers have the option to pay discount points - an upfront lump sum - to a lender in exchange for a reduced loan interest rate. Conversely, they can opt for negative points, which involves receiving credit from the lender and paying a higher loan interest rate. Hence, the observed racial differences in interest rates could be the result of endogenous decisions on discount points if there is a discrepancy in the preferences for discount points between minority and non-minority borrowers.

[28]Zhang and Willen (2021) also uphold this notion, asserting that there is no actual discrimination present in FHA loans.

into the beginning periods (before 2014) and end periods (after 2017). The fifth quarter prior to the effective date of the disclosure and earlier periods are used as the baseline periods.

[Insert Figure 3 about here]

From Figure 3, I discern no substantial difference in racial gaps in interest rates between the treated and control groups before the implementation of the disclosure policy. I note a sudden decrease in the racial gaps in interest rates for treated lenders compared to control lenders from the first quarter post-disclosure. Although some periods show a coefficient estimate not significantly different from zero, the overall impact remains negative up until the final period (the tenth quarter and all subsequent quarters post-disclosure). This trend reinforces the identification assumption that the racial gaps of interest rates in treated and control groups followed parallel trends before the policy's implementation, with effects only surfacing after the implementation of the disclosure policy. Furthermore, the dynamic trend displayed in Figure 3 also indicates that the disclosure of complaint narratives contributes to racial fairness over an extended period.

An alternative concern exists that another element, possibly a different regulation, could have concurrently influenced the racial disparities in interest rates within both treated and control banks, coinciding with the enforcement of the disclosure policy. Under these circumstances, parallel trends would still be noticeable, but the explanation for my primary outcomes could potentially be this factor rather than the disclosure law under investigation. To alleviate this worry, I scrutinize changes in the CFPB's regulatory policies and find no other concurrent regulations in 2015 that might affect my results.

4.3 Moderation Effects

In this section, I test the heterogenous effects of the CFPB disclosure policy, focusing on the varied reactions from banks in different scenarios. In particular, I explore whether banks respond differently to the publication of complaint narratives if: (i) the complaints received by banks involve aspects of discriminatory treatments, (ii) banks are located in areas where the CFPB garners substantial Google search attention, and (iii) the risk of discrimination litigation against banks is elevated.

In my first set of tests, I focus on discrimination complaints. While the CFPB publicly discloses complaint narratives for all supervised banks, a portion of these banks have complaints related to racial discrimination. Through textual analysis, I split the treated group into two subgroups based on whether they received complaints about racial discrimination in 2015.[29] One subgroup comprises banks under CFPB supervision that received discrimination complaints, while the other includes banks under CFPB supervision that did not receive such complaints.

Separately conducting regression for both groups based on the setting of Equation (1), I obtain the results presented in the first two columns in panel A of Table 4. Column (1) of panel A reports the changes in racial gaps after disclosure between treated banks that received discrimination complaints and control banks, providing a significantly negative coefficient on *Treat×Post×Minority*. In contrast, column (2) represents the results for treated banks that did not receive discrimination complaints, showing a negative but insignificant coefficient on the triple interaction term. These findings suggest that disclosure has a more evident mitigating effect on racial gaps among banks already engaged in discriminatory practices. These results suggest that banks with discriminatory practices are influenced by disclosure to reduce such illegal behaviors.

In the second test, I examine the moderation effect of social attention on banks' decision-making. This task is difficult due to the limited information regarding public interest in the disclosure. To navigate this challenge, I calculate the state-level variations in the Google Search Index for the term "CFPB" during the 12 months preceding the disclosure date. I set the *High* indicator to one for observations in states with above-median values, and to zero otherwise, following the approach of Dou et al. (2023).[30] Using this indicator, I divide the treated group into two subgroups according to the Google Search Index levels of the states where the banks are located.

In line with the same settings used in the analysis of discrimination complaints, my findings are displayed in columns (3) and (4) in panel A of Table 4. These outcomes, with one being statistically significant (column (3)) and the other not (column (4)), suggest that internet searches conducted by social groups, which represent a measure of social attention,

[29] For the method of identifying whether complaints contain discrimination, please refer to Li (2023). Within the HMDA-GSE merged dataset utilized for this section's analysis, 32.61% of treated banks received complaints pertaining to discrimination in 2015.

[30] Google monitors and aggregates the search volume of users by keywords for each state, then calculates the search volume index as the proportion of searches from a given state to those from the state with the highest search volume.

play a role in reducing racial disparities in the mortgage market. Social awareness may prompt banks to care about their reputation, thereby mitigating potential reputational risks and curtailing misconduct.[31]

[Insert Table 4 about here]

Finally, I explore if the impact of disclosure on reducing racial disparities is more significant during times when there are heightened litigation cases related to racial discrimination. Between 2011 and 2019, there are eight litigations concerning discrimination. The involved banks faced various penalties, and some were required to invest in subsidy programs to support minority borrowers.[32] To ascertain the efficacy of these potential litigation risks in mitigating racial disparities, I supplement Equation (1) with a moderating variable, *Litigation*, which recognizes the intensity of litigation over time in two forms: litigation number and penalty amount. These variables represent the number or penalty of litigations that occur every month. While identifying this effect, if the sample incorporates banks implicated in litigation, the effects could be biased by endogeneity issues. This is because legally penalized banks would have a strong motivation to minimize discriminatory actions. Hence, by monitoring the operation of their peers, I can gauge the reactions of these peer banks to potential litigation threats.

Upon excluding samples involving litigated banks, I estimate this moderation effect, with the results presented in panel B of Table 4. The first two columns take *Litigation* as the form of the total number of CFPB enforcements, while the last two represent *Litigation* as the penalty amount charged to lenders. Columns (2) and (4) take advantage of variations within the individual level using similar borrower fixed effects, consistent with the specification used in column (4) in Table 3. The findings in column (1) indicate that when the total number of litigations increases by one in a given month, the additional interest shouldered by minority borrowers drops by 6 basis points in the post-disclosure period. On the other hand, column (3) states that when the penalty of litigations escalates by one million dollars in a month, the additional interest borne by minority borrowers dwindles by 1.4 basis points

[31] Darian Dorsey, Chief of Staff of the CFPB, shares anecdotes about banks connecting executive bonuses to their responsiveness in handling complaints. This anecdotal evidence suggests that bank executives are incentivized to address complaints, given that a portion of their bonuses is tied to the efficacy of the banks' complaint resolution (Cortez (2015)).

[32] The data regarding these litigations are gathered from the CFPB website. For detailed information, see Table A6 in the Appendix.

in treated banks after disclosure. Both outcomes are statistically significant at the 5% level. These findings strongly suggest that the CFPB's actions decrease discrimination suffered by minority borrowers by imposing litigation threats on banks that the CFPB does not suit. During periods when law enforcement is strengthened and litigation risks are high, banks, aware of this threat, might reduce illegal behavior to reduce their exposure to litigation risk. This finding is also critical from a policy perspective, indicating the indirect disciplinary effect of the CFPB oversight on reducing discriminatory treatment in the lending market. To my best knowledge, my paper is the first to analyze the impact of the CFPB oversight on preventing discrimination in the mortgage market.

5 CFPB Disclosure and Outcome Tests: Evidence from Default Rates

5.1 Research Design

In this section, I concentrate on the default rate of loans. Since default actions are influenced by various factors and not solely determined by banks, I employ the "outcome test" approach to identify the presence of racial discrimination and the impact of disclosure policy on it (Becker, 1957, 1993). Outcome tests assess whether loans to marginal minority borrowers yield higher profits compared to those to marginal white borrowers. If it turns out that marginal minority borrowers indeed generate higher profits, it signifies that lenders raise the screening threshold for minority applicants due to racial prejudices. The profit that banks extract from consumers is influenced by two main factors: the interest rate affects the direct gains of banks, while the default rate results in losses for banks. In prior analyses, I establish that minority borrowers are subjected to elevated interest rates. This section primarily examines whether racial gaps also persist in default rates and if the mitigating role of the disclosure policy comes into play. If I detect a significant disparity in the default rate among marginal minority and White borrowers, this effect will not stem from omitted variables or statistical discrimination. Rather, it will imply racial biases within banks during the consumer selection procedure.[33]

However, there are at least two reasons that make precisely conducting outcome tests a challenge (Butler et al. (2023)). Firstly, researchers cannot directly observe the literal marginal borrower, referred to as the "infra-marginality problem" (Ayres (2002)). Because the definition of marginal borrower is neither public nor uniform among banks, researchers can only identify marginal borrowers by controlling covariates. Such identification could be inaccurate if these covariates fail to completely eliminate the difference between minority borrowers and whites in terms of creditworthiness. If so, the difference reflected in the default rate might not solely be the result of racial bias. In addition, if the distribution of creditworthiness for minorities remains lower than that for whites even after controlling for covariates, marginal minority borrowers might exhibit higher default rates than whites in the absence of racial bias. As a result, only when racial bias is present and powerful enough to counterbalance these confounding elements, I am able to witness lower default rates amongst marginal minority borrowers.

A second concern is that researchers cannot directly observe loan profitability. When focusing on the default rate, potential misestimations of the disparity between minority and White borrowers may occur due to neglecting other factors that influence banks' profitability assessments. For instance, the prepayment risk, which might be higher for White borrowers, could decrease banks' evaluation of the profitability of white borrowers. In such a case, banks may not mandate that minority borrowers maintain notably low default rates to generate profits surpassing those from White borrowers. This further exacerbates the difficulty in observing lower default rates among minorities.

While conducting outcome tests by comparing the default rates of marginal minority

[33] Discrimination faced by minority borrowers in the lending market could stem from two potential sources: banks' racial biases or statistical discrimination. Racial bias is defined as a combination of taste-based discrimination and miscalibrated beliefs (Becker (1957); Bordalo, Coffman, Gennaioli, and Shleifer (2016); Arnold, Dobbie, and Yang (2018); Egan, Matvos, and Seru (2022); Ewens and Townsend (2020)). Taste-based discrimination implies banks' discontent when approving minority borrowers' applications or satisfaction from approving those of White borrowers. Miscalibrated beliefs involve banks harboring incorrect stereotypes about minority borrowers. Since these biases are typically implicit and can contribute to discrimination, I group them together. An alternative explanation refers to the concept of statistical discrimination (Phelps (1972); Arrow (1974); Ewens, Tomlin, and Wang (2014)). In the context of this research, statistical discrimination is evident when banks treat minority and non-minority borrowers disparately due to the intrinsically greater risks that minority borrowers carry. As a result, from a business standpoint aimed at profit maximization, it is plausible that banks may decline a larger proportion of applications from minority borrowers.

borrowers with that of marginal white borrowers might not be perfect, it is evident from the above analysis that this method is indeed conservative. Only when there is significant racial bias in banks' consumer selection, I can detect that the default rate of marginal minority borrowers is significantly lower than that of marginal white borrowers through an outcome test. Hence, any evidence of lower default rates for minorities should be seen as compelling proof of discrimination. It indicates that banks use higher approval standards to deal with minority applicants.

The approach used in the outcome test has proven successful in the auto loan market (Butler et al. (2023)). Following Butler et al. (2023), my research investigates racial disparities in the mortgage market, additionally examining the impact of the disclosure policy on racial gaps in default rates, particularly amongst marginal borrowers. If, after disclosure, the racial gaps in default rates are reduced, in other words, marginal minority borrowers have higher default rates, it is compelling to argue that the disclosure of complaint narratives prompts banks to lessen their excessive requirements and use the same and fair standard to screen minority borrowers' loan application.

5.2 Outcome Test Results

To define default rates, I follow Butler et al. (2023) categorizing the loan as defaulted if the borrower becomes delinquent for 90 or more days. To alleviate the challenge of identifying marginal borrowers, I restrict the sample to those with credit scores below 660. This action notably diminishes the observation count.[34] Owing to the fact that factors influencing defaults differ from those influencing interest rates, the fixed effects designs employed here diverge slightly from those used in Section 4. Using the "outcome test" approach, my identification strategy relies on the specification in Equation (2):

$$
\begin{aligned}
&DefaultRate_{ilt} \\
&\qquad = \alpha + \beta_1 Treat_l \times Post_t \times Minority_i + \beta_2 Post_t \times Minority_i \\
&\qquad + \beta_3 Treat_l \times Minority_i + \beta_4 Minority_i + \gamma X_{ilt} + \mu_{Lender \times YearMonth} \\
&\qquad + \mu_{Zip \times Year} + \epsilon_{ilt}
\end{aligned}
\tag{2}
$$

[34]The handling of the sample here aligns with Section 4, excluding observations of large banks (those with total assets exceeding \$100 billion).

In the equation, the symbols i, l, and t retain the same significance as in Equation (1), representing loan applicants, lenders, and time (year-month) respectively. Table 5 outlines tests where the impact of disclosure on racial disparities in default rates is identified using a triple-difference approach. This approach takes into account loan characteristics such as interest rate, purpose, and the logarithm of the loan amount. Applicant attributes like gender, the logarithm of income, and the presence of a co-applicant are also considered, as represented by X_{ilt} in Equation (2). In addition, I factor in zip-by-year fixed effects to accommodate potential influences on loan default rates from changes in local economic conditions. To more effectively accommodate borrower creditworthiness, pricing grid-loan purpose fixed effects are included in column (3).

Columns (1)-(3) present the discriminatory treatment endured by minority borrowers in the subprime sample and the effect of the disclosure policy on reducing this unfair treatment. The negative and statistically significant results on the *Treat*×*Minority* coefficient affirm the presence of discrimination against minorities in treated banks. The *Treat*×*Post*×*Minority* coefficient shows an average increase of 28.8 percentage points (70.1% of one standard deviation) in the default rates of minorities within the treated group, relative to the control group, following the disclosure. This outcome mirrors the nearly vanished racial differences in default rates post-disclosure, emphasizing the robust influence of the disclosure policy.[35]

[Insert Table 5 about here]

In the final column of Table 5, I forgo the cutoff set for identifying marginal borrowers. This full sample outcome does not present sufficient evidence of discrimination against minorities. The full sample encompasses many borrowers distant from the intensive margin of credit provision, which weakens the test's sensitivity to margin differences. It suggests that applying the test to the subprime borrower sample, who are closer to the margin, is an appropriate identification approach.

[35]To address potential concerns about the parallel trend assumption, I also adopt an event study methodology to scrutinize the dynamic impacts of disclosure. For more details, refer to Figure A1 in the Appendix.

6 CFPB Disclosure and Racial Gaps in Rejection Rates

6.1 Overall Trend Analysis

Previous examinations indicate that the deployment of the disclosure policy almost wipes out racial gaps in default rates amongst marginal borrowers. These racial discrepancies might stem from banks setting tougher admission criteria for consumers, and the implementation of the disclosure policy potentially diminishes banks' propensity to establish such rigid standards. In this section, I focus on the denial of loan applications and try to answer the following two questions: (i) whether this unjust screening standard exists before the disclosure, and (ii) whether the disclosure policy alleviates these disparities. Initially, I analyze the trend of rejection rates on the full sample based on the HMDA origination dataset, presented in Figure 4.

Figure 4 illustrates the trend of racial disparities in residualized rejection rates among banks under and not under CFPB supervision, particularly around the time of the CFPB's complaint narratives disclosure in June 2015. By calculating differences between minority and non-minority groups for supervised banks and unsupervised banks separately, I sidestep the impacts of variations in loan screening standards between CFPB-supervised and unsupervised banks. This lays the foundation for a comparison of racial disparities between these groups of banks.[36] Further, by utilizing residualized rejection rates - residuals purged of specific observable variables tied to borrower risk, in conjunction with the fixed effects arrangement from Equation (3), I efficiently control for borrower creditworthiness and plot changes in residualized rejection rates. This approach furnishes a precise appraisal of the disclosure policy's influence on racial disparities after controlling for temporal effects and

[36] Suppose that the risk preferences between CFPB-supervised and unsupervised banks differ, with the CFPB-supervised banks being more risk-averse. Hence borrowers are more likely to be rejected in CFPB-supervised banks. Under such a scenario, comparing the disparity in rejection rates of minority borrowers between CFPB-supervised and unsupervised banks directly becomes untenable (given that the stringent selection criteria of CFPB-supervised banks differentiate the characteristics of minority borrowers between the two types of banks). However, if we first perform an intra-group subtraction (i.e., subtracting the rejection rate of White borrowers from that of minority borrowers), this will effectively neutralize the disparity brought about by non-discriminatory loan screening standards.

borrower traits.[37]

The trend of racial gaps in rejection rates presented in Figure 4 underscores that the discrepancy in rejection rates between minority and non-minority consumers is more pronounced in banks supervised by the CFPB. In other words, racial gaps are more substantial in banks operating under CFPB supervision. With the implementation of the disclosure in mid-2015, the decrease in excess rejection rates of minority borrowers is noticeably more apparent in banks supervised by the CFPB than in those without supervision. Additionally, the parallel trends in rejection rate differences across different bank groups before disclosure, lend support to the validity of the identification strategy used later in this study.

[Insert Figure 4 about here]

6.2 Empirical Analysis

In this section, I undertake an empirical evaluation to ascertain whether the disclosure policy alleviates the discrimination faced by minorities in terms of loan accessibility. This evaluation is based on the HMDA origination dataset, excluding the influence of large banks based on total assets, which aligns with previous analyses.[38] I employ the loan-level rejection dummy

[37] Though directly observing the disparity trend between minority and non-minority groups can partly lessen the disturbance caused by inter-bank heterogeneity, if minority consumers attracted by CFPB-supervised and CFPB-unsupervised banks exhibit notable characteristic differences, the racial gaps within these groups are still not directly comparable. By implementing residualized rejection rates, I can optimally mitigate interferences from both bank and consumer attributes. This residualization process aims to neutralize statistical discrimination within loan scenarios (Phelps (1972); Arrow (1974); Ewens et al. (2014)), where statistical discrimination refers to banks' reasonable rejection or approval decisions based on the specific features of minority and non-minority borrowers, done without racial bias and in the pursuit of maximizing profits.

[38] Another reason for excluding large lenders here is that some of them may possess their own credit risk models, including legitimate-business-necessity variables that are not visible to the GSE underwriter (and by extension, not to me as a researcher). If these lenders use fundamental models to selectively retain loans in their portfolios, my empirical model might inadvertently introduce credit risk into my estimates (Bartlett et al. (2022)). Therefore, to mitigate this concern, I exclude banks with total assets exceeding \$100 billion.

variable as the dependent variable, resulting in the following equation as the specification:

$$
\begin{aligned}
&RecjectionRate_{ilt} \\
&\qquad = \alpha + \beta_1 Treat_l \times Post_t \times Minority_i + \beta_2 Post_t \times Minority_i \\
&\qquad + \beta_3 Treat_l \times Minority_i + \beta_4 Minority_i + \mu_{Lender \times Year} \\
&\qquad + \mu_{Lender \times Similar\ Borrower} + \mu_{Lender \times Census\ Tract} + \mu_{Census\ Tract \times Year} \\
&\qquad + \epsilon_{ilt}
\end{aligned}
\tag{3}
$$

In Equation (3), the symbols i, l continue to denote loan applicants and lenders, while the symbol t has now been adjusted to indicate the year. Table 6 presents the results of these regressions. The first two columns show the baseline outcomes, where I adjust for lender-by-year fixed effects, lender-similar borrower joint fixed effects, and lender-census tract joint fixed effects in column (1),[39] and I introduce census tract-by-year fixed effects in column (2).[40] I find that minority applicants are 3.5 percentage points less likely to secure loan approval than White applicants in the control group, while this number increases by 4.2 percentage points in the treated group (column (2)), indicating that minority applicants are 7.7 percentage points less likely to secure loan approval than White applicants in treated banks. A rough estimation implies that this results in over 70,000 minority applicants in treated banks failing to obtain loans they would have been granted if they were White, each

[39] Given that the HMDA origination dataset includes loans that have been declined, it significantly expands the total sample size. This expansion provides an objective opportunity to employ a more granular fixed effects setting. Additionally, in the mortgage market, it is possible that a loan officer may discourage a prospective minority applicant from applying, or guide non-minority applicants to improve their probability of loan approval. Suppose this situation results from the behavior prevalent across a branch by loan officers. In that case, the lender by census tract fixed effects I use will allow me to measure discrimination in rejection rates at the branch level that exceeds this explicit prejudice against minority applicants at the lender level.

[40] The "similar borrower" variable incorporated in this test aligns closely with those used in Section 4, with the only difference being the replacement of the credit score and LTV group from the HMDA-GSE merged dataset with the decile of the median credit score and LTV at the census-tract level. This difference is due to the lack of individual-level credit score and LTV data in the HMDA dataset, thus the census tract median serves as an approximation. Bartlett et al. (2022) confirm that this approximation does not affect conclusions related to discrimination. For further clarification, please refer to Section 3.1.

year.[41] Nevertheless, following the disclosure, the discrimination faced by minorities in terms of loan accessibility eases by 1.6 percentage points, indicating that each year, over 14,000 minority households will successfully apply for a mortgage loan due to the disclosure policy.[42]

[Insert Table 6 about here]

As a further exploration of the disclosure impact, I also delve into whether banks react distinctively to the unveiling of complaint narratives if: (i) the complaints received by banks pertain to discriminatory treatments, and (ii) banks operate in regions where the CFPB attracts substantial Google search interest.

Columns (3) to (6) in Table 6 depict the moderating impacts of discrimination complaints and Google attention. The *Treat×Minority* coefficient, which is positive and significant in column (3), suggests that within the treated group, relative rejection rates for minorities are higher in banks with pronounced discrimination. The smaller value of the coefficient on the same variable in column (4) conveys that banks without discrimination complaints have smaller additional rejection rates. These findings corroborate the validity of my discrimination measurement. The primary results for the moderating effects of discrimination complaints, namely the coefficient of *Treat×Post×Minority*, emphasize that banks already involved in discriminatory practices primarily drive the observed treatment effect following disclosure (column (3)). Additionally, the results from columns (5) and (6) suggest that social attention also boosts the beneficial impacts of disclosure. Furthermore, I employ an event study approach to scrutinize the time-varying influences of disclosure, building upon the specification outlined in column (2). The findings are detailed in Figure A2 in the Appendix.

[41] I determine the estimates by taking the product of the annual aggregate of minority mortgage loan applications and the change in their probability of approval. The approval rate may either decrease due to discrimination or increase owing to the disclosure policy. Data from the HMDA origination dataset indicates that after 2015, the annual average of mortgage loan applications totals approximately 19.16 million, with 34.91% of these applications received by banks regulated by the CFPB and 13.77% from minority borrowers. Based on these numbers, I roughly calculate that there are about 0.92 million (19.16 million × 34.91% × 13.77%) minority mortgage loan applications per year in CFPB-supervised banks. Therefore, roughly 70.92 thousand (0.92 million × 7.7%) applicants may be denied annually due to racial bias.

[42] This calculation, built upon the previous framework, reveals that in the wake of the disclosure policy's implementation, an estimated 14.73 thousand (0.92 million × 1.6%) minority applicants stand to benefit each year. It is clear that my estimates in this subsection may be understated as the HMDA origination dataset does not encompass all applications in the U.S. mortgage market.

7 Reaction of Other Stakeholders

7.1 Rival Bank's Reaction Towards the Disclosure

In this section, I investigate if the implementation of the disclosure policy has sparked greater competition among banks in the local market. Dou et al. (2023) find that after the disclosure of the total number of complaints against CFPB banks in 2013, rival banks learn about the service quality of CFPB banks from the total number of complaints and thus enter areas where complaints are more intense. In a similar vein, I carry out an investigation to understand if rival banks exploit complaint narratives to shape their market entry policy. In particular, if CFPB incumbent banks in a certain region engage in extensive discriminatory practices, it is likely that their rival banks may expand their market reach and seize market share by addressing the needs of underserviced minority borrowers. To carry out this test, I aggregate the HMDA origination dataset to the county-year level and calculate the density of banks at the county level. I use this as the dependent variable and estimate the ensuing model:

$$BankDensity_{it} = \alpha + \beta_1 Share_i \times Post_t + \gamma X_{it} + \mu_{State\times Year} + \mu_{County} + \epsilon_{ilt} \tag{4}$$

In Equation (4), symbols i and t denote county and year, respectively. The dependent variable, *BankDensity*, is represented by the total number of unique bank brands per ten thousand residents. The primary independent variable, $Share \times Post$, captures the varying degrees of impact on market structures in different counties following the implementation of the disclosure policy. I utilize two continuous measures to gauge the degree of disclosure's impact across distinct counties: (i) *Amount Share*, which is the market share occupied by treated banks (that is, those CFPB-supervised banks with total assets exceeding $10 billion but less than $100 billion) within each county in 2015; (ii) *Complaint Share*, calculated as the total number of complaints related to discrimination received per county in 2015 divided by the count of loans issued to minority applicants. By interacting these two variables with the *Post* term, which equals one following the disclosure policy implementation, I identify the varied impact of disclosure across counties based on the specific share of treated banks. In this analysis, I account for the lagged average approval rate and the lagged average bank deposits, represented by X_{it} (Dou et al. (2023)). Furthermore, I account for county-level fixed effects and state-by-year joint fixed effects to absorb the potential impact of local economic and temporal shocks. In the regressions, standard errors are clustered at the county level, and these results persist even when I apply standard error clustering at both the county and year levels.

Table 7 depicts the response of rival banks to disclosure. Columns (1) to (3) reflect the heterogeneous effects of disclosure on the total number of banks per ten thousand residents in the current period, lagged one period, and lagged two periods, as identified based on the continuous treatment variable *Amount Share*. The results imply that subsequent to the disclosure, there is an escalation in rival bank entry, which may increase the market competition. Column (2) suggests that an increase of one standard deviation in *Amount Share*$\times$*Post* within a county will lead to an addition of 1.3 new unique bank brands per ten thousand people (4.9% of one standard deviation) in the next year. Columns (4) to (6) present the outcomes when we use the *Complaint Share* as the measure of a county's exposure to the disclosure policy. The significant positive coefficients continue to lend support to the previous hypothesis.

These results indicate that peer banks may enhance their market standing by gleaning insights from the disclosed weaknesses in their competitors' operations, particularly in areas with deficient customer service and discriminatory treatments. In other words, if a county experiences a greater impact from the disclosure, and the service quality disclosed by the CFPB is inferior (evidenced by a higher number of discrimination complaints), rival banks may seize this opportunity to penetrate the local market, thereby heightening competition. As advancements in technology streamline the collection and sharing of these complaint narratives promptly and accurately, it is likely that such disclosures will become increasingly valuable as a policy tool to encourage market competition.[43] The increased competition may protect minority borrowers from discriminatory treatment in the mortgage lending market (Li (2023)).

[43]Banks are motivated to utilize the complaint database in order to enhance the quality of their mortgage services. This is because they frequently measure their performance against competitors using metrics from the database, as outlined in the Consumer Financial Protection Bureau (CFPB) report of 2013.

7.2 Stock Market's Reaction Towards the Disclosure

In this section, I examine the reaction of investors in the stock market following the enforcement of the disclosure policy on CFPB-supervised banks. Based on the 2013 disclosure of complaint counts by the CFPB, Dou and Roh (2023) confirm that the creation of a complaint database aids in the spread of novel information that the stock market can detect. With the CFPB upgrading its disclosure of complaints in 2015 to include complaint narratives, I gain the capacity to pinpoint complaints related to discrimination. Consequently, I can closely observe the reaction of the stock market towards banks involved in discriminatory behaviors as compared to those that are not.

In evaluating the market's response, I build a sample including 341 listed banks from the HMDA origination dataset. These institutions have no missing daily returns over three, five, or seven-day event windows. By leveraging the U.S. Daily Event Study function offered by WRDS, I compute the Cumulative Abnormal Returns (CAR) within event days [-1, +1], [-2, +2], and [-3, +3] as the difference between a bank's daily return and the value-weighted CRSP market return. To ensure robustness, I compute the CAR based on the Capital Asset Pricing Model (CAPM) and the Market Adjusted Model (denoted as *Market* in this section). I then carry out cross-sectional regressions linking banks' cumulative abnormal returns to their involvement in receiving complaints related to discrimination:

$$CAR_i = \alpha + \beta_1 Complaint_i + \beta_2 Non\text{-}Complaint_i + \gamma X_i + \epsilon_i \tag{5}$$

In Equation (5), *CAR* represents the abnormal returns for each bank derived from the CAPM or Market Adjusted Model across various event windows. For identification, I categorize the banks in the sample into three groups: those supervised by the CFPB and with a record of discrimination complaints in 2015, termed as *Complaint*; those supervised by the CFPB but without any record of discrimination complaints in 2015, *Non-Complaint*; and banks not supervised by the CFPB, which act as a control group for the first two categories. In order to control for potential confounding variables, I introduce measures of the banks' total assets, equity-to-assets ratio, return on assets, and total deposits, all of which are established at the end of 2014 (Dou and Roh (2023)).

Table 8 presents the stock market's reaction to banks in the *Complaint* group (or *Non-*

Complaint group) relative to those not supervised by the CFPB. Each of the first three columns depicts the outcomes for the event windows of [-1, +1], [-2, +2], and [-3, +3] trading days, respectively. Furthermore, I conduct a t-test for the two coefficients estimated in every column to test if there are significant variations between them. The results show a negative market reaction post-disclosure among the CFPB-supervised banks. The market response seems more adverse for banks that are subjected to discrimination complaints. The estimated coefficients suggest that, compared to banks not under supervision, banks in the Complaint group witness a drop in CAR by roughly 1.3 to 2.6 percentage points subsequent to the disclosure. The difference between this subset of banks and those without discrimination complaints is statistically significant, particularly in shorter event windows (such as [-1, +1]). Columns (4) to (6) in Table 8, which utilize cumulative abnormal returns based on Market Adjusted Model, yield consistent results.

These observations highlight the profound consequences of the disclosure, bolstering the notion that the market perceives the unveiling of such information as an adverse shock that elicits significant reactions. On the one hand, the enforcement against discriminatory practices in the U.S. market is strict, demanding significant economic and reputational costs once courts have adjudicated the presence of illegal discriminatory lending practices.[44] This situation could potentially evoke investor concerns regarding the future performance of these banks, thereby triggering the disposal of stocks associated with such potential litigation risks.[45] On the other hand, investors might exhibit distaste for inequality, as the significance of Socially Responsible Investing is on the rise (Hartzmark and Sussman (2019)). They could be hesitant to invest in banks deemed to be socially irresponsible as these institutions appear to have treated minority consumers unfairly.[46]

[44]In Table A6 of the Appendix, I catalog litigations penalizing banks supervised by the CFPB due to racial discrimination. In addition, as displayed in footnote 6, over the past decades, the U.S. Department of Justice has taken action against numerous major mortgage lenders for contravention of fair lending principles during the housing boom, resulting in settlements surpassing $500 million.

[45]For instance, as a result of litigation and fines related to discriminatory practices, Wells Fargo shares fell 1.3 percent on a down day. Refer to `https://www.reuters.com/article/us-wells-lending-settlement-idUSBRE86B0V220120712`.

[46]Existing studies suggest that worries regarding inequality might have a significant influence within the financial markets (Pan et al. (2022)).

8 Conclusion

The topic of racial disparities continually fuels discussions among scholars and policymakers. In this study, I present the first comprehensive exploration into the impacts of complaint narrative disclosure on DEI within the financial market. I utilize innovative identification methods such as leveraging GSE's pricing grid or "outcome test" strategy, with the intention to discern racial bias between minority and white borrowers in the mortgage market, while carefully controlling for potential differences in risk and creditworthiness. In closely scrutinizing the interest rates, default rates, and rejection rates for minority borrowers, I ascertain that the notable racial gaps, previously existing, are significantly diminished due to the implementation of the disclosure policy. My research conveys that through the deployment of the disclosure policy, minority borrowers in the mortgage market save an average of $102 million each year. Furthermore, the disclosure policy facilitates more than 14,000 minority applicants to procure a mortgage loan each year successfully. Also, the reactions from other stakeholders affirm these outcomes and provide channels for the effective execution of the disclosure policy.

At present, approximately 93% of developed nations possess regulatory entities with the ability to acknowledge and resolve customer complaints about financial services. Half of these countries have dedicated financial regulatory bodies focusing on consumer rights protection. However, except for the CFPB in the United States, nearly no other financial regulatory agencies in other countries opt to share consumer complaint information publicly.[47] My research demonstrates that the public disclosure of customer complaints alleviates discriminatory and unfair treatment of clients in the financial system via various channels in the US. It is possible that other nations can draw insights from this disclosure policy and establish their strategies for managing and disclosing consumer complaints. Implementing such measures could hold substantial potential in fostering DEI on a worldwide scale.

Lastly, with the aim to support minority borrowers in the United States in circumventing potential bias in mortgage lending, I establish an online query platform.This system grants

[47] Only a few countries provide partial citations or summaries of such data through case studies or annual reports, rather than full disclosure. For additional details regarding this information, refer to Table A7 in the Appendix.

the public direct and transparent access to data on banks' discriminatory practices at detailed location levels. I determine each bank's level of unfair treatment using the excess rejection rate and interest rate applied to minority borrowers. Subsequently, I formulate rankings of banks based on levels of unfair treatment. Additionally, I disclose information related to discriminatory complaints from the CFPB on my website. Upon accessing this website, consumers can acquire comprehensive knowledge of banks' discrimination levels in their communities without the need for advanced data analysis skills. My website lowers the threshold to accessing information about discrimination in mortgage lending markets and presents discriminatory treatments in an accessible manner. Armed with my website and sophisticated data analytics abilities, minority borrowers can enhance their financial literacy and steer clear of discriminatory banks.

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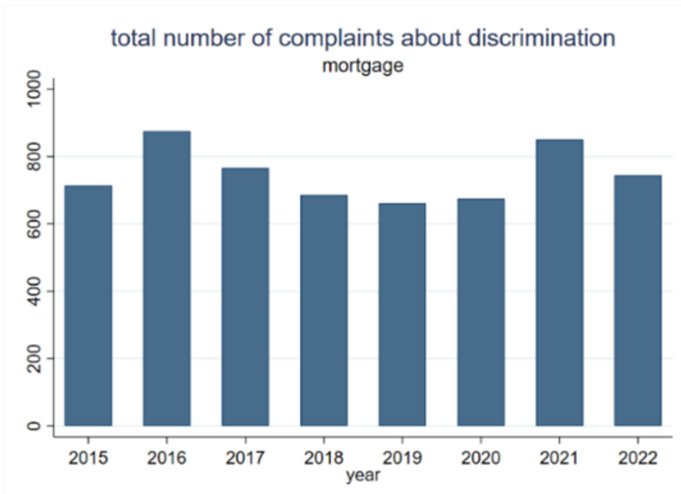
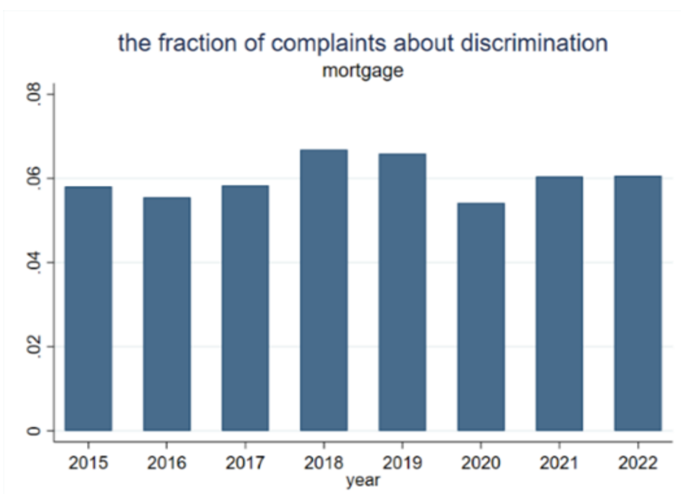
Figures and Tables

Figure 1. Number and Fraction of Complaints about Discrimination in Mortgage Market

These two graphs respectively depict the total number and proportion of consumer complaints related to discrimination in the mortgage market regulated by the CFPB from 2015 to 2022.



(a) Total number of complaints about discrimination



(b) The fraction of complaints about discrimination

Figure 2. Sample Representation of the GSE Grid

The figure illustrates the 2018 LLPA (loan-level price adjustment) grid of Fannie Mae, sourced from the Fannie Mae Selling Guide, published on June 5, 2018. Fannie Mae's LLPA grid has a corresponding grid at Freddie Mac, known as the Credit Fees in Price chart. These matrices dictate the additional g-fee (guarantee fee) that lenders owe the GSE for the mortgage guarantee, fully determined by credit score and LTV.

Table 1: All Eligible Mortgages – LLPA by Credit Score/LTV Ratio

Representative Credit Score	LTV Range									
	Applicable for all mortgages with terms greater than 15 years									
	≤ 60.00%	60.01 – 70.00%	70.01 – 75.00%	75.01 – 80.00%	80.01 – 85.00%	85.01 – 90.00%	90.01 – 95.00%	95.01 – 97.00%	>97.00%	SFC
≥ 740	0.000%	0.250%	0.250%	0.500%	0.250%	0.250%	0.250%	0.750%	**0.750%**	N/A
720 – 739	0.000%	0.250%	0.500%	0.750%	0.500%	0.500%	0.500%	1.000%	**1.000%**	N/A
700 – 719	0.000%	0.500%	1.000%	1.250%	1.000%	1.000%	1.000%	1.500%	**1.500%**	N/A
680 – 699	0.000%	0.500%	1.250%	1.750%	1.500%	1.250%	1.250%	1.500%	**1.500%**	N/A
660 – 679	0.000%	1.000%	2.250%	2.750%	2.750%	2.250%	2.250%	2.250%	**2.250%**	N/A
640 – 659	0.500%	1.250%	2.750%	3.000%	3.250%	2.750%	2.750%	2.750%	**2.750%**	N/A
620 – 639	0.500%	1.500%	3.000%	3.000%	3.250%	3.250%	3.250%	3.500%	**3.500%**	N/A
< 620[1]	0.500%	1.500%	3.000%	3.000%	3.250%	3.250%	3.250%	3.750%	**3.750%**	N/A

Figure 3. Dynamic Trend of the Impact of Disclosure on Interest Rate

This figure represents the quarterly coefficient estimates for racial disparities in interest rates among treated lenders relative to control lenders. The illustration contains outcomes from five quarters before the second quarter of 2015 - the starting point of the disclosure policy - and continues through ten quarters after its application, that is, between 2014 and 2017. Samples outside of this chosen span are grouped into the initial and final periods. During the estimation, the fifth quarter prior to the disclosure and earlier periods are used as the baseline period. The data come from the HMDA-GSE merged dataset spanning 2011-2019. The Y-axis reflects the magnitude of the racial disparities in interest rates, while the X-axis signifies varying periods, with period zero corresponding to the disclosure policy's implementation. The regression specification used to generate this figure is consistent with that of column (2) in Table 3. Black circles symbolize the coefficient estimates for different periods, and the black vertical lines denote the 95% confidence intervals.

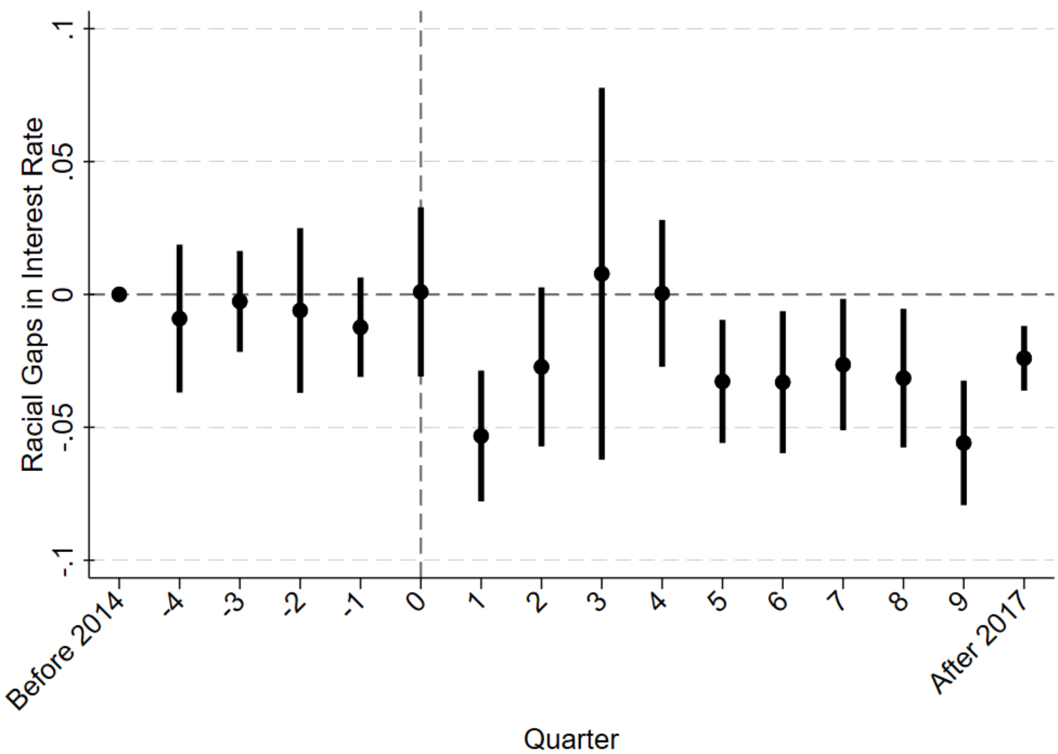


Figure 4. The Trend of Racial Disparities in Rejection Rates between CFPB-supervised and CFPB-unsupervised Banks

This figure shows the average excess rejection rates of minority borrowers relative to non-minority borrowers across both CFPB-supervised and CFPB-unsupervised banks from 2012 to 2019. The data for the diagram are drawn from the HMDA origination dataset. I utilize the residualized rejection rates after accounting for observable differences by applying lender-by-year fixed effects, lender-similar borrower fixed effects, lender-census tract fixed effects, and census tract-by-year fixed effects, as demonstrated in Equation (3). Furthermore, I utilize a 3-year moving average for a more accurate depiction of the actual trend. The figure features a vertical dashed line symbolizing mid-2015, the point in time when the CFPB disclosed the complaint narratives.

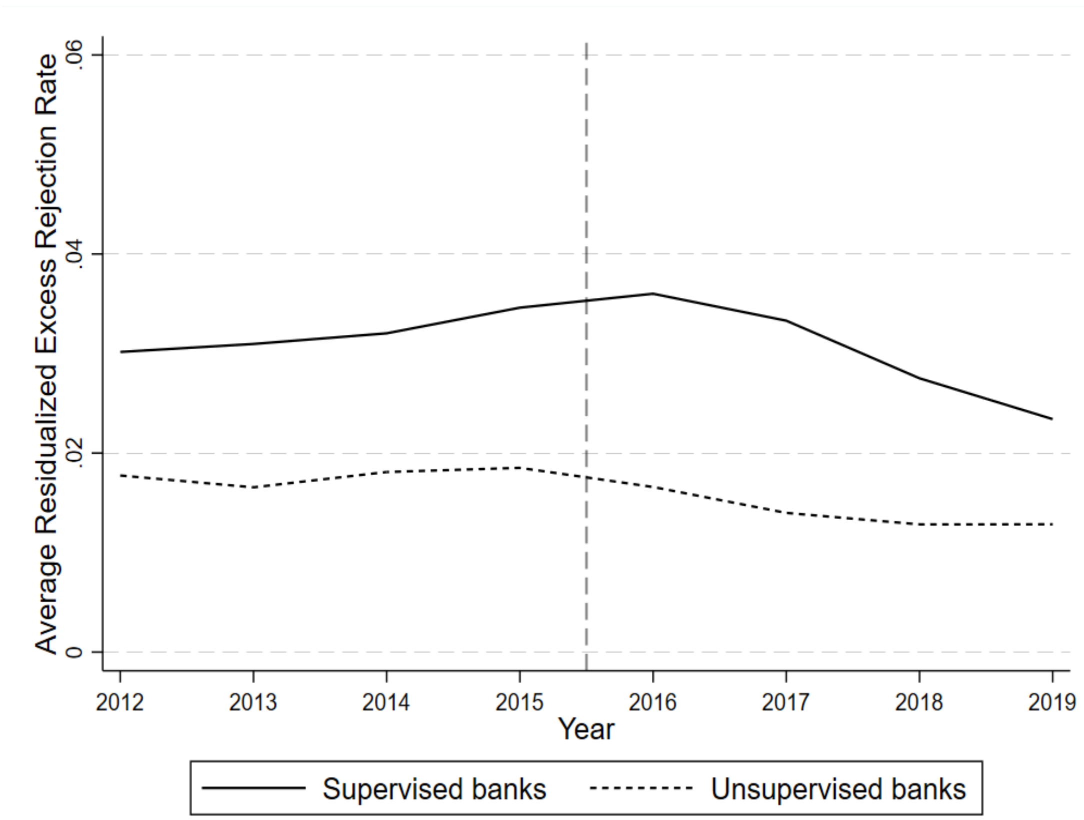


Table 1. Discrimination Complaint Example

This table displays a consumer complaint example concerning "Applying for a mortgage or refinancing an existing mortgage," as publicly disseminated by the CFPB. This includes components such as "Date received", "Product", "Consumer complaint narrative", "Company", and "Company response to consumer", among others.

Date received	2021/1/28
Product	Mortgage
Subproduct	Conventional home mortgage
Issue	Applying for a mortgage or refinancing an existing mortgage
Consumer complaint narrative	I was denied a mortgage loan from Bank of America for a property in XXXX XXXX, NJ on XX/XX/2021. I haven't received written confirmation yet, but the verbal reasoning is due to my employment history and employment gaps. The loan officer sounded very condescending when she told me that I was denied. It doesn't make sense to me to be denied for that reason alone as my employment history was stated on Day 1 and I was pre-qualified for the loan. To make matters worse, I was denied after having an appraisal done on the property so I was fairly far into the process with a refund unlikely for the $570.00 I was charged for the appraisal. I believe that I am being discriminated against because I disclosed my race as XXXX on Section X of the XXXX loan application. I would greatly appreciate it if this could be looked into to ensure that Bank of America didn't discriminate against me by showing that they also denied mortgage loans to people of other races, particularly XXXX people, with similar credit, income or debt-to-income ratio, savings, educational, and employment backgrounds as me. Quick summary of my background: I have excellent credit, my credit score is over XXXX. My 2 employment gaps greater than 30 days were related to school. I have a XXXX XXXX XXXX and currently in XXXX XXXX seeking a XXXX. I work full time as a mortgage loan advisor where I earn over $45000.00 annually. I have savings of $30000.00. The house I was looking to purchase cost $180000.00.
Company	BANK OF AMERICA, NATIONAL ASSOCIATION
State	PA
Submitted via	Web
Company response to consumer	Closed with monetary relief
Company disputed	No

Table 2. Summary Statistics of the HMDA-GSE Merged Dataset

This table presents summary statistics for the key variables derived from the HMDA-GSE merged dataset, which I use to identify the effects of the disclosure policy on interest rates and default rates when consumers apply for mortgage loans. The treated banks are those with total assets of 10 to 100 billion prior to the policy's implementation, while the control banks have total assets ranging from 0 to 10 billion. The variables are averaged from 2011 to May 2015, the pre-disclosure period. The table provides unconditional means, standard deviations, and p-values for the differences in means between the treated and control groups before treatment. The interest rate variable undergoes winsorization at the 1% level. For the t-test, standard errors are clustered at the bank level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All(Treated&Control)			*Treated*		*Control*		*t − Test*
	Observations	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*p − Value*
Minority	340,320	0.082	0.274	0.067	0.250	0.084	0.278	0.466
Interest Rate	340,320	4.203	0.473	4.112	0.467	4.217	0.472	0.096
Default Rate	340,320	0.065	0.246	0.059	0.236	0.066	0.248	0.633
LTV	340,320	77.200	14.210	76.310	14.300	77.340	14.190	0.443
Credit Score	340,285	752.800	54.950	759.200	42.070	751.800	56.660	0.018
Gender	340,320	0.727	0.445	0.729	0.444	0.727	0.446	0.867
Income	338,509	100.900	74.740	107.100	88.200	99.910	72.350	0.117
Loan Amount	340,320	246.100	127.400	239.100	127.600	247.200	127.300	0.606
Co-applicant	340,320	0.534	0.499	0.559	0.496	0.530	0.499	0.236
Cash-out Refinance	340,320	0.181	0.385	0.163	0.370	0.184	0.388	0.390
Purchase	340,320	0.492	0.500	0.514	0.500	0.489	0.500	0.712
Refinance	340,320	0.326	0.469	0.323	0.467	0.327	0.469	0.931

Table 3. The Impact of Disclosure on Interest Rate

This table reports results on the effect of complaint narrative disclosure on the racial gaps in interest rates. The data come from the HMDA-GSE merged dataset spanning 2011-2019. The dependent variable is the interest rate on originated fixed-rate mortgages. Each column provides estimated coefficients on four independent variables, with other coefficient groups (*Treat*, *post*, and their interaction term *Treat×Post*) being absorbed by fixed effects due to collinearity. The key estimated coefficient, *Treat×Post×Minority*, denotes the effect of disclosure on racial gaps in interest rates. In column (1), fixed effects for the interaction of lender and time, and pricing grid-loan purpose-time joint fixed effects are controlled. Column (2) incorporates controls for borrower characteristics. Column (3) combines the two fixed effects from column (1) into lender-pricing grid-loan purpose-time joint fixed effects. Column (4), building on column (3), replaces borrower characteristics with the more stringent similar borrower fixed effects. Column (5) introduces joint fixed effects between lenders and similar borrowers, based on column (2). Standard errors, shown in parentheses, are clustered at the lender and year level. The symbols *, **, and *** correspond to significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dep. Var =	Interest Rate				
Treat×Post×Minority	-0.023***	-0.023***	-0.023***	-0.023***	-0.028**
	(0.006)	(0.006)	(0.005)	(0.005)	(0.009)
Post×Minority	-0.001	0.002	-0.001	-0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Treat×Minority	-0.002	-0.009*	-0.004	-0.006	0.000
	(0.004)	(0.005)	(0.005)	(0.004)	(0.006)
Minority	0.028***	0.025***	0.028***	0.029***	0.028***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Lender×Year-Month FE	YES	YES			YES
Bucket×Loan Purpose ×Year-Month FE	YES	YES			YES
Lender×Bucket×Loan-Purpose×Year-Month FE			YES	YES	
Borrower Characteristics FE		YES	YES		
Similar Borrower FE				YES	
Lender×Similar Borrower FE					YES
Observations	1,305,738	1,273,848	1,031,982	1,023,277	803,991
R-squared	0.756	0.772	0.799	0.808	0.816

Table 4. Moderation Effect of the Impact of Disclosure on Interest Rates

This table presents findings on the moderating effect of disclosure on racial disparities in interest rates, with data drawn from the HMDA-GSE merged dataset spanning the years 2011-2019. The dependent variable is the interest rate on originated fixed-rate mortgages. Panel A illustrates heterogeneous outcomes related to discrimination complaints and Google search attention by representing the contrasting outcomes between two subgroups of the treated group, in comparison to the same control group. The treated group in columns (1) and (2) is categorized based on the incidence of discrimination complaints, whereas the treated group in columns (3) and (4) is categorized based on Google search attention. The estimated coefficient on *Treat×Post×Minority* identifies the treatment effect in the subsample analysis. All four columns in panel A control for joint fixed effects of lender-pricing grid-loan purpose-time as well as borrower characteristics fixed effects. Panel B employs the continuous variable *Litigation* as the moderating variable, with the first two columns discussing the number of litigations and the last two discussing the penalty amounts (in one million dollars). Columns (1) and (3) control for the same fixed effects as in panel A, whereas columns (2) and (4) replace borrower characteristics with more stringent similar borrower fixed effects. Standard errors in this table, indicated in parentheses, are clustered at the lender and year level. The symbols *, **, and *** correspond to significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Discrimination Complaint and Search Attention

	(1)	(2)	(3)	(4)
	Complaint		Google Search Index	
	Yes	No	High	Low
Dep. Var =	Interest Rate			
Treat×Post×Minority	-0.028^{**}	-0.002	-0.036^{***}	-0.007
	(0.011)	(0.017)	(0.004)	(0.007)
Lender×Bucket×Loan Purpose×Year-Month FE	YES	YES	YES	YES
Borrower Characteristics FE	YES	YES	YES	YES
Observations	987,148	984,186	983,219	977,896
R-squared	0.796	0.796	0.797	0.796

Panel B. Litigation Risk				
	(1)	(2)	(3)	(4)
	Number		Penalty	
Dep. Var =	Interest Rate			
Treat×Post×Minority×Litigation	-0.059**	-0.052*	-0.014***	-0.012**
	(0.020)	(0.026)	(0.003)	(0.004)
Lender×Bucket×Loan Purpose×Year-Month FE	YES	YES	YES	YES
Borrower Characteristics FE	YES		YES	
Similar Borrower FE		YES		YES
Observations	972,084	963,400	972,084	963,400
R-squared	0.795	0.805	0.795	0.805

Table 5. Impact of Disclosure on Default Rates of Subprime Minority Borrowers

This table reports results on the effect of complaint narrative disclosure on the racial gaps in default rates. The data come from the HMDA-GSE merged dataset spanning 2011-2019. The dependent variable denotes whether the loan falls into the delinquency of 90 or more days. Columns (1)-(3) limit the sample to those with credit scores under 660, showcasing the results concerning subprime minority borrowers, while column (4) outlines results from the entire sample. Each column provides estimated coefficients on four independent variables, with other coefficient groups (*Treat*, *Post*, and their interaction term *Treat*×*Post*) being absorbed by fixed effects due to collinearity. The key estimated coefficient, *Treat*×*Post*×*Minority*, denotes the effect of disclosure on racial gaps in default rates. Column (1) solely controls for lender-time (year-month) fixed effects and zip-by-year fixed effects, and column (2) incorporates controls for loan traits such as interest rate, loan purpose, and the logarithm of the loan amount, applicant characteristics like gender, the logarithm of income, and the presence of a co-applicant. Column (3) extends column (2) by including pricing grid-loan purpose fixed effects. The model specification in column (4) is consistent with column (2). Standard errors, shown in parentheses, are clustered at the lender and year level. The symbols *, **, and *** correspond to significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Marginal Borrowers			Full
Dep. Var =	Default rate			
Treat×*Post*×*Minority*	0.304***	0.288***	0.286***	0.012
	(0.035)	(0.051)	(0.046)	(0.009)
Post×*Minority*	-0.012	-0.008	-0.010	0.009**
	(0.043)	(0.034)	(0.036)	(0.004)
Treat×*Minority*	-0.289***	-0.289***	-0.290***	-0.009
	(0.025)	(0.024)	(0.021)	(0.009)
Minority	0.029	0.026	0.027	0.018***
	(0.042)	(0.034)	(0.036)	(0.003)
Control		YES	YES	YES
Lender×Year-Month FE	YES	YES	YES	YES
Zip×Year FE	YES	YES	YES	YES
Bucket×Loan Purpose FE			YES	
Observations	25,759	24,187	24,185	1,243,580
R-square	0.491	0.500	0.502	0.149

Table 6. The Impact of Disclosure on Rejection Rates

This table reports results on the effect of complaint narrative disclosure on the racial gaps in rejection rates. The data come from the HMDA origination dataset spanning 2011-2019. The dependent variable is the loan-level rejection status. Each column provides estimated coefficients on four independent variables, with other coefficient groups (*Treat*, *Post*, and their interaction term *Treat×Post*) being absorbed by fixed effects due to collinearity. The key estimated coefficient, *Treat×Post×Minority*, denotes the effect of disclosure on racial gaps in rejection rates. The first pair of columns present the fundamental results, where I account for lender-by-year fixed effects, lender-similar borrower combined fixed effects, and lender-census tract combined fixed effects in column (1), whereas I also include census tract-by-year fixed effects in column (2). Columns (3) through (6) display the moderation effects of discrimination complaints and Google attention, based on the specification detailed in column (2). Standard errors, shown in parentheses, are clustered at the lender and year level. The symbols *, **, and *** correspond to significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline		Complaint		Google Search Index	
			Yes	No	High	Low
Dep. Var =	Rejection Rate					
Treat×Post ×Minority	-0.018*	-0.016*	-0.033***	-0.005	-0.019*	-0.013
	(0.009)	(0.008)	(0.010)	(0.005)	(0.009)	(0.008)
Post×Minority	-0.002	-0.003	-0.003	-0.003	-0.003	-0.004
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Treat×Minority	0.043***	0.042***	0.066***	0.020***	0.046***	0.038***
	(0.010)	(0.009)	(0.008)	(0.006)	(0.010)	(0.008)
Minority	0.034***	0.035***	0.035***	0.035***	0.035***	0.035***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Lender×Year FE	YES	YES	YES	YES	YES	YES
Lender×Similar-Borrower FE	YES	YES	YES	YES	YES	YES
Lender×Census-Tract FE	YES	YES	YES	YES	YES	YES
Census Tract×Year FE		YES	YES	YES	YES	YES
Observations	17,384,084	17,377,686	15,822,695	15,952,011	15,853,326	15,585,749
R-squared	0.459	0.477	0.481	0.482	0.484	0.486

Table 7. Rival Bank's Reaction to the Disclosure

This table reports results on the effect of complaint narrative disclosure on the entry of rival banks. The data, sourced and consolidated from the HMDA origination dataset for the years 2011 to 2019, are aggregated at the county-year level. The dependent variable, *BankDensity*, is calculated as the number of unique bank brands per ten thousand individuals at the county level. The table showcases the estimated results for the *Share*×*Post* independent variable, with other coefficient groups (*Share* and *Post*) being subsumed by fixed effects due to collinearity. This coefficient identifies changes in the unique bank brand number per ten thousand people in counties affected by the disclosure. I use two different *Share* proxies to gauge the degree of exposure to disclosure effects: (i) *Amount Share*, representing the market share held by treated banks within each county in 2015; (ii) *Complaint Share*, calculated as the total number of complaints related to discrimination received per county in 2015 divided by the number of issued loans to minority applicants. In all columns, I account for the lagged average approval rate and the lagged average bank deposits and control for county-level fixed effects and state-by-year joint fixed effects. Based on the *Amount Share*, columns (1) to (3) display variations in the quantity of unique banks per ten thousand individuals in the present period (t), the next year (t+1), and two years later (t+2). The only difference between columns (4) to (6) and the first three columns is that the former employs *Complaint Share* as a proxy for *Share*. Standard errors, shown in parentheses, are clustered at the county level. The symbols *, **, and *** correspond to significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Amount Share			Complaint Share		
	T	T+1	T+2	T	T+1	T+2
Dep. Var =	Bank Density					
Share×*Post*	7.189***	8.600***	10.897***	1.935***	1.793***	1.342**
	(2.442)	(3.248)	(2.865)	(0.599)	(0.504)	(0.542)
Control	YES	YES	YES	YES	YES	YES
State×Year FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Observations	17,886	14,984	12,909	17,938	15,017	12,935
R-squared	0.782	0.801	0.824	0.781	0.801	0.824

Table 8. Market Reaction to the Disclosure

This table reports results on the effect of complaint narrative disclosure on the behavior of investors in the stock market. The data for analysis come from all listed banks within the HMDA origination dataset. Using the U.S. Daily Event Study function offered by WRDS, I estimate their Cumulative Abnormal Return (CAR) based on the disclosure date of June 25, 2015. The dependent variables represent the CAR calculated based on the Capital Asset Pricing Model (CAPM) and the Market Adjusted Model (referred to as *Market*), during the three event windows of [-1, +1], [-2, +2], and [-3, +3] trading days. The table primarily showcases two independent variables, namely a dummy representing treated banks that have received discrimination complaints in 2015, labeled as *Complaint*, and a dummy symbolizing treated banks that have not received discrimination complaints in 2015, termed *Non-Complaint*. In all columns, I control for the banks' total assets, equity-to-assets ratio, return on assets, and total deposits, and execute a t-test to compare the coefficients of two primary independent variables. The robust standard errors are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var =	CAR (CAPM)			CAR (Market)		
	[-1, +1]	[-2, +2]	[-3, +3]	[-1, +1]	[-2, +2]	[-3, +3]
Complaint	-0.013**	-0.026***	-0.018*	-0.013**	-0.026***	-0.019*
	(0.006)	(0.009)	(0.010)	(0.006)	(0.009)	(0.010)
Non-Complaint	-0.004	-0.015**	-0.013	-0.004	-0.015**	-0.013
	(0.004)	(0.007)	(0.011)	(0.004)	(0.007)	(0.011)
P-value for Equality Test	0.041	0.183	0.550	0.040	0.184	0.506
Control	YES	YES	YES	YES	YES	YES
Observations	341	341	341	341	341	341
R-squared	0.033	0.095	0.027	0.033	0.101	0.031

Internet Appendix for Does the Disclosure of Consumer Complaints Reduce Racial Disparities in the Mortgage Lending Market?

Contents

Appendix A. Supplementary Figures and Tables

Figure A1. Dynamic Trend of the Impact of Disclosure on Default Rates

This figure represents the coefficient estimates for racial disparities in default rates among treated lenders relative to control lenders. The illustration contains outcomes from five quarters before the second quarter of 2015 - the starting point of the disclosure policy - and continues through eleven quarters after its application. Samples outside of this chosen span are grouped into the initial and final periods. During the estimation, the fifth quarter prior to the disclosure and earlier periods are used as the baseline period. For brevity, I combine three quarters into one bin. The data come from the HMDA-GSE merged dataset spanning 2011-2019. The Y-axis reflects the magnitude of the racial disparities in default rates, while the X-axis signifies varying periods, with period zero corresponding to the disclosure policy's implementation. The regression specification used to generate this figure is consistent with that of column (2) in Table 5. Black circles symbolize the coefficient estimates for different periods, and the black vertical lines denote the 95% confidence intervals.

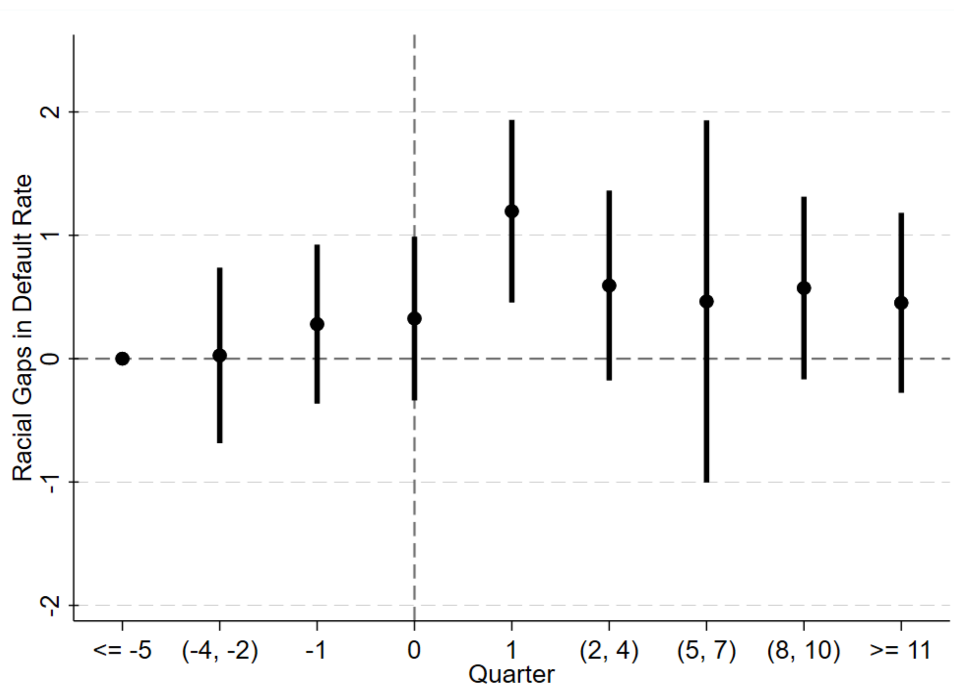


Figure A2. Dynamic Trend of the Impact of Disclosure on Rejection Rate

This figure represents the yearly coefficient estimates for racial disparities in rejection rates among treated lenders relative to control lenders. The illustration contains outcomes from three years before 2015 - the starting year of the disclosure policy - and continues through three years after its application, that is, between 2012 and 2018. Samples outside of this chosen span are grouped into the initial and final periods. During the estimation, the first year prior to the disclosure is used as the baseline period. The data come from the HMDA-GSE merged dataset spanning 2011-2019. The Y-axis reflects the magnitude of the racial disparities in rejection rates, while the X-axis signifies varying periods, with period zero corresponding to the disclosure policy's implementation. The regression specification used to generate this figure is consistent with that of column (2) in Table 6. Black circles symbolize the coefficient estimates for different periods, and the black vertical lines denote the 95% confidence intervals.

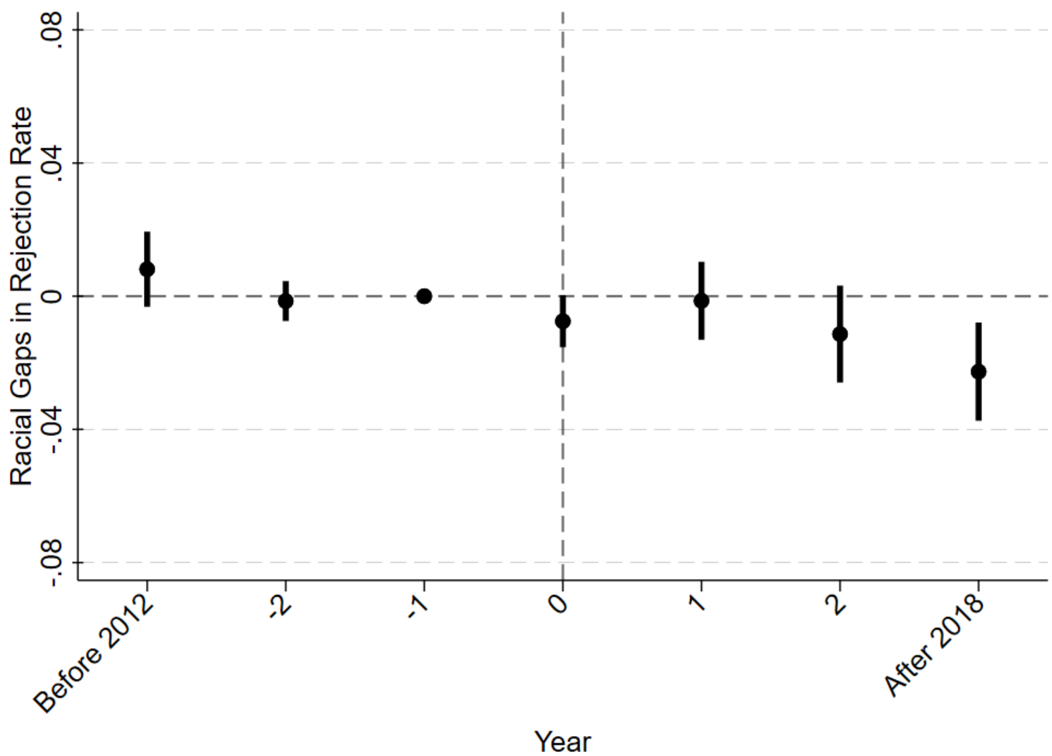


Table A1. Variable Definitions

Variable	Definition
HMDA LARS 2011-2019	
Rejection	An indicator variable indicating whether a loan was approved at application, marked as 1 for approval, and 0 otherwise.
Application Number	A continuous variable indicating the number of applications received by a ZIP code in different years.
Minority	An indicator variable indicating if the loan applicant is a minority, marked as 1 for Latinx or African American, and 0 for Asian or White.
Gender	An indicator variable indicating if the loan applicant is a man, marked as 1 for male, and 0 for female.
Loan Amount	A continuous variable indicating the amount of a particular loan.
Income	A continuous variable indicating the income level of the loan applicant.
Co-applicant	An indicator variable indicating whether the loan has a co-applicant or not.
Census Tract	An categorical variable indicating the 11-digit code of the Census Tract of a loan.
Zip Code	An categorical variable indicating the 5-digit zip-code of the bank's location.
County	An categorical variable indicating the 5-digit county code of the bank's location.
State	An categorical variable indicating the 2-digit state code where the bank is situated.
GSE 2011-2019	
Interest Rate	A continuous variable indicating the interest rate of a loan

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Table A1 – *Continued from previous page*

Variable	**Definition**
Default	An indicator variable represents if a loan has not been repaid within a designated term. It is marked as 1 if the duration of default exceeds 90 days, and 0 otherwise.
LTV Group	An indicator variable categorizing the continuous Loan-To-Value (LTV) into eight divisions (effectively seven). This classification follows the method of Bartlett et al. (2022).
Credit Score Group	An indicator variable categorizing the continuous Credit Score into eight sections. The categorization is in line with Bartlett et al. (2022).
Loan Purpose	An indicator variable indicating the category of a loan, with the primary types being Cash-out Refinance, Purchase, and Refinance in this study.
Other Sources	
Complaints Number	A continuous variable indicating the number of complaints a bank received in 2015, with data gathered from the CFPB dataset.
Penalty	A continuous variable indicating the amounts of fines related to discrimination lawsuits a bank face in a given year, with data gathered from the CFPB website.
Google Index Diff	A continuous variable indicating the increase in the Google Index for a state in 2015 relative to 2014, where Google Index refers to the search volume for the CFPB.
Population	A continuous variable indicating the population of a county in different years, sourced from the Census dataset.
Total Deposits	A continuous variable the total deposits of a bank in different years, sourced from SOD.
Total Assets	A continuous variable indicating the total assets of a bank sourced from WRDS.

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Table A1 – *Continued from previous page*

Variable	**Definition**
Equity	A continuous variable indicating the equity of a listed bank sourced from WRDS.
Net Profit	A continuous variable indicating the net profit of a listed bank sourced from WRDS.
CAR (CAPM)	A continuous variable indicating the cumulative abnormal returns of a listed bank, sourced from WRDS.
CAR (Market)	A continuous variable indicating the market adjusted returns of a listed bank, sourced from WRDS.

Table A2. Summary Statistics for the Main Datasets

HMDA-GSE Merged Dataset					
	(1)	(2)	(3)	(4)	(5)
Variables	N	Mean	SD	Min	Max
Minority	1,330,621	0.111	0.314	0	1
Interest Rate	1,330,621	4.299	0.499	3.375	5.625
Default Rate	1,330,621	0.0808	0.273	0	1
LTV	1,330,621	77.85	14.41	30	95
Credit Score	1,330,482	748.9	108.8	620	9,999
Gender	1,330,621	0.679	0.467	0	1
Income	1,297,045	101.0	69.42	0	5,602
Loan Amount	1,330,621	259.2	128.7	40	1,375
Co-applicant	1,330,621	0.478	0.500	0	1
Cash-out Refinance	1,330,621	0.197	0.398	0	1
Purchase	1,330,621	0.569	0.495	0	1
Refinance	1,330,621	0.234	0.423	0	1

Table A3. The Impact of Disclosure on Interest Rate (Clustered at the Lender Level)

This table reports results on the effect of complaint narrative disclosure on the racial gaps in interest rates, with standard errors clustered at the level of the lender. The data come from the HMDA-GSE merged dataset spanning 2011-2019. The dependent variable is the interest rate on originated fixed-rate mortgages. Each column provides estimated coefficients on four independent variables, with other coefficient groups (*Treat*, *post*, and their interaction term *Treat×Post*) being absorbed by fixed effects due to collinearity. The key estimated coefficient, *Treat×Post×Minority*, denotes the effect of disclosure on racial gaps in interest rates. In column (1), fixed effects for the interaction of lender and time, and pricing grid-loan purpose-time joint fixed effects are controlled. Column (2) incorporates controls for borrower characteristics. Column (3) combines the two fixed effects from column (1) into lender-pricing grid-loan purpose-time joint fixed effects. Column (4), building on column (3), replaces borrower characteristics with the more stringent similar borrower fixed effects. Column (5) introduces joint fixed effects between lenders and similar borrowers, based on column (2). Standard errors, shown in parentheses, are clustered at the lender level. The symbols *, **, and *** correspond to significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dep. Var =	Interest Rate				
Treat×Post×Minority	-0.023**	-0.023**	-0.023**	-0.023**	-0.028**
	(0.010)	(0.011)	(0.011)	(0.012)	(0.012)
Post×Minority	-0.001	0.002	-0.001	-0.001	0.001
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Treat×Minority	-0.002	-0.009	-0.004	-0.006	-0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Minority	0.028***	0.025***	0.028***	0.029***	0.028***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Lender×Year-Month FE	YES	YES			YES
Bucket×Loan-Purpose×Year-Month FE	YES	YES			YES
Lender×Bucket×Loan-Purpose×Year-Month FE			YES	YES	
Borrower Characteristics FE		YES	YES		
Similar Borrower FE				YES	
Lender×Similar Borrower FE					YES
Observations	1,305,738	1,273,848	1,031,982	1,023,277	803,991
R-squared	0.756	0.772	0.799	0.808	0.816

Table A4. Replication - Interest Rate Differentials

This table replicates Table 3 in Bartlett et al. (2022). The utilized data are sourced from the HMDA-GSE merged dataset for the years 2011-2019, with the same model specification as in Bartlett et al. (2022). The dependent variable is the interest rate associated with originated fixed-rate mortgages. The independent variable is assigned a value of 1 if the borrower is Black or Latinx, and 0 in other cases. Standard errors, shown in parentheses, are clustered at the lender level. The symbols *, **, and *** correspond to significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	Purchase	Refinance
Dep. Var =	Interest Rate	
Minority Borrower	0.036***	0.014***
	(0.004)	(0.003)
Lender×Year-Month FE	YES	YES
Bucket×Loan Purpose×Year-Month FE	YES	YES
Amount decile FE	YES	YES
Observations	1,034,355	792,849
R-squared	0.755	0.762

Table A5. Racial Disparities in Discount Points

This table examines the difference in racial disparities concerning discount points between the treated and control groups. The data used are derived from the HMDA-GSE merged dataset for the years 2018-2019. The dependent variable is the discount points chosen by borrowers. The calculated outcome of *Treat×Minority* in the table tests whether minority borrowers in the treat and control groups exhibit different preferences for discount points. In column (1), fixed effects for the interaction of lender and time, and pricing grid-loan purpose-time joint fixed effects are controlled. Column (2) incorporates controls for borrower characteristics. Column (3) combines the two fixed effects from column (1) into lender-pricing grid-loan purpose-time joint fixed effects. Column (4), building on column (3), replaces borrower characteristics with the more stringent similar borrower fixed effects. Column (5) introduces joint fixed effects between lenders and similar borrowers, based on column (2). Standard errors, shown in parentheses, are clustered at the lender and year level. The symbols *, **, and *** correspond to significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dep. Var =	Discount Point				
Treat×Minority	-31.368	6.687	28.633	6.591	12.368
	(42.806)	(20.827)	(29.835)	(33.724)	(41.193)
Control	YES	YES	YES	YES	YES
Lender×Year-Month FE	YES	YES			YES
Bucket×Loan-Purpose×Year-Month FE	YES	YES			YES
Lender×Bucket×Loan-Purpose×Year-Month FE			YES	YES	
Borrower Characteristics FE		YES	YES		
Similar Borrower FE				YES	
Lender×Similar Borrower FE					YES
Observations	260,131	249,639	206,534	195,851	121,219
R-squared	0.360	0.447	0.517	0.575	0.630

Table A6. Summary of CFPB Litigation Penalty

Bank Name	Date Filed	Civil Money Penalty	Loan Subsidy Program Investment
Washington Federal	9/10/2013	$34,000	-
Mortgage Master, Inc.	9/10/2013	$425,000	-
National City Bank	23/12/2013	-	-
Provident Funding Associates, L.P.	28/5/2015	-	-
Hudson City Savings Bank, F.S.B.	24/9/2015	$5.5 million	$25 million
BancorpSouth Bank	29/6/2016	$3 million	$4 million
Nationstar Mortgage LLC	15/3/2017	$1.75 million	-
Freedom Mortgage Corporation	5/6/2019	$1.75 million	-
Townstone Financial, Inc. and Barry Sturner	15/7/2020	-	-
Washington Federal, N.A.	27/10/2020	$200,000	-
1st Alliance Lending, LLC, John Christopher DiIorio, Kevin Robert St. Lawrence, and Socrates Aramburu	15/1/2021	-	-

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Table A6 – *Continued from previous page*

Bank Name	Date Filed	Civil Money Penalty	Loan Subsidy Program Investment
Trustmark National Bank	22/10/2021	\$5 million(\$4 million would be remitted as a penalty paid to the Office of the Comptroller of the Currency)	\$3.85 million
Trident Mortgage Company, LP	27/7/2022	\$4 million	\$18.4 million

Table A7. Financial Regulatory Authorities in Developed Countries

Country	Financial Regulatory Authority	Specifically Established for Consumer Protection	Formed Year	Receiving Complaints	Starting Year of Receiving Complaints	Complaints Disclosure
Australia	Australian Financial Complaints Authority	Yes	2018	Yes	2018	No
Austria	Austrian Financial Market Authority	No	2002	Yes	2002	No
Belgium	Financial Services and Markets Authority	Yes	2011	Yes	2011	No
Canada	The Financial Consumer Agency of Canada	Yes	2001	Yes	2001	No
Croatia	Croatian Financial Services Supervisory Agency	No	2005	Yes	2005	No
Czech Republic	Czech National Bank	No	1993	Yes	2021	No
Denmark	Danish Financial Complaint Board	Yes	2015	Yes	2015	No
Finland	Finnish Financial Ombudsman Bureau	Yes	2009	Yes	2009	No
France	Autorité de Contrôle Prudentiel et de Résolution	No	2010	No	-	-
Germany	Federal Financial Supervisory Authority	No	2002	Yes	2002	No
Hungary	Hungarian National Bank	No	1924	Yes	2020	No

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Table A7 – *Continued from previous page*

Country	Financial Regulatory Authority	Specifically Established for Consumer Protection	Formed Year	Receiving Complaints	Starting Year of Receiving Complaints	Complaints Disclosure
Iceland	Complaints Committee on Transactions with Financial Firms	Yes	2022	Yes	2022	No
Ireland	Financial Services and Pensions Ombudsman	Yes	2017	Yes	2018	No
Italy	Institute for the Supervision of Insurance	No	2013	Yes	2013	No
Japan	Supervision Bureau	No	2000	No	-	-
Korea	Financial Supervisory Service	No	1998	Yes	2011	No
Netherlands	Netherlands Authority for the Financial Markets	No	2002	Yes	2002	No
New Zealand	Financial Markets Authority	No	2011	Yes	2011	No
Norway	Norwegian Financial Services Complaints Board	Yes	2014	Yes	2014	No
Portugal	Bank of Portugal	No	1846	Yes	2020	No
Singapore	Financial Industry Disputes Resolution Centre	Yes	2005	Yes	2005	No
Slovakia	National Bank of Slovakia	No	1993	Yes	2020	No
Slovenia	Financial Consumer Protection Department	Yes	2015	Yes	2015	No

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Table A7 – *Continued from previous page*

Country	**Financial Regulatory Authority**	**Specifically Established for Consumer Protection**	**Formed Year**	**Receiving Complaints**	**Starting Year of Receiving Complaints**	**Complaints Disclosure**
Spain	Bank of Spain	No	1782	Yes	2004	No
Switzerland	Swiss Banking Ombudsman	Yes	1993	Yes	1993	No
United Kingdom	Financial Ombudsman Service	Yes	2001	Yes	2001	No
United States	**Consumer Financial Protection Bureau**	**Yes**	**2011**	**Yes**	**2011**	**Yes**

Appendix B. Clarifications on the Process of Merging Datasets

HMDA-GSE Merged Dataset: Linkage Process

My research utilized two datasets, namely the Home Mortgage Disclosure Act (HMDA) and Government-Sponsored Enterprises (GSE), which contain valuable information about loan origination. Unfortunately, there is currently no commonly available mapping file that connects these two datasets. Following Law and Mislang (2022), I adopt the "fuzzy data matching" methods to overcome this challenge. These methods leverage the substantial overlap in variables shared by both datasets. When the information in these overlapping fields demonstrates consistent patterns between the two datasets, my matching process becomes efficient.

To establish a connection between the HMDA and GSE datasets, I make use of the tools provided by the *Fedmatch* R package developed by Cohen et al. (2021). This specific matching approach involves separating each dataset based on geography and lender ID. Subsequently, I apply the matching algorithm at the loan level.

Regarding the initial step, the GSE dataset includes lender names, which I integrated into the HMDA dataset using the Robert Avery file. However, for small lenders whose names present challenges in recognition within the GSE dataset, I employed accurate name matching techniques based on Jaccard string similarity and manual proofreading. Once I successfully match the lender IDs, I discuss the loan matching process.

To enhance the accuracy of the matching process, I divide each dataset into smaller partitions based on lender ID and geographic information. However, it's important to note that there is no exact correspondence between the two datasets in terms of geography. I use 3-digit zip codes to correspond to HMDA's census tracts and counties. In the "grid" formed by lender ID and geographic information, I match each loan based on observable characteristics at the time of loan origination. Furthermore, it's worth mentioning that certain variables in the GSE dataset have undergone changes since 2018. As a result, I have several additional variables available for use as matching references, including interest rate, manufactured property status, and loan purpose.

HMDA-GSE Merged Dataset: Filtering Process

To omit loans not conforming to standard lending criteria, I implement filtering on this dataset according to Bartlett et al. (2022), resulting in a final sample of 1,869,345 mortgage loans. During the filtering process, I remove GSE loans with credit scores below 620 (10,310 observations), LTVs under 0.3 (76,779 observations), and above 0.95 (121,430 observations). I also remove loans with interest rates below 2.75% or higher than 8% (10,273 observations), loans amounting to less than $40,000 (14,207 observations), and loans whose term is not equal to 360 months (769,736 observations). Thus, the final sample includes 56.53% (1,056,807 observations) of purchase mortgages and 43.47% (812,538 observations) of refinance loans.

Please note that for the actual analysis, I utilize the subsample from this final collection, where total assets range from $0 to $100 billion to perform the primary analysis. This subsample consists of 1,330,621 loans, accounting for 71.18% of the total sample. This refined sample allows for a more accurate and comprehensive examination of the mortgage market, thereby aiding in comprehending borrower and lender attributes, loan conditions, as well as the impact of the disclosure on pricing and approval rates.

HMDA Origination Dataset: Variable Supplementation Process

Besides dictating the loan interest rate, the lender also possesses the authority to either endorse or dismiss a loan application entirely. After the 2008 mortgage crisis, numerous lenders have imposed their personalized, more rigorous, approval stipulations over and above those stipulated by the GSE. Hence, although a loan application may garner creditworthiness approval within the GSE underwriting system, the lender retains the privilege to refuse the application.

A significant caveat is that I lack loan-level data on several crucial underwriting variables, such as the borrower's credit score or LTV ratio, since rejected loans are never issued. These data constraints imply that, unlike the interest-rate analysis in the main paper, any analysis of rejection rates is invariably subject to the omitted-variable problem addressed in the introduction part. I cannot be completely confident that any discrepancies in rejection rates are attributable to discrimination rather than differences in unobservable variables. Nonetheless, the HMDA data permit me to control for loan-level lender, year, borrower income, and loan amount. In addition, I employ proxies for these in my analysis using the median credit scores and LTVs of the census tract, which I estimate using the merged HMDA-GSE data. Controlling for these variables, along with census tract level median credit scores and LTVs, mitigates the omitted-variable problem (Bartlett et al. (2022)). I also apply the same filter to the loan amount and loan term that is used for variables in the HMDA-GSE merged dataset.[48]

Moving towards the matching process, I carry out it in three stages. In the first stage, I retain the census tract information, time information (i.e., year), LTV, and credit score information in the HMDA-GSE dataset. Consequently, I obtain the applicants' LTV and credit scores for multiple loan records per census tract per year. I then calculate the median of LTV and credit scores at the census tract level (Bartlett et al. (2022)). I maintain the two median variables produced here along with the census tract and year, and I can then easily aggregate the data to the census tract-year level.

Subsequently, I match the LTV and credit score indicators at the census tract-year level back to the original HMDA using the census tract and year. Since LTV and credit score

[48] Before 2018, the HMDA origination datasets do not include the loan term variable, so I employ the filter for loan term only in the years after 2018.

information primarily come from the GSE, and this database only includes records of loan applications that were not rejected, I cannot find corresponding values in the original HMDA dataset for about 21.65% of the samples in this step.

Finally, to discuss the impact of complaints disclosure in more detail, I match the number of bank complaints published by the CFPB in 2015 and the total bank assets values from the Call Report database for the first quarter of 2015 (Fuster et al. (2021)) into the aforementioned dataset using the arid (an identification number of banks) and year, to obtain the revised HMDA dataset to analyze the influence of disclosure on rejection. The final dataset comprises 42,198,230 loans, with 31,634,238 observations (accounting for 74.97% of the full sample) belonging to lenders whose total assets range from $0 to $100 billion.

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