Loan Officers, Same-Sex Couple Mortgages and Non-discrimination Law

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Abstract

We examine the effect of non-discrimination law (NDL) on loan officers' decisions for LGBTQ+ applications in the home mortgage market. We find that NDL widens the denial gap between same-sex and different-sex couple applications. This increased denial gap cannot be explained by a backlash in opinions against NDL. It can be attributed, however, to loan officers' inexperience of soft information on the creditworthiness of same-sex couples, e.g., the commitment in their relationships vis-à-vis servicing the loan, compared to different-sex couples. This imbalance in the utilization of soft information serves as a key determinant explaining both the pre- and post-NDL denial gaps. In further analysis, we show that experienced loan officers attenuate the post-NDL denial gap. Our findings imply a new non-discrimination training mandate for loan officers.

Keywords: Loan officers, Non-Discrimination Laws, Same-Sex Couple Applicants, Mortgage Application Denied, Soft Information

1. Introduction

Impermissible discriminatory practices, e.g., loan decisions based on a protected characteristic of a loan applicant such as ethnicity, gender, or race, prevail in housing and financial markets. Scholars report evidence of such discrimination in loan pricing disparities (Bhutta and Hizmo, 2021; Bartlett *et al.*, 2022), discretionary fees (Clarke and Rothenberg, 2018), APR spreads (Bhutta and Ringo, 2015; Bayer *et al.*, 2016) and loan

For helpful comments and suggestions, we thank Elena Carletti, Josef Zechner, Ronan Powell, Jule Byrne, Oliver Browne, Xu Han, Andreas Hoepner, Haoran Wu, Ankit Kariya, and participants at the IFABS 2025 Oxford Conference, 2025 IAF Cork PhD Conference.

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application rejection rates (Munnell *et al.*, 1996). Discriminatory lending practices can not only violate an individual's civil right of equal treatment but can, ultimately, undermine social cohesion and foster conflict, and it can lead to financial instability and crises (Kumhof *et al.*, 2015; Dong and Xu, 2020). Policymakers, thus, have long been concerned about unequal and unfair treatment of poor and minority borrowers by financial institutions (Ambrose *et al.*, 2021).[1]

In this paper, we examine if non-discrimination law (NDL) impacts the mortgage decisions of loan officers for same-sex couple borrowers. In the United States, persons in the LGBTQ+ community have faced a persistent history of discrimination.[2] Nearly half of these individuals still lack safeguards against discrimination in essential domains such as credit, education, employment, housing, and public accommodation.[3] According to the National Association of Gay & Lesbian Real Estate Professionals fourth annual LGBT real estate report, the LGBT population represents approximately 4.5% of the total U.S. population, with a purchasing power of over $1 trillion. However, the home ownership rate among the LGBT community remains significantly lower at 49%, compared to the national average of 65%.[4] Indeed, scholarship has revealed the challenges faced by the LGBTQ+ community in the home mortgage market (Sun and Gao, 2019; Dillbary and Edwards, 2019; Hagendorff *et al.*, 2022).

Our study examines 7,525,620 matched home mortgage applications, available due to the Home Mortgage Disclosure Act (HMDA), for the period 2010 to 2023. We identify same-sex borrowers following Sun and Gao (2019), and we classify a loan application as same-sex if the applicant and co-applicant are of the same gender. Following Cortés *et al.* (2016), we distinguish local banks, and hence loan officer decisions on loan applications, by excluding loan applications submitted to lenders which do not have a branch in the county of the mortgage property. In this way, we infer the location of the loan officer and

[1] See the Community Reinvestment Act, and Section 1071 of the Dodd-Frank Act, and the Equal Credit Opportunity Act where fair lending practices at financial institutions is legislated. This includes a requirement to collect and submit specific data regarding credit applications from women-owned, minority-owned and small businesses.

[2] See `https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6864400/`

[3] See `https://williamsinstitute.law.ucla.edu/publications/lgbt-nondiscrimination-statutes/`

[4] See `https://www.housingwire.com/articles/lgbt-community-still-faces-hurdles-to-homeownership/`

determine whether the loan application falls under the protection of NDL.

In light of federal inaction before 2021,[5] housing NDL had been enacted in 33 states, providing legal protections against housing discrimination based on sexual orientation. NDL aims to safeguard the right of same-sex couple applicants to equal access to mortgage lending.[6] It protects LGBTQ+ individuals from discrimination in all housing-related activities, including obtaining loans to buy, build, repair, or improve a home.[7] It, whether enacted at the state or federal levels, is the principal point of focus in this study.

We use a "staggered" difference-in-differences (DiD) specification (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021) to estimate the effectiveness of NDL. To address potential borrower selection bias and creditworthiness demand variations we employ the Mahalanobis Kernel Distance Matching approach (Li and Takeuchi, 2023; Jann, 2017). This ensures covariate balance between the treatment and control groups. Our treatment group includes same-sex applications submitted after the implementation of NDL, while the control group comprises same-sex applications submitted before the NDL and different-sex applications submitted both before and after the NDL. To perform a clean comparison of the differences in loan denial rates between same-sex and different-sex borrowers within the same bank, county, and year, our regressions include bank-county-year fixed effects.

We outline our findings. We confirm that same-sex loan applicants face significantly higher denial rates than different-sex applicants (Sun and Gao, 2019; Hagendorff *et al.*, 2022). Critically, we find that NDL increases the denial gap between same-sex appli-

[5] On February 11, 2021, the U.S. Department of Housing and Urban Development (HUD) issued a memorandum (HUD No. 21-021), which formally affirmed that housing discrimination on the basis of sexual orientation constitutes a violation of the Fair Housing Act. This federal directive effectively extended non-discrimination protections to the remaining states that had not yet implemented NDL. In the same year, the Consumer Financial Protection Bureau also implemented NDL across states to protect against sexual orientation discrimination in the mortgage market.

[6] Movement Advancement Project, *LGBTQ+ Equality Maps: Housing Nondiscrimination Laws*, available at `https://www.lgbtmap.org/img/maps/citations-nondisc-housing.pdf`.

[7] Credit NDL also protects loan applicants' against mortgage discrimination based on sexual orientation. For instance, see the legal frameworks established in California (`https://leginfo.legislature.ca.gov/faces/codes_displayText.xhtml?lawCode=GOV&division=3.&title=2.&part=2.8.&chapter=6.&article=2`) and Illinois (`https://www.ilga.gov/legislation/ilcs/documents/077500050K1-102.htm`) Credit NDL, in our sample, is implemented concurrently or after the enactment of housing NDL.

cants and different-sex applicants. The enactment of NDL widens the gap by 54 percent, from a denial gap of 2.85 to 4.39 percentage points. This increased denial gap cannot be explained by a "backlash" in opinions against NDL. It can be attributed, however, to "information friction" i.e., loan officers' inexperience of 'soft' information on the creditworthiness of same-sex couples. We show that experienced loan officers attenuate the post-NDL denial gap.

We conduct a series of robustness tests on our main findings. Specifically, we examine the dynamic effects of NDL, test for delayed impacts of NDL, and apply stacked regressions to address treatment effect heterogeneity in staggered DiD settings. To test if our results are solely driven by the NDL impact on same-sex borrowers, we perform separate regressions for same-sex and different-sex borrowers. We split our dataset by median income/loan amount, gender, bank size, and the COVID-19 period to examine if our results are robust to variations in borrower composition, bank characteristics, and external shocks. Additionally, we test if our main results are driven by the misidentification of same-sex borrowers (e.g., father and son) by analyzing only different-race borrowers. We also test if our main results are driven by local economic conditions or migration effects by comparing counties on opposite sides of state borders. Across all these tests, our findings remain consistent.

To address potential omitted creditworthiness variable concerns, we follow Bartlett *et al.* (2022). We restrict our analysis to Federal Housing Administration (FHA) loans. Since FHA loans are government-insured, they are risk-free and they guarantee the same expected return for lenders, regardless of the applicant's creditworthiness. Our findings remain robust in this restricted sample. Furthermore, we merge the HMDA and Fannie Mae datasets to obtain loan performance data. We train a logistic regression model to predict default probabilities for each loan application and include these probabilities as a control variable in our regression analysis. We find that higher default probabilities increase the likelihood of loan rejection by loan officers, while our main results remain unchanged.

As indicated, we propose two channels to explain the post-NDL increased denial gap faced by same-sex applicants: the opinion backlash channel and the information friction channel. Bishin *et al.* (2016), in political science scholarship, argue that backlash effects can lead to greater disapproval of an issue. Additionally, Ofosu *et al.* (2019) show evidence of opinion backlash following federal legalization of same-sex marriage, states that had not previously enacted similar legislation experienced an increase in antigay bias. To test whether backlash effects can account for the increased denial gap around NDL, we examine local attitudes in three ways. First, local complaints to financial institutions about customer mistreatment. Second, the local enactment of same-sex marriage laws and, third, the LGBTQ+ percentage of the local population. We find that variation in local attitudes do not drive the main result of an increased denial gap. Then, we examine if, consistent with the opinion backlash channel, the cost of a same-sex couple borrower loan increases and/or the default risk of their loans decreases. We find no such evidence. We conclude that backlash effects cannot explain the observed increase in the denial gap.

The second channel which we test is information friction. Loan officers, due to inexperience with same-sex borrower mortgage applications, and facing a surge in such applications after the enactment of NDL, can find it too challenging to interpret soft information on this cohort of borrowers. Consequently, they may rely more on hard information for these borrowers[8], and this can lead to an increased denial gap between same-sex and different-sex borrowers post-NDL. We present broad evidence supporting this channel. First, same-sex borrower loan contracts became more standardized consistent with the use of more hard information in these lending decisions (Skrastins and Vig, 2019). Second, following Hagendorff *et al.* (2022), we estimate a reduced utilization of soft information in same-sex borrower loan decisions. Third, we find fewer loan officers post NDL which can further exacerbate the dilemma of loan officer inexperience (Drexler and Schoar, 2014). Fourth, we find that local bank competition can attenuate the post NDL increase in the denial rate, and this is consistent with less reliance on soft information by loan officers when competition is high (Heider and Inderst, 2012). Fifth, we find that a

[8]Bhutta *et al.* (2024) show that lenders often impose "overlays", stricter credit related hard information restrictions, compared to the requirements of, for instance, Government Sponsored Enterprises.

comparatively unwieldy bank hierarchy (Liberti and Mian, 2008) can exacerbate the post NDL denial rate increase in loan officers' decisions. Finally, we show that the increased denial gap can be mitigated by loan officers with more experience (Bohren *et al.*, 2019) of same sex couple borrower applications. Invariant to the test performed, our findings indicate that the information friction channel can help explain why same-sex borrowers face higher rejection rates following NDL inception.

Two closely related papers to our work are those of Dillbary and Edwards (2019) and Hagendorff *et al.* (2022). Dillbary and Edwards (2019) examine the impact of state level non-discrimination law on mortgage decisions. Hagendorff *et al.* (2022) examine the impact of same sex marriage law on mortgage decisions. Dillbary and Edwards (2019) show, using FHA loan data across three states (i.e., three instances of fair lending NDL implementation) and pooling all lender types (fintech, local-bank loan officers and correspondent lenders), that fair lending NDLs reduce the loan denial rate only for Black male couple borrowers.[9] Our contribution, in contrast, relates to a much larger dataset (31 states). We use only the initial enactment of pertinent NDL, and we deliberately focus on loan applications processed by local-bank loan officers. These loan officers have more scope to engage in impermissible discrimination, as they use soft information to make loan decisions (Berg *et al.*, 2020). Unlike Dillbary and Edwards (2019), we demonstrate that, similar to the effect of same-sex marriage laws documented in Hagendorff *et al.* (2022), NDLs lead to an increased denial gap between same-sex and different-sex borrowers, which can be attributed to information friction. However, unlike Hagendorff *et al.* (2022), we focus on the direct and binding NDL impact on loan officers' decisions, as opposed to the possibility that 'laws change minds' and improved public attitudes influence the loan officers' decisions after same sex marriage legalization. Our work, further, reveals that the increased denial gap after NDL can be mitigated by experienced loan officers, with implications for loan officer training.

[9] Both credit and housing non-discrimination laws protect same-sex borrowers applying for home mortgages. However, credit NDLs and housing NDLs may be enacted in different years. For example, in Dillbary's research design, Maine adopted a housing non-discrimination law in 2012. However, the credit NDL had already been in effect since 2005, potentially leading to redundancy and inaccurate inference in Dillbary and Edwards (2019).

Our paper contributes to several active research areas. First, our study adds to the literature on discrimination against distinct groups in mortgage lending. While most of these studies focus on impermissible discrimination on the basis of race (Ambrose *et al.*, 2021), ethnicity (Bayer *et al.*, 2018) or gender (De Andrés *et al.*, 2021), Sun and Gao (2019) find sexual orientation discrimination in the home mortgage market. We broadly contribute to this literature by reporting new evidence of a persistent denial gap in loan officers' decisions which adversely affects same-sex couple mortgage applicants relative to different-sex applicants.

Second, our paper contributes to research on the effects of law on financial outcomes (e.g., La Porta *et al.*, 2006). We focus on the financial impact of NDL for borrowers in the LGBTQ+ community. While prior studies emphasize the employment (Sansone, 2019), firm innovation (Hossain *et al.*, 2020) and economic growth benefits of these minority protection laws. Our findings suggest that, despite new legal protections, same-sex borrowers continue to experience discrimination in the mortgage market. In fact, NDL has unintended adverse effects, leading to an increased post-NDL denial gap between same-sex and different-sex loan applicants.

A final upshot of our work is in relation to financial education programs (OECD, 2015). As established by Kaiser *et al.* (2022), these programs have been shown to have causal impact on both financial knowledge and financial decisions. As a result, our finding of the importance of 'information friction' to account for the increase in loan application denial rates after NDL can enhance loan officers' lending decisions. It can inform a tailored non-discrimination training program, focused on the soft creditworthiness traits of persons in the LGBTQ+ community, for loan officers.

The remainder of the paper is organized as follows. Section 2 discusses the related literature and develops our hypotheses. Section 3 introduces the development and content of housing NDL. Section 4 describes our data and methodology. Section 5 presents the main empirical results. Section 6 conducts a series of robustness tests which serve to validate our findings. Section 7 performs additional analyses to address potential omitted variable bias. Section 8 explores the underlying channels that can explain our main results. Finally, Section 9 concludes the paper with a summary of key findings and their implications.

2. Literature review and hypotheses development

Since the foundational study by Sun and Gao (2019) on discrimination against same-sex couple borrowers in the mortgage market, recent research suggests that same-sex applicants can face diverse forms of discrimination in the mortgage lending process. Compared to different-sex applicants with the same default risk, same-sex borrowers are not only more likely to be denied loans (Sun and Gao, 2019; Dillbary and Edwards, 2019; Hagendorff *et al.*, 2022) but also can be charged higher interest rates on approved loans (Sun and Gao, 2019).

The prohibition of such discrimination based on sexual orientation could lead to more equitable lending. Dillbary and Edwards (2019) argue that prohibiting discrimination based on sexual orientation may influence lenders' behaviors, as local laws could increase compliance due to enforcement efforts and the fear of penalties. Therefore, we hypothesize that the loan denial rate for same-sex borrowers can decrease following the enactment of NDL.

Hypothesis 1. (H1): Same-sex borrowers will face reduced mortgage loan denial rates after the implementation of state non-discrimination law.

However, recent studies, such as Ofosu *et al.* (2019) and Hagendorff *et al.* (2022) highlight the potential dis-improvement in lending decision outcomes for the LGBTQ+ community around federal same-sex marriage legalization. To account for this unintended discrimination, two principal mechanisms have been proposed: the opinion backlash effect and information friction.

These mechanisms, we argue, are also pertinent to anticipate the upshot of sexual orientation NDL on lending decisions. The two mechanisms predict an increase in the denial rate for same-sex borrowers after the implementation of state sexual orientation related NDL. The opinion back lash channel highlights potential related adverse shifts in public attitudes which can impede policy gains by the marginalized LGBTQ+ group. It is a long-recognized consequence of the tension between the sovereignty of popular opinion and democratic values like liberty and equality. The information friction channel highlights a reduction in loan officers use of soft information utilization, around NDL. As a result of these outlined mechanisms, we focus on the alternative hypothesis to **H1** and test whether the denial gap between same-sex borrowers and different-sex borrowers will increase following the implementation of state NDL.

2.1. Discerning between the backlash effect and information friction hypotheses

Our first set of tests focuses on the opinion backlash hypothesis. As indicated above, this explanation can be motivated by the the shift in local attitudes due to same-sex marriage laws (Ofosu *et al.*, 2019 and Bishin *et al.*, 2016) and can lead to increased disapproval of an issue. We argue, same-sex borrowers could face higher denial rates, if the enactment of NDL induces an opinion backlash among loan officers against same-sex borrowers. We hypothesize and test whether the increase in the denial gap is less pronounced in states with low levels of anti-LGBTQ+ sentiment.

Hypothesis 2. (H2): In states with a more supportive local attitude to the LGBTQ+ community, loan officers are less likely to experience opinion backlash, leading to a less pronounced increase in the denial gap.

To evaluate the backlash hypothesis, we, hence, test whether the increase in the denial gap following the implementation of NDL is positively associated with shifting in different local anti-LGBTQ+ sentiment proxies, such as local complaints, same-sex marriage (SSM) law and LGBTQ+ Percentage. We argue, in states with low local complaints, same-sex marriage protections, high LGBTQ+ percentage, loan officers are less likely experience opinion backlash. Thus, the increase in denial gap should be less pronounced among these states.

We then turn to discerning the importance of the information friction hypothesis to account for the higher loan denial rate around the implementation of NDL. This hypothesis suggests that hard information (e.g. credit score) requirements for same-sex loan applicants will be relatively high due to the aversion of loan officers to collect costly soft information on same-sex borrowers. This aversion can follow due to their inexperience with this cohort of loan applicants and, thus, the additional workload required. We hypothesize that if information friction arises between loan officers and same-sex borrowers, following the implementation of NDL, same-sex borrowers can face a higher probability of loan denial.

Hypothesis 3. (H3): Increased information friction between same-sex borrowers and loan officers following the implementation of NDL laws will lead to higher denial rates for same-sex borrowers.

Skrastins and Vig (2019) posit that a loss of information can lead to more standardized loan contracts. As a result, loan contracts for same-sex borrowers can become more standardized following the implementation of NDL. The reduced use of soft information in making loan decisions is consistent with a loss of information on the borrower's capacity to service a loan. Hence, we test if loan contracts for same-sex borrowers become more standardized around NDL, as this would constitute *prima facie* evidence in support of the information friction hypothesis.

Drexler and Schoar (2014) suggest that loan officer turnover may contribute to a loss of soft information about borrowers at a financial institution, as departing loan officers have little incentive to voluntarily transfer this soft information. Consequently, a reduction in the number of loan officers after NDL implementation may exacerbate information friction. For instance, this could result in loan applications from same-sex borrowers being handled by unfamiliar or inexperienced loan officers who may rely on hard information in lending decision rather than soft information, thereby increasing the likelihood of loan denial.

Impersonal lending at a distance by banks may render the use by local bank loan officers of soft information unprofitable (Petersen and Rajan, 2002). In highly competitive environments, banks may, moreover, choose to largely disregard soft information and rely solely on hard data for credit approval decisions (Heider and Inderst, 2012) even if this can ultimately result in a higher loan default rate (Agarwal and Ben-David, 2018). Accordingly, counties with high levels of bank lending competition should be less affected by the reduced use by loan officers of soft information on same sex loan applicants in loan grant decision-making following the implementation of the NDL. This is as they have historically relied less on soft information prior to NDL implementation. Following Gao and Zhang (2017), we use the Herfindahl-Hirschman Index (HHI) to distinguish between high- and low-competition counties. In a county with a high level of bank competition, we, hence, argue that, the increase in the denial gap is likely to be less pronounced.

On the importance of soft information, to further test the information friction hypothesis we examine whether the implementation of NDLs result in a reduction in soft information utilization by loan officers after NDL. Our calibration of soft information in the lending decision follows Fisman *et al.* (2017) and Skrastins and Vig (2019), and we test if, consistent with the information friction hypothesis, there is a reduction in the use of borrower level soft information after NDL. Finally, we test if loan officer experience with same sex couple applicants attenuates the increase in the denial rate for this type of loan applicant after the implementation of NDL.

3. Housing non-discrimination law

In this section, we describe the development and the nature of housing non-discrimination law.

3.1. State housing non-discrimination law

The two primary federal statutes prohibiting mortgage discrimination based on race, color, religion, national origin, marital status, age, or sex are the Equal Credit Opportunity Act (ECOA) of 1974 and the Fair Housing Act (FHAct) of 1968. The ECOA applies to all credit transactions, while the FHAct specifically governs residential real estate transactions. The U.S. Department of Housing and Urban Development (HUD) serves as the primary regulator of the Fair Housing Act, which prohibits discrimination by housing providers, lending institutions, and homeowner insurance companies. The Consumer Financial Protection Bureau is the principal regulatory authority for the Equal Credit

Opportunity Act, overseeing compliance among banks, savings associations, and credit unions.

Although all states have enacted fair housing laws, only thirty-three states include provisions prohibiting sexual orientation discrimination in housing. State housing non-discrimination laws are designed to protect LGBTQ+ individuals from discrimination in all housing-related activities, including securing loans for purchasing, constructing, repairing, or improving a home. In response to this protection, and consistent with (Dillbary and Edwards; 2019), as shown in Figure 1, we observe an increase in loan demand from same-sex borrowers following the enactment of NDL.

[Figure 1 about here.]

3.2. Federal decision on housing non-discrimination law

On June 15, 2020, the Supreme Court ruled in *Bostock v. Clayton County, Georgia* that the prohibition against sex discrimination under Title VII of the Civil Rights Act of 1964 (Title VII) includes discrimination based on sexual orientation and gender identity. Following this landmark decision, President Biden issued Executive Order 13988 on January 20, 2021, titled "Preventing and Combating Discrimination on the Basis of Gender Identity or Sexual Orientation." In response to this Executive Order, HUD's Office of Fair Housing and Equal Opportunity released a memorandum on February 11, 2021, titled "Implementation of Executive Order 13988 on the Enforcement of the Fair Housing Act," which specifically addresses discrimination based on actual or perceived sexual orientation and gender identity under the Fair Housing Act.[10] The HUD memorandum on housing non-discrimination laws extended coverage to the remaining states that had not yet implemented NDL at that time. This policy ensured nationwide access to equitable housing credit for same-sex couples, regardless of their state of residence.

HUD's application of the *Bostock* ruling to the Fair Housing Act is particularly significant for LGBT individuals, as housing remains an area where many face high levels of

[10] U.S. Department of Housing and Urban Development, *Housing Discrimination and Persons Identifying as LGBTQ*, available at `https://www.hud.gov/program_offices/fair_housing_equal_opp/housing_discrimination_and_persons_identifying_lgbtq#_File_Housing_Discrimination_Complaint`.

discrimination.[11] Consequently, when discrimination occurs against LGBT individuals, HUD is now mandated to investigate complaints alleging violations of the Fair Housing Act on these grounds. According to data provided by the National Fair Housing Alliance (NFHA), following HUD's 2021 decision, the overall number of complaints increased by 5.74 percent in 2022 compared to 2021. The data specifically showed a rise in complaints based on sources of income and domestic violence. In fact, the 33,007 fair housing complaints received in 2022 by private non-profit fair housing organizations, HUD, FHAP agencies, and the Department of Justice represent the highest number of complaints ever reported in a single year. Notably, in 2022, there were 2,490 complaints based on sexual orientation, the highest number recorded since NFHA began collecting data on sexual orientation complaints in 2005.[12]

4. Data and empirical methodology

In this section, we present the source of our data and processing procedures, the identification methodology for same-sex borrowers, the summary statistics of the matched sample, and the adopted Mahalanobis matching and difference-in-differences research methodology.

4.1. Loan level data

We utilize mortgage data from the Home Mortgage Disclosure Act (HMDA), spanning the years 2010 through 2023. We obtain variables including the applicant's race, ethnicity, gender(and co-applicant gender), income, loan amount, approval status, loan type, loan purpose. Following Hagendorff *et al.* (2022), we exclude applications that are incomplete, withdrawn, for non-owner-occupied properties, or those with missing values or without a co-applicant.

To identify local banks who rely on loan officer made decision, we adopt the methodology proposed by Cortés *et al.* (2016). We distinguish local banks by using bank branches

[11]Movement Advancement Project, *Brief on the Equality Act: SAGE and MAP*, available at https://www.lgbtmap.org/file/2021-brief-equality-act-sage-map.pdf

[12]National Fair Housing Alliance, *2023 Fair Housing Trends Report*, available at https://nationalfairhousing.org/wp-content/uploads/2023/08/2023-Trends-Report-Final.pdf

information from FDIC Summary of Deposits (SOD).[13] We exclude loan applications submitted to banks that do not have a branch in the county where the mortgaged property is located. These exclusions primarily encompass broker-originated applications directed to external processing centers, where the loan officer's location cannot be reliably inferred from the property's location.[14] Furthermore, applications processed at external centers may be handled in a different state, making it difficult to determine whether they are subject to the protection of NDL.[15] Additionally, we exclude states where housing NDLs and credit NDLs were enacted in different years.

4.2. Identification of same-sex borrowers in HMDA Data

We follow the method outlined in Sun and Gao (2019) to identify same-sex borrowers, where a borrower is classified as same-sex if the reported gender of the main applicant matches the reported gender of the co-applicant. Figure 2 shows the proportion of same-sex borrowers by state in our dataset and the strong correlation with ACS data [16] (correlation 0.6943). Figure 3 illustrates the rapid growth in the number of same-sex households reported by the ACS from 2010 to 2023. Consistent with this, a survey conducted by *Gallup* revealed that nearly one in ten adults in the United States identifies as LGBTQ+. [17] The LGBTQ+ community is increasingly becoming a significant demographic among borrowers across the United States. Addressing and eliminating unlawful discrimination against this group can yield substantial macroeconomic benefits, fostering

[13] see `https://www.fdic.gov/resources/bankers/call-reports/call-summary-of-deposits.html`

[14] One concern is whether our results are influenced by the Credit NDL. We believe this is unlikely because our study employs a staggered Difference-in-Differences (DID) design, excluding states that had already passed the Nondiscrimination Law before the start of our dataset. Our dataset begins in 2010, mainly because we needed to restrict our sample to those processed by loan officers. Additionally, SOD did not provide RSSID data before 2010, which prevented us from matching bank branch information with HMDA data. After excluding the states that had already enacted the law, we found that the remaining states either only passed the Housing Nondiscrimination Law or passed both the Credit and Housing Nondiscrimination Laws in the same year.

[15] For example, American Internet Mortgage Inc., a fintech lender, reduces costs by utilizing automated underwriting systems and other technologies while originating loans nationwide from a single location in San Diego, California. As a result, loan applications to this lender from states without nondiscrimination laws may still be protected. For more details, see this link.

[16] The American Community Survey reports the number of same-sex households in each state, except for the year 2020. For details, see: https://www.census.gov/data/tables/time-series/demo/same-sex-couples/ssc-house-characteristics.html

[17] `https://www.nytimes.com/2025/02/20/upshot/lgbtq-survey-results.html`

greater financial inclusivity and economic stability.

[Figure 2 about here.]

[Figure 3 about here.]

4.3. Mahalanobis Distance Matching with Exact Matching approach

To address potential selection bias[18] and demand, characteristics change after NDL,[19] we implement the Mahalanobis Distance Matching (MDM) approach. MDM helps identify control units that closely match the characteristics of treatment units (Li and Takeuchi, 2023; Jann, 2017). MDM measures the similarity between observations using the Mahalanobis distance, where a smaller distance indicates greater similarity in covariates. In this way, each treated observation is matched with one or several control observations.

In line with Hagendorff *et al.* (2022), our matching covariates include income, gender, race, ethnicity, loan amount, loan type, and loan purpose. The treatment group includes same-sex applications submit after NDL, while the remaining three groups are controls groups. We exclude treated observations that do not have corresponding observations in any of the three control groups to ensure common support. In Table A3, we report the matching results.[20] The covariate distributions are similar between the treatment group and the control groups, which validates the effectiveness of our matching procedure. We also incorporate these three sets of matching weights into our DiD estimator. The main estimation is specified as follows:[21]

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[18]For instance, same-sex applicants with risky profile may self-select to become joint applicants after the NDL.

[19]Table A4 shows that same-sex borrowers tend to have a riskier profile after the enactment of the NDL. Using unmatched home mortgage applications, we show that the proportion of same-sex borrowers exhibits an increase and these borrowers have a riskier profile in the post-NDL period. This underscores the necessity of applying a matching approach in our analysis.

[20]We also employ a three-way propensity score matching approach based on the same set of covariates, and our results remain robust.

[21]where $w_{\boldsymbol{NDL}=1}^{\text{Same-Sex}=0}$ contains the weights for different-sex applications after NDL, $w_{\boldsymbol{NDL}=0}^{\text{Same-Sex}=1}$ for same-sex applications before NDL, and $w_{\boldsymbol{NDL}=0}^{\text{Same-Sex}=0}$ for different-sex applications before NDL.

$$\left\{E[y_{ist} \mid \text{Same-Sex}_i = 1, NDL_{st} = 1] - w_{NDL=1}^{\text{Same-Sex}=0} \cdot E[y_{ist} \mid \text{Same-Sex}_i = 0, NDL_{st} = 1]\right\}$$
$$- \left\{w_{NDL=0}^{\text{Same-Sex}=1} \cdot E[y_{ist} \mid \text{Same-Sex}_i = 1, NDL_{st} = 0]\right.$$
$$\left. - w_{NDL=0}^{\text{Same-Sex}=0} \cdot E[y_{ist} \mid \text{Same-Sex}_i = 0, NDL_{st} = 0]\right\} \tag{1}$$

4.4. Summary Statistics

Table 1 presents summary statistics for local banks, including 7,525,620 matched home mortgage applications from 2010 to 2023. In Panel A, consistent with Sun and Gao (2019), the average denial gap between same-sex and different-sex applicants is 6.94%(=22.86%-15.92%).[22] In line with the dataset employed by Hagendorff *et al.* (2022), same-sex applicants represent approximately 4.58% of the sample. The average applicant reports an income of $116,485 and applies for a loan amount of $197,085. Among the mortgage applicants, approximately 79.82% are male, while the proportions of Hispanic and Black applicants account for 4.48% and 2.22%, respectively. In terms of loan types, around 50.5% of applicants applied for a government-insured FHA loan. Furthermore, 51.49% of applicants sought loans primarily for refinancing purposes.

[Table 1 about here.]

4.5. Empirical specification

To examine how the mortgage denial rates for same-sex applicants changed relative to different-sex applicants following the implementation of NDL, we employ a difference-in-differences model(Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). The model is specified as follows:

$$Denial_{ibsct} = \alpha \times \text{Same-Sex}_{it} + \beta \times \text{Same-Sex}_{it} \times \text{NDL}_{st} + \mathbf{X}'_{it}\gamma + \delta_{bct} + \varepsilon_{ibsct} \tag{2}$$

[22]Sun and Gao (2019) suggest that average denial gap between same-sex and different-sex applicants is around 3–8%.

We index county by c, state by s, bank by b, and year by t. Thus, $Denial_{ibsct}$ denotes the outcome of loan application i, submitted to bank b in county c of state s in year t. The variable *Same-Sex* equals 1 if the reported sex of the main applicant is the same as the reported sex of the co-applicant, and 0 otherwise. *NDL* equals 1 if the mortgage application is submitted in a state in the year or after the year when NDL was enacted, and 0 otherwise. The terms X_{it} and δ_{bct} represent loan characteristics and bank-by-county-by-year fixed effects, respectively.

We incorporates bank-county-year fixed effects in the regression to perform a clean comparison of loan denial rates between same-sex and different-sex borrowers within the same bank, county, and year. This set of high-dimensional fixed effects absorbs a range of factors that could influence loan decisions, such as lending supply constraints, variations in lending models, heterogeneity in state- or county-level regulatory or enforcement conditions, protections for same-sex groups, and aggregate shocks to local banks (e.g., same-sex marriage law). Additionally, it accounts for differences in demographics and labor market conditions in a given county at a given time, as well as other heterogeneity in branch characteristics.

5. Baseline results

In this section, we present our main results on the impact of non-discrimination law on loan-level mortgage decisions for same-sex borrowers.

5.1. Main effects

Table 2 presents the results of our regression, the outcome variable is *Denial* across all columns. The coefficient for *Same-Sex* indicates that same-sex applicants are 2.85% more likely to be denied a loan. Our main coefficient, *Same-Sex*NDL*, is positive and statistically significant, indicating that the enactment of NDLs has widened this gap by an additional 1.54%, resulting in a total denial rate of 4.39%. This increase corresponds to a 9.48% (= 0.0154 / 0.1624)marginal effect relative to the average denial rate and 4.18%(= 0.0154 / 0.3688) of standard deviation. The increase in the 2.85% percentage point excess decline rate for same sex borrowers by 1.54 percentage points as a 54 %(= 0.0154 / 0.0285) rising.

In Columns (1) to (4) of Table 2, we further decompose the main effect by examining various applicant and loan characteristics. We find that our main coefficient, *Same-Sex*NDL*, remains postive and significant. In Appendix Table A5, we incorporate different levels of fixed effects in our regression, and our results remain consistent. Our results are consistent with Friedman *et al.* (2013), who finds similar adverse impacts of NDL on same-sex couples in the rental market.

Loan officers may occasionally misclassify opposite-sex applicants as same-sex applicants, thereby subjecting these individuals to discrimination similar to that experienced by actual same-sex applicants. As noted by Dillbary and Edwards (2019), such misclassification does not imply a flaw in the analysis; rather, it highlights that discrimination occurs not only against same-sex applicants but also against those perceived to belong to this group. This phenomenon may result in what can be termed "overdiscrimination"—that is, discrimination directed both at the targeted group and at others mistakenly identified as members of that group.

[Table 2 about here.]

6. Robustness testing

In this section, we conduct several robustness tests to validate our main results.

6.1. Parallel trend assumption

The validity of our difference-in-differences (DiD) approach relies on the parallel trends assumption. To assess the plausibility of this assumption, we examine the dynamic effects of NDLs on the denial gap between same-sex and different-sex borrowers. Specifically, we analyze the timing of changes in the denial gap relative to the enactment of these laws to ensure that any observed effects are attributable to the policy change rather than pre-existing trends.

To examine the dynamics of the main effect in Table 2 Column (5), we use Equation. 3 as follows:

$$Denial_{ibsct} = \alpha_0 \times \text{Same}-\text{Sex}_{it} + \sum_{j=-5}^{5} \beta_j \times \text{Same}-\text{Sex}_{it} \times \text{TIME}_{sj} + \mathbf{X}'_{it}\gamma + \delta_{bct} + \varepsilon_{ibsct} \quad (3)$$

Figure 4 shows that there is no evidence of a difference in the trends of the denial gap between same-sex and different-sex applicants prior to treatment, suggesting that the parallel trends assumption holds. Additionally, we observe an increase in the denial gap following the implementation of NDL, which is consistent with our main results as shown in Table 2.

[Figure 4 about here.]

6.2. Alternative definition of NDL

In our primary analyses, we define *NDL* as taking a value of 1 if the mortgage application is submitted in a state on or after the year in which *NDL* is legalized. To ensure the robustness of our findings, we redefine *NDL* to take a value of 1 beginning in the year following its legalization, as well as two years after its legalization, and re-estimate our regression under these alternative specifications.

The results, presented in Table 3, Panel A, columns 1 and 2, corresponding to a one-year and two-year delay, respectively, indicate that our main coefficient remains positive and significant. This suggests that our findings are robust to delayed effects of *NDL*.

6.3. Stacked DID estimate

To address concerns that treatment effects may vary over time and staggered DiD is treatment effect heterogeneity(Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021), we implement stacked DiD estimates(Cengiz *et al.*, 2019). Specifically, we construct cohort datasets based on the years in which nondiscrimination laws (NDL) are passed. Each cohort incorporates treated observations and clean controls from states that never adopt NDL within a [-2,2] time window.

Subsequently, we stack the cohort datasets to obtain the average effects of NDL legalization. Follow Hagendorff *et al.* (2022), we include Cohort*Bank*County*Relative time fixed effects. The results presented in Table 3, Panel A Column (3), show that *Same-Sex*NDL* remains positive and statistically significant, suggesting that our findings are robust when using the "clean" control group.

6.4. NDL impacts on Same-sex borrower and Different-sex borrowers

Our results could be driven by different-sex applicants experiencing a lower denial rate after SSM legalization, rather than by same-sex applicants facing an increased denial rate, despite the intended protection of same-sex applicants by NDL. To address this concern, we divide the dataset into same-sex and different-sex groups, and then perform regressions for each group separately.[23] The results presented in Table 3 Panel B show that same-sex applicants experience higher loan rejection rates after the implementation of NDL, while the coefficient for the different-sex group is insignificant. This suggests that our baseline results are driven by the effects of the NDL on same-sex borrowers.

6.5. Local Economic Factors and the Migration of Same-Sex Borrowers

heider2015certain gao2017employment It is possible that the adoption of NDL is driven by local economic or demographic conditions that in turn the increased the denial gap. To account for unobservable local business conditions, we focus on counties located on one side of a state border and their neighboring counties on the other side. We exploit the fact that economic conditions are likely to be similar in neighboring states, whereas the effects of NDL stop at state borders. This discontinuity in NDL enables us to account for unobserved confounding factors, as long as they influence both the treated counties and their neighboring counties in a similar manner.[24] By comparing the denial gap in a county to its neighboring counties, we can better isolate the extent to which the observed

[23]Due to the lack of variation within each bank–county–year, the regressions incorporate bank-year and county fixed effects instead.

[24]Following Heider and Ljungqvist (2015) and Gao and Zhang (2017), the underlying assumption is that if the enactment of NDL is driven by unobserved changes in local economic conditions—and it is these conditions, rather than the laws themselves, that affect lending outcomes—then both banks in treated states and their counterparts in adjacent, untreated states would exhibit similar changes in denial rates, due to the spillover nature of economic conditions across state borders. In such a scenario, we would expect no significant difference in the change in denial rates to same-sex borrowers between treated states and their neighboring untreated counterparts.

change in the denial gap is attributable to NDL rather than other shocks to local business conditions.

Controlling for changes in local business conditions by comparing the denial gap between treated and control counties on either side of a state border, we still observe a significant increase in the denial gap following NDL enactment, as shown in Table 3, Panel C, Column (1). These results suggest that the observed increase in the denial gap following the enactment of NDL is not driven by local economic shocks.

Additionally, in the Appendix Table A6, follow Gao and Zhang (2017), we re-estimate our main regression by incorporating additional controls for local economic conditions, such as state GDP, personal income, population, unemployment rate, and the percentage of same-sex households. Our findings remain robust.

Furthermore, NDL may encourage same-sex borrowers to relocate to neighboring states that have already passed NDL, potentially altering the creditworthiness profile of same-sex borrowers in those states. Consequently, the observed increase in the denial gap could be partially explained by the movement of lower-creditworthiness same-sex borrowers. To test this hypothesis, we exclude counties that are not located in border states. As shown in Table 3, Panel C, Column (2), our results remain positive and significant. Our findings are not driven by selective migration of same-sex borrowers with lower creditworthiness into states that adopt non-discrimination law.

6.6. During covid-19 period

Previous literature suggests that the LGBTQ population has been disproportionately affected by COVID-19 in terms of financial stability and employment (Nowaskie and Roesler, 2022), which may cause the creditworthiness of same-sex borrowers to change during this special period. During COVID-19, same-sex borrowers are thus more likely to face loan rejections compared to other periods. To address the concern that our results are not driven by covid-19 period, we divide the sample into two periods: 2010–2019 and 2020–2023. Our findings, presented in Table 3 Panel D, in both the pre- and post-COVID-19 periods, our main results remain postive and significant.

[Table 3 about here.]

6.7. High/Low borrower income and loan amount

If our results are primarily driven by the impacts on low-creditworthiness same-sex borrowers, such as applicants with lower incomes, we would expect that the denial gap for high-income same-sex borrowers would not show a similar increase. In this case, an observed increase in the denial gap could be attributed to factors such as "legitimate business necessity" rather than discriminatory behavior. To investigate whether our findings are primarily driven by lower-income same-sex borrowers, we partition the sample based on the median values of applicant income and loan amount. We then re-estimate the baseline specification separately for each subgroup.

The results presented in Table 3 Panel E indicate that the coefficients on the interaction term *Same-Sex*NDL* are positive and statistically significant across all subgroups of applicant quality. This suggests that the widening denial gap persists not only among lower-income or lower-quality applicants but also among higher-quality same-sex applicants. Thus, the observed increase in the denial gap cannot be attributed to the lower creditworthiness of same-sex borrowers. Instead, it provides further evidence that the denial gap is a consistent pattern across different applicant quality categories.

6.8. Male/Female group

Previous studies have shown that male and female same-sex borrowers may be treated differently. For example, Sun and Gao (2019) argue that lesbian co-borrowers do not experience higher rejection rates. Their findings of discrimination are concentrated in gay co-borrowers. Additionally, Liao *et al.* (2023) and Badgett *et al.* (2021) document that gay men face more wage gaps but not lesbian women. As shown in Table 3 Panel F , the coefficients on all main coefficients remain significantly positive for both female and male same-sex applicants. This indicates that both female and male same-sex couples experience a higher likelihood of loan denial, and the denial gap for both groups has increased following the legalization of *NDL*.

6.9. Large and small banks

A possible source of variation that may be driving the results is the differences between lenders themselves. Given the within-bank-county analysis conducted in this study, there may be factors related to the operations of larger versus small banks that could influence our results. For example, larger banks are less likely to discriminate because they may be more compliant with regulations. Similarly, smaller banks, which tend to rely more on relationship lending compared to larger banks, may be more likely to lend to same-sex borrowers with whom they have a good relationship. Therefore, the increase in the denial gap may not appear among large and small lenders. To ensure that our results are robust across both large and small lenders, we split the data based on the ten largest banks in terms of loan applications received. These banks account for about 49 percent of the loan applications in our database, while we identify the smallest banks as those handling the bottom 25 percent of loan applications. Our results, shown in Table 3 Panel G, we find that our main coefficient remains positive and statistically significant.

6.10. Validation of identifying same-sex borrowers

To alleviate concerns that we may misidentify family members (e.g., fathers and sons, mothers and daughters) as same-sex borrowers, we separately exclude samples where the applicant and co-applicant share the same race for males and for females. If the applicant and co-applicant have different races, they are less likely to be father-son or mother-daughter pairs. The results are presented in Table 3 Panel H, where our main results remain consistent.

[Table 4 about here.]

7. Additional analysis: Robustness for omitted creditworthiness variables

In this section, we test for the effect of NDL on loan officers' decisions for same-sex couple borrowers, accounting for the probability of default and in a sample of credit risk free FHA loans.

7.1. Prediction on default probabilities

Although Table 9 shows that the average default risk of same-sex and different-sex borrowers does not differ following the legalization of NDL, we do not control for individual-level default risk. To address this concern, we train a logistic regression model to predict individual default probabilities and include these probabilities as an additional control in our regression.

To achieve this, we merge HMDA data with Fannie Mae loan performance data,[25][26] selecting common variables from both datasets as our target features. Following Hagendorff *et al.* (2022), we define *Default* as an indicator variable equal to one if a mortgage becomes 90 days delinquent within the first three years of its life and zero otherwise.

Given the imbalance in the default status variable(0.6%), models trained on such data can prioritize the prevalent class of not default loans over the minority class, and this can compromise their capacity to accurately predict loan defaults. To address this concern, we follow Agarwal *et al.* (2023) and employ under-sampling, over-sampling, and hybrid-sampling techniques to mitigate class imbalance. Over-sampling increases the representation of the minority class by randomly duplicating observations to match the majority class size, though it may lead to overfitting and higher computational costs. Under-sampling, on the other hand, randomly removes observations from the majority class to balance the distribution, but at the risk of discarding valuable information. Hybrid sampling combines both approaches by applying under-sampling to the majority class and over-sampling to the minority class, thereby achieving a more balanced class distribution.

Our features include year, loan amount, income, county, sexual-orientation status, gender (male), race/ethnicity (Hispanic, Black, Asian, Other races), and refinance status. The model achieves a prediction accuracy of 0.68 0.71 0.74 and AUC scores 0.74 0.63 0.68 respectively by using under-, over-, and hybrid-sampling techniques for on the test

[25]For the methodology on merging HMDA data and Fannie Mae loan performance data, we follow Sun and Gao (2019).

[26]Fannie Mae single-family loan performance data is available at: `https://singlefamily.fanniemae.com`.

dataset, indicating its effectiveness in predicting individual default probabilities (Tantri, 2021).

In Table 4, column (1), we show that the variable for default probabilities is positive and significant, indicating that higher default probabilities lead to higher denial rates, this results are robust to using under-, over-, and hybrid-sampling techniques. Importantly, our main coefficient remains unchanged.

7.2. Using FHA loan data

Our findings may be subject to omitted variable bias, as lenders have access to certain factors in their risk assessments that we cannot observe in our dataset. One of the most notable examples is credit scores, which are likely the strongest predictor of risk and a key factor in lenders' decision-making.

To address this concern, we follow Bartlett *et al.* (2022) and Dillbary and Edwards (2019) by re-estimating our regression using only FHA loans. A key characteristic of FHA loans is that they present the same minimal risk to lenders. Borrowers approved for these loans need to pay an FHA insurance premium, ensuring that in the event of a default, lenders recover their losses through government-backed insurance. This structure means that, regardless of an applicant's demographic characteristics, every FHA loan carries the same level of risk and expected return for the lender. Consequently, any disparate treatment in FHA loan denials is unlikely to stem from an unobserved measure of risk that is unavailable to researchers. Since FHA loans are insured against default, lenders' decisions should be less influenced by risk-based considerations.

Specifically, we first extract only FHA loans from the original dataset and then apply the MDM methodology, as described in Section 4. We do not include the same control variables in the regression, as the FHA loan dataset consists solely of FHA loans, excluding other loan types such as VA and FSA/RHS.

Our results are reported in table 4 column (2), the main coefficient remain positive and significant, indicating our results are not driving by omitted risk controls.

[Table 5 about here.]

7.3. Different Modes of NDL Implementation

The implementation of NDL varies across states. As described in Section 3, the introduction of NDL can be traced back to both state legislation and federal decisions. This variation in the mode of implementation helps sharpen our identification strategy. Specifically, NDL legislation that hinges on a federal decision is less likely to be influenced by public opinion, making it easier to argue for the exogeneity of the policy. Changes in loan underwriting practices for same-sex applicants following federal decisions, therefore, help strengthen the case for policy exogeneity.

Conversely, NDL legislation introduced by state legislatures may be unexpected and at odds with prevailing public opinion, or it may stem from a referendum, potentially reflecting shifts in awareness and evolving social attitudes within the state. This could, in turn, correlate with changes in lending policies. To address this, we test whether our results remain robust across different modes of NDL implementation.

Our findings are presented in Table 5. The coefficients on state legislation and federal decisions are both positive and statistically significant, indicating that both court orders and state legislation are associated with an increased likelihood of credit denial for same-sex borrowers.

7.4. Spillover Effects on Other Minorities

Same-sex borrowers may also belong to other minority groups, such as Black, Asian, or Hispanic communities. Although the proportion of same-sex borrowers in our dataset who belong to these minority groups is relatively small (Same-sex Asian borrowers: Mean=0.0022, Same-sex Black borrowers: Mean=0.0026, Same-sex Hispanic borrowers: Mean=0.0046), it is still important to investigate whether the introduction of NDL also increases the likelihood of loan denials for other minority groups. To test this, we interact NDL with Black, Asian, and Hispanic status.

In Table 5, the coefficients on these minority groups are all statistically insignificant. We find no evidence that NDL significantly increases the likelihood of loan denials for other minority groups.

[Table 6 about here.]

8. Economic Channel

In this section, we explore the mechanisms driving this increased denial gap and analyze how the increased denial gap can be mitigated.

8.1. Backlash effect

People who oppose rule changes promoting LGBTQ equality attempt to steer culture away from equality and use their own backlash efforts to engage in counter-rule making, thereby reversing or limiting these changes(Sobel, 2019). For instance, Ofosu *et al.* (2019) provide evidence of backlash, finding that following federal legalization, states that did not pass similar legislation exhibited an increase in antigay bias. In light of these findings, it is plausible that our results could be influenced by loan officers' opinion backlash due to other protected legalizations that may shape local attitude.

To test backlash hypothesis, we investigate how our main results are affected by local complaints, same-sex marriage (SSM) law and LGBTQ+ Percentage.

To proxy local attitudes, we first collect mortgage complaints at the county level from the CFPB dataset.[27] *Local complaints* is defined as the logarithm of the number of mortgage complaints in a given county. Furthermore, on June 26, 2015, the U.S. Supreme Court passed the same-sex marriage law, determining that all same-sex couples have the legal right to marry in the United States. The existing literature shows that the legalization of same-sex marriage increased loan demand by same-sex borrowers and influenced lenders' decisions (Hagendorff *et al.*, 2022). To capture the effect of this ruling, we define *SSM* as an indicator variable equal to 1 if a mortgage application is submitted in the year or after the year in which same-sex marriage was legalized in that state, and 0 otherwise. We also consider county-level LGBTQ+ households percentage to capture variations in local attitudes. *LGBTQ+ Percentage* is defined as the proportion of same-sex households in a given state.

The main coefficient of interest in this analysis is the triple interaction term, which captures the heterogeneity in the increase in the denial gap across different regulatory pro-

[27] For more details, see the Consumer Financial Protection Bureau (CFPB) data repository at `https://www.consumerfinance.gov/data-research/consumer-complaints/`.

tections. As shown in Table 6, *Same-Sex*NDL*Local Complaints*, *Same-Sex*NDL*SSM*, and *Same-Sex*LGBTQ+ Percentage* are all statistically insignificant, suggesting that our findings are not driven by backlash effects.

[Table 7 about here.]

8.2. Information friction in Post-NDL period

As described in Section 2, both hard and soft information are important for lending decisions. Following the enactment of non-discrimination law, same-sex borrowers may face higher rejection rates due to two main reasons: (1) a reduction in the utilization of soft information by loan officers when assessing same-sex borrowers (identical same-sex borrowers are more likely to be denied in the post-NDL period due to the lack of soft information); and (2) additional underwriting requirements, or "overlays," imposed specifically on same-sex borrowers (different-sex borrowers are not affected by NDL,[28] and these "overlays" further widen the denial gap between the two groups).

Bartoš *et al.* (2016) use correspondence studies to examine the idea that disparities can arise when decision makers must exert effort to acquire information. Jo and Liu (2024) document that during periods of low loan application volume, loan officers may spend more time assisting marginal applicants by helping them gather the necessary information for loan approval. However, during high-volume periods, when a large number of applications are pending, loan officers may lack the time or capacity to provide such individualized support. In Figure 1, we observe a notable increase in loan demand from same-sex borrowers following the implementation of NDL. Since the collection of soft information is time-intensive and potentially costly, this increased demand may reduce the ability of loan officers to gather soft information or offer assistance to same-sex borrowers. As a result, loans that might have been approved under normal conditions may face higher rejection rates in this period.[29]

[28]See Table 3 Panel B

[29]This argument is not inconsistent with our later argument that loan officer experience increases with the number of same-sex applications processed. When the enactment of NDL leads to a surge in mortgage applications from same-sex borrowers, all loan officers may face challenges in maintaining the same level of soft information collection as before. However, loan officers who have previously processed more

Calomiris *et al.* (1994), using the concept of "cultural affinity," argue that when loan officers are culturally disconnected from applicants—due to differences such as race or identity—they may be less willing to invest in additional soft information collection and instead rely more heavily on hard information. Similarly, Hagendorff *et al.* (2022) demonstrate that, due to informational frictions, loan officers require same-sex borrowers to meet relatively higher hard information standards for loan approval.

We test whether the enactment of non-discrimination law is associated with increased information frictions and whether bank-imposed overlays can explain our main results.

8.2.1. Contract standardization

To test information friction, we draw on the framework proposed by Skrastins and Vig (2019), which posits that a loss of information results in reduced dispersion in lending decisions, leading to more standardized loan contracts. Conversely, increased information collection enables lenders to better distinguish between high-quality ("good") and low-quality ("bad") applicants, resulting in greater differentiation in lending decisions and less standardization in contracts. Thus, an increase in information would be reflected by greater dispersion in lending decisions.

We utilize two widely employed metrics in the literature to measure the extent of information captured through variation in loan quantities: the interquartile range (IQR) and the standard deviation of debt. Both measures indicate that greater information corresponds to higher values. Our unit of analysis is at the bank-county-year level.

As shown in the Table 7, the standard deviation of debt (Columns 1, 3, and 5) and the interquartile range of debt (Columns 2, 4, and 6) for same-sex borrowers declined following the implementation of NDL. This result remains robust across different specifications of fixed effects controls. Specifically, the standard deviation of debt in Column 1 and the interquartile range of debt in Column 2 decreased by 1.03% and 1.64%, respectively. This indicates greater standardization of loan contracts(less dispersion) and increased information friction after NDL.

applications from same-sex borrowers are more experienced in collecting and utilizing soft information, and are therefore less affected by such disruptions compared to other loan officers.

[Table 8 about here.]

8.2.2. "Quasi" R-squared

Information friction can due to the loss in soft information. Soft information that is difficult to measure and transmit affects lenders' decisions (Hau *et al.*, 2021). (Liberti and Petersen, 2019), Berger *et al.* (2005), Bursztyn *et al.* (2019), and Hagendorff *et al.* (2022) show that it is beneficial for mortgage lenders to process soft information.

Following the approach of Hagendorff *et al.* (2022), we provide direct evidence of the reduced utilization on soft information to same-sex borrowers following the enactment of NDL. Specifically, we calculate $1 - R^2$ for each loan-decision regression at the bank–county–year level, separately for same-sex and different-sex applicants. Since the R^2 statistic reflects the extent to which loan officers rely on observable hard information in their approval decisions, $1-R^2$ serves as a measure of the reliance on soft information.

In Figure 5, we present evidence that there are no significant differences in the trends of soft information utilization by loan officers for same-sex and different-sex applicants prior to the treatment. However, following the legalization of the NDL, loan officers begin to exhibit a reduced reliance on soft information when evaluating applications from same-sex borrowers. Moreover, we do not observe an increase in the use of soft information following the adoption of the non-discrimination law. Correspondingly, the denial gap remains elevated during this period, as illustrated in Figure 4. This suggests that the collection and utilization of soft information play a crucial role in mitigation denial gap between same-sex borrowers and different-sex borrowers. The loss of soft information may lead to increased information friction, which could, in turn, contribute to the widened denial gap between same-sex and different-sex borrowers following the enactment of NDL.

[Figure 5 about here.]

Frame *et al.* (2025) suggest that minority loan officers may be better equipped to generate soft information about minority borrowers. Their study finds that 84.59% of loan officers are White, while only 1.76% are Black. This indicates that Black applicants may be systematically evaluated with less soft information. Furthermore, according to data from Zippia[30], even among mortgage lenders with strong commitments to diversity and inclusion, only 8% of brokers identify as LGBTQ. These patterns imply that same-sex applicants may be subject to significantly different treatment in terms of the use of soft information compared to their heterosexual counterparts. This imbalance in information usage may be a key factor contributing to the higher denial rates experienced by same-sex applicants.

To quantify this, we construct a measure of soft information imbalance at the bank-county-year level, defined as the deviation in $1 - R^2$ between same-sex and different-sex applicants. We hypothesize that greater soft information imbalance is associated with a higher likelihood of denial for same-sex applicants. Moreover, we expect that this relationship becomes more pronounced in the post-NDL period, leading to a more significant denial gap.

We present our empirical findings in Table 8 (Column 1). The primary coefficient of interest is the triple interaction term *Same-Sex*NDL*SF-Imbalance* is statistically significant. This result suggests that in bank-county branches with more imbalanced soft information usage, the increase in denial rates for same-sex applicants post-NDL is more pronounced.

In addition, the interaction term *Same-Sex*SF-Imbalance* is also statistically significant, indicating that same-sex applicants face a higher probability of denial in branches characterized by higher levels of soft information imbalance. These findings support the view that imbalanced use of soft information is a key mechanism underlying discriminatory outcomes for same-sex mortgage applicants.

8.2.3. Local competition

To further demonstrate that local banks relied less on soft information after the NDL, we explore how the use of soft information by loan officers changes in a competitive environment. Competition may render the use of soft information unprofitable for banks, even though this information is readily available and could improve loan screening. The

[30] `https://nationalmortgageprofessional.com/news/lenders-commit-lgtbq-inclusion?`

finding that competition leads to more reliance on hard information complements the common understanding that the greater availability and use of hard information reduces the distance between lenders and borrowers, thereby enhancing competition (Petersen and Rajan, 2002).

Consistent with this, Heider and Inderst (2012) show that in highly competitive environments, banks may choose to disregard soft information and rely solely on hard data for credit approval decisions. In our context, if loan officers reduce their reliance on soft information in decision-making after the implementation of the NDL, states with high competition should be less affected by this shift, as they have historically utilized little soft information prior to the NDL implementation. Therefore, we expect the increase in the denial gap to be less pronounced in counties with high competition.

To assess market competitiveness, we utilize the Herfindahl-Hirschman Index (HHI). The HHI is calculated based on the market share, which is defined as the proportion of loan applications received by each lender within a given state and county. A county is considered to have high competition if its HHI exceeds that of the state.

The results in Table 8 (Column 2) show that the coefficients on the triple interaction terms are negative and statistically significant, indicating that the denial gap is less pronounced for high competition counties after NDL.

8.2.4. Bank compliance and risk aversion

Large banks are subject to more stringent regulatory oversight. Regulatory examinations by agencies like the Office of the Comptroller of the Currency (OCC), the Federal Reserve, and the Consumer Financial Protection Bureau (CFPB) can incentivize these institutions to implement standardized, risk-based underwriting procedures; reduce discretion; and more rigorously comply with the Equal Credit Opportunity Act (ECOA) and the Fair Housing Act(Tran and Winters, 2024; Liu and Liang, 2025).

As a result, loan officers at these institutions may be more inclined to comply with nondiscrimination laws. When processing loan applications from same-sex applicants, these banks may rely exclusively on hard information due to risk aversion. A similar rationale applies to national banks, which face comparable regulatory expectations.[31]

The use of hard information offers certain legal and practical advantages. As noted by Bartlett *et al.* (2022), courts have allowed lenders to invoke a legitimate business necessity defense for the use of variables and practices intended to assess creditworthiness, even when these practices may result in worse outcomes for minority borrowers. Hard information, therefore, can be considered a defensible component of such an assessment, strengthening a bank's position in potential litigation. One implication is that in institutions with stricter compliance behavior, soft information may be more readily applied when evaluating different-sex applicants than same-sex applicants.[32] This asymmetry may further contribute to the widening of the denial gap between the two groups.

Accordingly, we expect that the increased denial gap following the implementation of NDL would be more pronounced among large and national banks, owing to their greater risk aversion and regulatory compliance.

Consistent with this expectation, in Table 8, Columns (3) and (4), the coefficients on the triple interaction terms are positive and statistically significant. This result suggests that the risk-averse and compliance-oriented behavior of large banks may intensify this form of unintended discrimination.

[Table 9 about here.]

8.2.5. "Overlays" on same-sex borrowers

When the collection of soft information becomes more difficult, loan officers may impose stricter lending standards on same-sex applicants compared to different-sex applicants(Calomiris *et al.*, 1994; Hagendorff *et al.*, 2022). In such cases, loan officers may prefer to approve loans for same-sex borrowers only when they exhibit stronger creditworthiness—such as higher credit scores—relative to their different-sex counterparts. To test this hypothesis, we utilize merged HMDA–Fannie Mae loan data as described in Section 7, which consist exclusively of approved loans. Consistent with this conjecture,

[31] For the list of national banks, see `https://www.occ.treas.gov/topics/charters-and-licensing/financial-institution-lists/national-by-name.pdf`.

[32] Consistent with this view, we do not observe a significant effect of NDL on the denial rate for different-sex applicants in Table 3 Panel B.

in column (1), we find that same-sex borrowers are required to have higher credit scores for approved loans. This provides further evidence that the loss of soft information may result in stricter reliance on hard information.

However, are these hard information overlays justified by a legitimate business necessity? As Becker (1993) argues in his Nobel Prize lecture while commenting on lending discrimination against minorities, "If banks discriminate against minority applicants, they should earn greater profits on the loans made to them than on those to Whites." In the context of our study, if after the enactment of non-discrimination law, same-sex borrowers are required to have higher credit scores for loan approval, but are also charged higher interest rates without exhibiting higher levels of risk or default, such patterns would suggest intentional rather than unintended discrimination.

To further explore this, we regress the interaction term Same-Sex*NDL on interest rate, debt-to-income ratio, and default rate in columns (2), (3), and (4) of Table 9, respectively. Across all three specifications, the coefficient on Same-Sex*NDL is statistically insignificant. We do not find evidence that loan officers charge higher interest rates to same-sex borrowers following the adoption of NDL. Furthermore, same-sex borrowers do not exhibit higher risk or default rates. These findings further support the argument that the increased denial gap observed after the implementation of NDL is not profit-driven, but rather stems from other factors, such as the disruption in soft information collection.

[Table 10 about here.]

8.2.6. Mitigating the insufficient use of soft information

Loan officers may be unwilling (rather than unable) to incorporate soft information. However, in Figure 5, we observe that this reduced soft information utilization is temporary, rather than persistent over time. This pattern aligns with the dynamics of belief-based discrimination described in Bohren *et al.* (2019) and Hagendorff *et al.* (2022), who suggest that the insufficiency in the use of soft information can be mitigated as loan officers update their beliefs and gain more experience in understanding and gathering soft information over time. Inspired by this, we further investigate whether previous exposure to applications from same-sex borrowers mitigates the impact of information frictions.

Loan officers who process a higher volume of applications from same-sex borrowers may possess an advantage in collecting and processing soft information specific to this group. To assess this, we calculate the number of same-sex mortgage applications received by each bank in each county for each year. We define *Loan-officer Experience* as the number of same-sex mortgage applications received by a specific bank-county-year.[33] *Loan-officer Experience* increases as loan officers process more same-sex mortgage applications. We interact *Loan-officer Experience* with Same-Sex*NDL, with this triple interaction term being our main coefficient of interest. In Table 10, column (1), we find that the coefficient on the triple interaction term is negative and significant at the 1% level. This supports our hypothesis that loan officers with more exposure and experience in processing soft information related to same-sex borrowers are less likely to deny applications from same-sex borrowers.

To further account for the potential bias introduced by the number of loan officers, we obtain data on the number of loan officers in each state-year.[34] We evaluate *State Loan-officer Experience* by the number of same-sex mortgage applications divided by the total number of loan officers in each state-year. We expect that in states with higher *Loan-officer Experience*, the denial gap following the enactment of NDL will be smaller compared to other states. Table 10 presents results consistent with this view. In column (2), our main coefficient on the triple difference interaction terms is negative and significant, indicating that the denial gap is less pronounced in states with more experienced loan officers following the enactment of NDL.

[Table 11 about here.]

9. Conclusion

Non-Discrimination Law related to sexual orientation based discrimination has been shown to produce significant real-world benefits, including higher employment rates and

[33]According to Cortés *et al.* (2016), each bank typically has only one to two loan officers per county branch.
[34]See `https://www.bls.gov/oes/tables.htm`

better wages (Sansone, 2019), improved business performance (Hossain *et al.*, 2020), and even nationwide economic growth (Badgett, 2020). Policymakers have long expressed concern over the unequal and unfair treatment of minority customers by financial institutions (Ambrose *et al.*, 2021). The impact of sexual orientation related housing non-discrimination law on the credit decisions at financial institutions is unknown and is of far reaching importance for civil rights in the LGBTQ+ community and for the optimal allocation of credit in the United States. We, thus, test legislative interventions to mitigate unfairness in lending decisions against members of the LGBTQ+ community.

This study demonstrates that although many states have enacted nondiscrimination law to prohibit discrimination against same-sex couple applications in mortgage lending, a denial gap persists and has even widened for the decisions of loan officers in local banks. We find that an opinion backlash against the LGBTQ+ community is unlikely to account for the denial gap around the enactment of housing nondiscrimination law. We show that information friction, between loan officers and same sex couple borrowers, can explain a post non discrimination law increased denial gap between same-sex applicants and different-sex applicants. As loan officers gain experience of same sex couple applications, the denial gap after the enactment of the non-discrimination law is shown to diminish. Our findings, hence, provide policymakers with important new insight. The findings underscore the need to incorporate information friction considerations, between loan officers and same-sex couple borrowers, into policy formulation. A tailored non-discrimination training program for loan officers, with a focus on soft information and lending in the LGBTQ+ minority group, could potentially accelerate the dissipation of the discrimination.

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Table 1: Summary Statistics

Panel A: Denial rates

Variable	(1) Mean	(2) Standard Deviation
Denial	0.1624	0.3688
Same-Sex Denial	0.2286	0.4160
Different-Sex Denial	0.1592	0.3659

Panel B: Borrower/ loan traits

Variable	(1) Mean	(2) Standard Deviation
Same-Sex	0.0458	0.2090
NDL	0.3078	0.4724
Ln Loan Amount	4.9720	0.8942
Ln Applicant Income	4.5798	0.5954
Loan Amount/Income	1.9428	2.3066
Male	0.7925	0.4055
Hispanic	0.0448	0.2068
Black	0.0222	0.1472
Asian	0.0236	0.1519
Other Races	0.0031	0.0559
FHA Loan	0.0505	0.2190
VA Loan	0.0110	0.1043
FSA/RSH Loan	0.0026	0.0508
Home Improvement	0.1340	0.3407
Refinance	0.5149	0.4998

Note: This table presents summary statistics for local banks, including 7,525,620 matched home mortgage applications from 2010 to 2023. Definitions of variables are listed in the internet appendix Table A1.

Table 2: Non-discrimination law and same-sex borrowers' loan level mortgage decisions.

	Dependent variable = *Denial*				
	(1)	(2)	(3)	(4)	(5)
Same-Sex	0.0311***	0.0329***	0.0306***	0.0287***	0.0285***
	(0.0027)	(0.0025)	(0.0028)	(0.0030)	(0.0027)
*Same-Sex*NDL*	0.0148***	0.0158***	0.0152***	0.0160***	0.0154***
	(0.0030)	(0.0027)	(0.0031)	(0.0028)	(0.0025)
Male		-0.0244***			-0.0026
		(0.0025)			(0.0023)
Hispanic		0.0795***			0.0582***
		(0.0040)			(0.0027)
Black		0.1561***			0.1328***
		(0.0057)			(0.0049)
Asian		0.0593***			0.0581***
		(0.0060)			(0.0048)
Other Races		0.1195***			0.0875***
		(0.0144)			(0.0106)
FHA Loan			-0.0202**		-0.0022
			(0.0080)		(0.0049)
VA Loan			-0.0589***		-0.0233***
			(0.0079)		(0.0060)
FSA/RSH Loan			0.0163		0.0368**
			(0.0176)		(0.0159)
Home Improvement				0.2637***	0.2603***
				(0.0215)	(0.0208)
Refinance				0.0856***	0.0849***
				(0.0081)	(0.0073)
Ln Applicant Income					-0.0778***
					(0.0034)
Loan Amount/Income					0.0023*
					(0.0013)
Bank*County*Year fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.1790	0.1903	0.1793	0.2196	0.2443
Observations	7,525,620	7,525,620	7,525,620	7,525,620	7,525,620

Note: This table presents the regression results of non-discrimination law impacts on denial rates for same-sex borrowers at local banks. Definitions of variables are listed in the internet appendix Table A1. In parentheses are standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 3: A series of robustness testing analyses (Dependent variable = *Denial*).

	Panel A: Delayed impact and "Clean" counterfactual			Panel B: Same-Sex vs. Different-Sex Groups	
	(1)	(2)	(3)	(1)	(2)
Same-Sex	0.0313***	0.0343***	0.0325***		
	(0.0025)	(0.0025)	(0.0037)		
*Same-Sex * NDL*	0.0141***	0.0097***	0.0205***		
	(0.028)	(0.0034)	(0.0037)		
NDL				0.0107*	0.0018
				(0.0057)	(0.0041)
Control Variable	Yes	Yes	Yes	Yes	Yes
Bank*Year FE	No	No	No	Yes	Yes
County FE	No	No	No	Yes	Yes
Bank*County*Year FE	Yes	Yes	Yes	No	No
Adjusted R-squared	0.2443	0.2443	0.2446	0.1818	0.1556
Observations	7,525,620	7,525,620	3,707,873	344,570	7,181,050

	Panel C: Counties adjacent to state borders		Panel D: Pre and Post Covid-19	
	Adjacency	Non-Adjacency	Pre-Covid	Post-Covid
Same-Sex	0.0327***	0.0268***	0.0271***	0.0352***
	(0.0035)	(0.0027)	(0.0029)	(0.0034)
*Same-Sex * NDL*	0.0118***	0.0168***	0.0141**	0.0088***
	(0.0036)	(0.0027)	(0.0040)	(0.0031)
Control Variable	Yes	Yes	Yes	Yes
Bank*County*Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.2351	0.2490	0.2480	0.2404
Observations	2,669,372	4,856,248	5,276,674	2,248,946

Note: This table presents a series of robustness tests to validate our main results. Panel A estimates the delayed impact of the NDL on mortgage denial rates, with delays of one year and two years, respectively. Column (3) re-estimates the main results using stacked regression with "clean" control variables. Panel B examines the effect of NDL on mortgage denial rates, comparing same-sex and different-sex groups. Panel C examines the effects of NDL on mortgage denials among counties adjacent to state borders and those not adjacent to state borders. Panel D examines our main results in the pre- and post-COVID-19 periods. Definitions of variables are listed in the internet appendix Table A1. In parentheses are standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 3: *(continued)*

	Panel E: Borrower Income & Loan amount				Panel F: Male & Female	
	Low income	High income	Low Loan amount	High Loan amount	Male	Female
Same-Sex	0.0311***	0.0232***	0.0459***	0.0168***	0.4680***	0.0081***
	(0.0032)	(0.0027)	(0.0035)	(0.0022)	(0.0034)	(0.0027)
*Same-Sex * NDL*	0.0252***	0.0072***	0.0234***	0.0075***	0.0103***	0.0217***
	(0.0033)	(0.0027)	(0.0028)	(0.0026)	(0.0025)	(0.0039)
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes
Bank*County*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.2991	0.2440	0.2825	0.2168	0.2664	0.2678
Observations	3,753,766	3,771,854	3,723,592	4,508,506	5,963,968	1,561,652

	Panel G: Large vs. Small Banks		Panel H: Different race same-sex applicants	
	Large Bank	Small Bank	Exclude Father-son	Exclude Mother-daughter
Same-Sex	0.0232***	0.0256***	0.0181***	0.0456***
	(0.0024)	(0.0038)	(0.0033)	(0.0034)
*Same-Sex * NDL*	0.0223**	0.0125***	0.0152***	0.0102***
	(0.0030)	(0.0045)	(0.0055)	(0.0026)
Control Variable	Yes	Yes	Yes	Yes
Bank*County*Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.2391	0.2446	0.1866	0.2653
Observations	3,838,333	1,875,070	1,692,111	6,014,978

Note: This table presents a series of robustness tests to validate our main results. Panel E restricts the sample to low- and high-creditworthy groups, while Panel F restricts the sample to male and female groups. Panel G looks at large vs. small banks, and Panel H examines the effects of excluding father-son or mother-daughter relationships. Definitions of variables are listed in the internet appendix Table A1. In parentheses are standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4: Additional analyses: Omitted creditworthiness variables.

	Dependent variable = *Denial*			
	Hybrid-Sampling	Under-Sampling	Over-Sampling	FHA loan
	(1)	(2)	(3)	(4)
Same-Sex	0.0414***	0.0285***	0.0285***	0.0127***
	(0.0036)	(0.0027)	(0.0026)	(0.0019)
*Same-Sex * NDL*	0.0164***	0.0153***	0.0151***	0.0070**
	(0.0028)	(0.0025)	(0.0025)	(0.0040)
Probability of Default	0.0308***	0.4753***	0.6279***	
	(0.0061)	(0.1117)	(0.0637)	
Control Variable	Yes	Yes	Yes	No
Bank*County*Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.2443	0.2445	0.2451	0.2937
Observations	7,525,620	7,525,620	7,525,620	526,446

Note: This table reports two additional analyses to alleviate omitted variable bias. Columns (1)-(3) report the results using hybrid, undersampling, and oversampling techniques to generate a balanced dataset, which we use for training the default probability prediction model. This model is then employed to predict default probabilities for each application in our HMDA data. Column (4) re-estimates the main results using FHA loan data. Definitions of variables are listed in the internet appendix Table A1. In parentheses are standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 5: Different modes of NDL implementation and spillover effects on other minorities

	Dependent variable = *Denial*	
	(1)	(2)
Same-Sex	0.0285***	0.0284***
	(0.0027)	(0.0027)
*Same-Sex*Federal Decision*	0.0155***	
	(0.0025)	
*Same-Sex*State Legislation*	0.0154***	
	(0.0036)	
*Same-Sex*NDL*		0.0156***
		(0.0026)
*Black*NDL*		0.0090
		(0.0081)
*Asian*NDL*		0.0045
		(0.0076)
*Hispanic*NDL*		0.0073
		(0.0047)
Control Variables	Yes	Yes
Bank*County*Year fixed effects	Yes	Yes
Adjusted R-squared	0.2443	0.2443
Observations	7,525,620	7,525,620

Note: This table reports the effects of different modes of NDL implementation and potential spillover effects on other minority groups. Column (1) defines NDL based on alternative implementation modes, while Column (2) examines interactions between race/ethnicity and NDL. Standard errors are clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Economic Channel analyses: Backlash effect and public attitudes.

	Dependent variable = *Denial*		
	(1)	(2)	(3)
Same-Sex	0.0363***	0.0268***	0.0261***
	(0.0042)	(0.0028)	(0.0041)
*Same-Sex*NDL*	0.01113**	0.0135***	0.0167**
	(0.0050)	(0.0032)	(0.0085)
*Same-Sex*Local Complaints*	-0.0026**		
	(0.0011)		
*Same-Sex*NDL*Local Complaints*	-0.0008		
	(0.0011)		
*Same-Sex*SSM*		0.0050	
		(0.0045)	
*Same-Sex*NDL*SSM*		0.0009	
		(0.0056)	
*Same-Sex*LGBTQ+ Percentage*			0.0033
			(0.0051)
*Same-Sex*NDL*LGBTQ+ Percentage*			-0.0021
			(0.0102)
Control Variables	Yes	Yes	Yes
Bank*County*Year fixed effects	Yes	Yes	Yes
Adjusted R-squared	0.2374	0.2445	0.2445
Observations	7,525,620	7,525,620	7,525,620

Note: This table reports how the increased denial gap is affected by local attitudes. Column (1), Column (2), and Column (3) estimate whether our main results vary by local complaints, SSM, and LGBTQ+ percentage. Definitions of variables are listed in the internet appendix Table A1. In parentheses are standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 7: Economic channel analyses: Information friction and contract standardization.

Dependent variable =	$\ln\left(\sigma_{\text{loan}_{b,c,t}}\right)$	$\ln\left(\text{IQR}_{b,c,t}\right)$	$\ln\left(\sigma_{\text{loan}_{b,c,t}}\right)$	$\ln\left(\text{IQR}_{b,c,t}\right)$	$\ln\left(\sigma_{\text{loan}_{b,c,t}}\right)$	$\ln\left(\text{IQR}_{b,c,t}\right)$
	(1)	(2)	(3)	(4)	(5)	(6)
Same-Sex	0.0098***	0.0101***	0.0057***	0.0080***	0.0069***	0.0070***
	(0.0014)	(0.0031)	(0.0009)	(0.0018)	(0.0009)	(0.0017)
*Same-Sex*NDL*	-0.0103***	-0.0164**	-0.0071***	-0.0127***	-0.0066***	-0.0124***
	(0.0030)	(0.0060)	(0.0014)	(0.0025)	(0.0008)	(0.0018)
Bank fixed effects	Yes	Yes	No	No	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	No	No
Year fixed effects	Yes	Yes	No	No	No	No
Bank*Year fixed effects	No	No	Yes	Yes	No	No
County*Year fixed effects	No	No	No	No	Yes	Yes
Adjusted R-squared	0.4679	0.4202	0.6766	0.5967	0.5920	0.5312
Observations	7,525,620	7,525,620	7,525,620	7,525,620	7,525,620	7,525,620

Note: This table presents the impact of non-discrimination laws (NDL) on contract standardization using various metrics. Columns (1), (3), and (5) estimate contract standardization following the implementation of the non-discrimination law, using the standard deviation of debt. Columns (2), (4), and (6) estimate contract standardization following the implementation of the non-discrimination law, using the interquartile range of debt. $\ln\left(\text{IQR}_{b,c,t}\right)$ is the logarithm of the interquartile range of loan amounts at the bank-county-year level. $\ln\left(\sigma_{\text{loan}_{b,c,t}}\right)$ is the logarithm of the standard deviation of loan amounts for each bank-county-year. Standard errors (in parentheses) are clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Economic Channel analyses: Information friction, bank compliance and risk aversion.

	Dependent variable = *Denial*			
	(1)	(2)	(3)	(4)
Same-Sex	0.0213***	0.0283***	0.0360***	0.0356***
	(0.0037)	(0.0027)	(0.0028)	(0.0034)
*Same-Sex*NDL*	0.0186***	0.0158***	0.0077**	0.0069***
	(0.0045)	(0.0026)	(0.0032)	(0.0030)
*Same-Sex*SF-Imbalance*	0.2290***			
	(0.0144)			
*Same-Sex*NDL*SF-Imbalance*	0.0483**			
	(0.0186)			
*Same-Sex*Competition*		0.0088		
		(0.0056)		
*Same-Sex*NDL*Competition*		-0.0215**		
		(0.0097)		
*Same-Sex*National Bank*			-0.0120**	
			(0.0030)	
*Same-Sex*NDL*National Bank*			0.0125***	
			(0.0039)	
*Same-Sex*Large Bank*				-0.0116**
				(0.0030)
*Same-Sex*NDL*Large Bank*				0.0144***
				(0.0042)
Control Variables	Yes	Yes	Yes	Yes
Bank*County*Year fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.2065	0.2443	0.2443	0.2443
Observations	4,325,093	7,525,620	7,525,620	7,525,620

Note: This table reports how the increased denial gap is affected by soft information imbalance, local competition, bank compliance and risk aversion. Column (1) investigates information friction via soft information imbalance. Column (2) investigates information friction via local competition. Column (3) and Column (4)investigate information friction among large banks and national banks. Definitions of variables are listed in the internet appendix Table A1. In parentheses are standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 9: Economic channel analyses: Lending standard, profit and borrower default risk.

Dependent variable =	Credit Scores	Interest Rate	DTI Ratio	Default Risk
	(1)	(2)	(3)	(4)
Same-Sex	-0.0223***	0.0286***	0.6502***	0.0008
	(0.0046)	(0.0051)	(0.1368)	(0.0012)
*Same-Sex*NDL*	0.0326**	-0.0121	0.2143	-0.0016
	(0.0143)	(0.0188)	(0.3370)	(0.0039)
Bank*County*Year fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.0881	0.3978	0.1328	0.0786
Observations	131,046	131,110	131,109	131,045

Note: This table reports credit quality of same-sex borrowers after the legalization of non-discrimination law. The four credit quality proxies are indicated at the top of each column. Definitions of variables are listed in the internet appendix Table A1. In parentheses are standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 10: Economic Channel Analyses: Information friction and Loan Officer Experience

	Dependent variable = *Denial*	
	(1)	(2)
Same-Sex	0.0315***	0.0169***
	(0.0028)	(0.0033)
*Same-Sex*NDL*	0.0177***	0.0033***
	(0.0026)	(0.0008)
*Same-Sex*Loan-Officer Experience*	-0.0001***	
	(0.0000)	
*Same-Sex*NDL*Loan-Officer Experience*	-0.0002***	
	(0.0000)	
*Same-Sex*State Loan-Officer Experience*		0.0285**
		(0.0040)
*Same-Sex*NDL*State Loan-Officer Experience*		-0.0036***
		(0.0011)
Control Variables	Yes	Yes
Bank*County*Year Fixed Effects	Yes	Yes
Adjusted R-squared	0.2444	0.2445
Observations	7,525,620	7,525,620

Note: This table examines if experienced loan officers can mitigate information friction. Column (1) uses branch-level loan officer experience, while Column (2) uses state-level loan officer experience. Definitions of variables are listed in the internet appendix Table A1. Standard errors clustered at the state level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

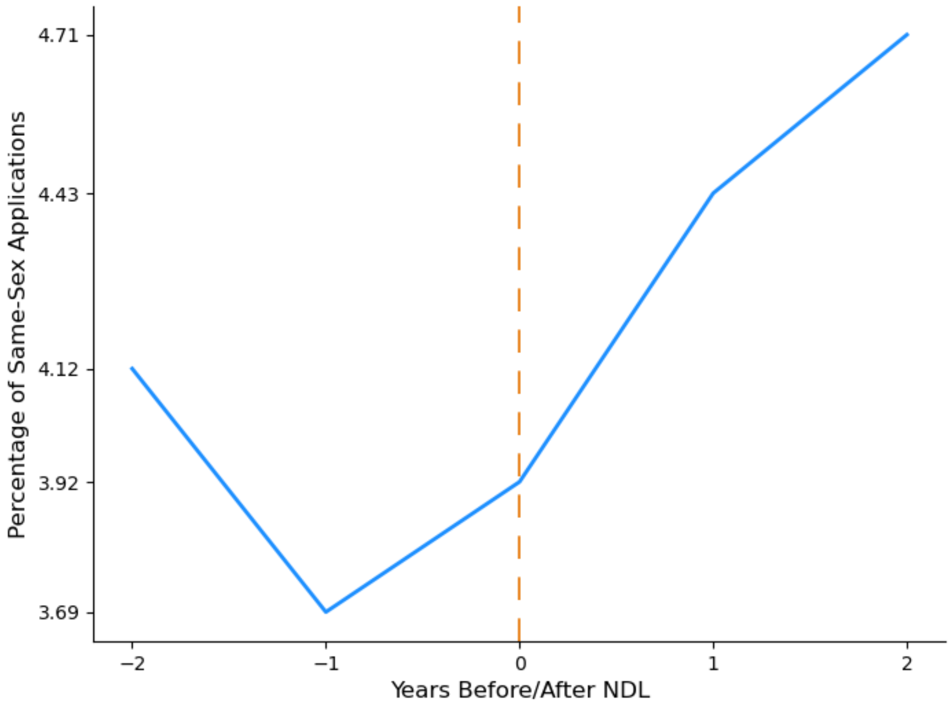

Figure 1: Variation in same-sex loan applications Pre- and Post-NDL
This figure illustrates the variation in same-sex loan applications prior to and following the implementation of non-discrimination laws.

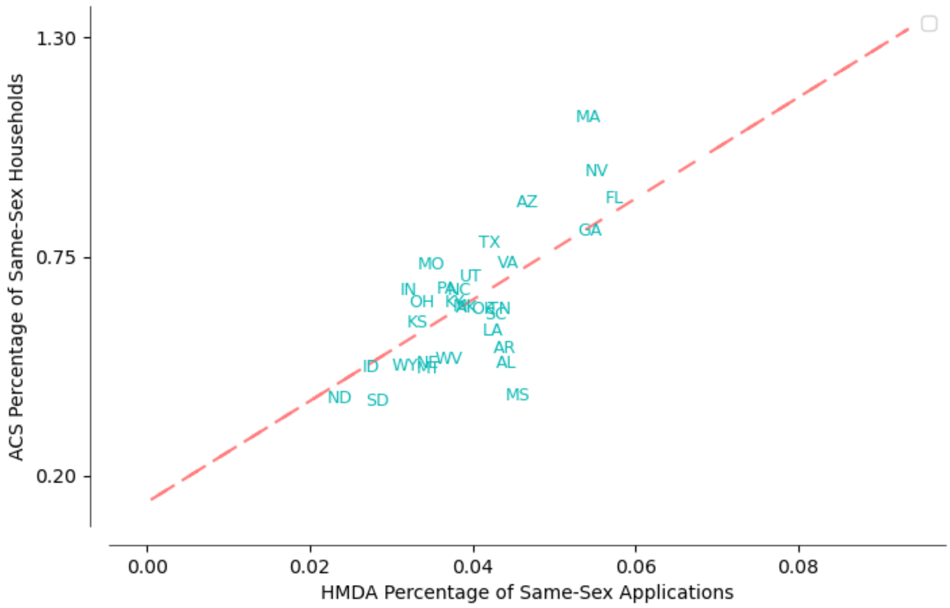

Figure 2: Scatter plot of same-sex households and same-sex mortgage applications
This figure presents a scatter plot of the relationship between the state-level percentage of same-sex households from the American Community Survey (ACS) dataset (on the vertical axis) and the percentage of same-sex mortgage applications at the state level in the HMDA dataset (on the horizontal axis). The ACS identifies same-sex households based on responses from householders where a spouse or unmarried partner is reported to be of the same-sex as the respondent. The dotted line represents the predicted values from an OLS regression.

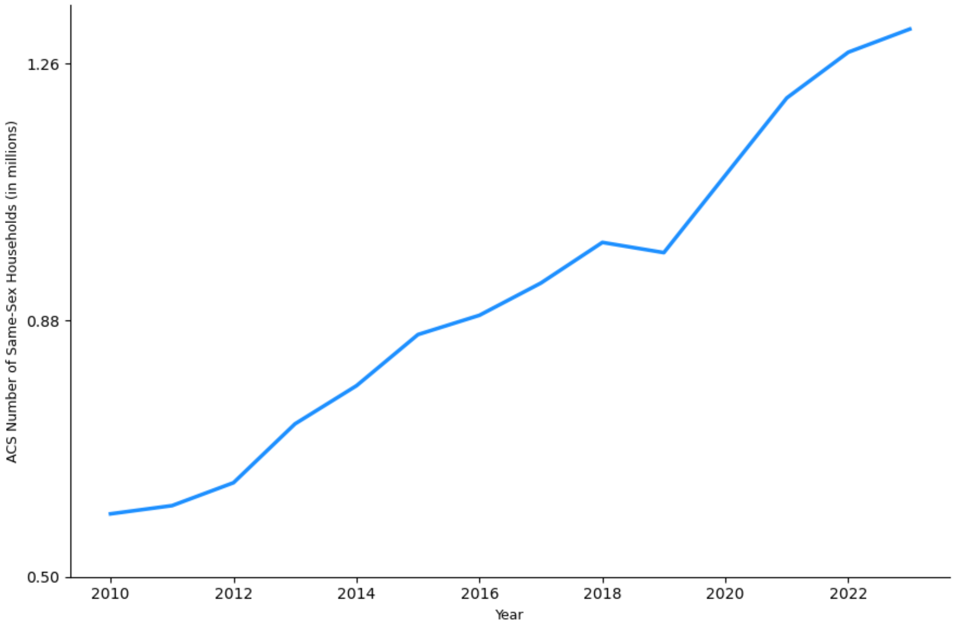

Figure 3: Change in number of same-sex households over time
This figure presents the changes in the total number of Same-Sex Households between 2010 and 2023. The ACS identifies same-sex households based on responses from householders where a spouse or unmarried partner is reported to be of the same-sex as the respondent.

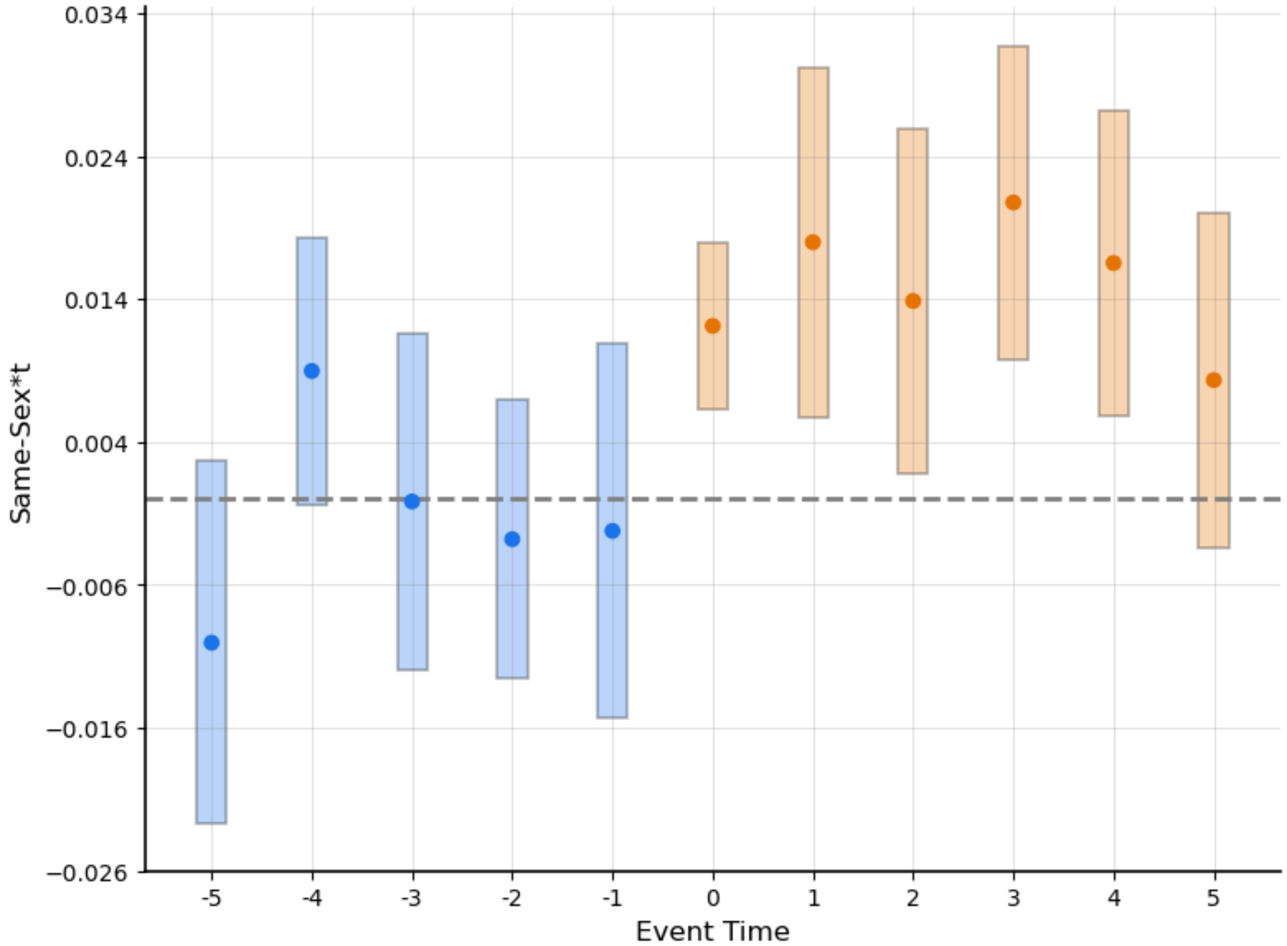

Figure 4: Dynamic effects of non-discrimination laws on the mortgage denial gap: Local Bank.
This figure plots the coefficient of the interaction between Same-Sex and time dummies for [-5, ≥5] years relative to the passage of non-discrimination law (NDL) legislation. The dependent variable is Denial, which equals 1 when a mortgage application is denied and 0 otherwise. The control variables are the same as in Column (5) in Table 2. Bank*County*Year fixed effects are included in this analysis.

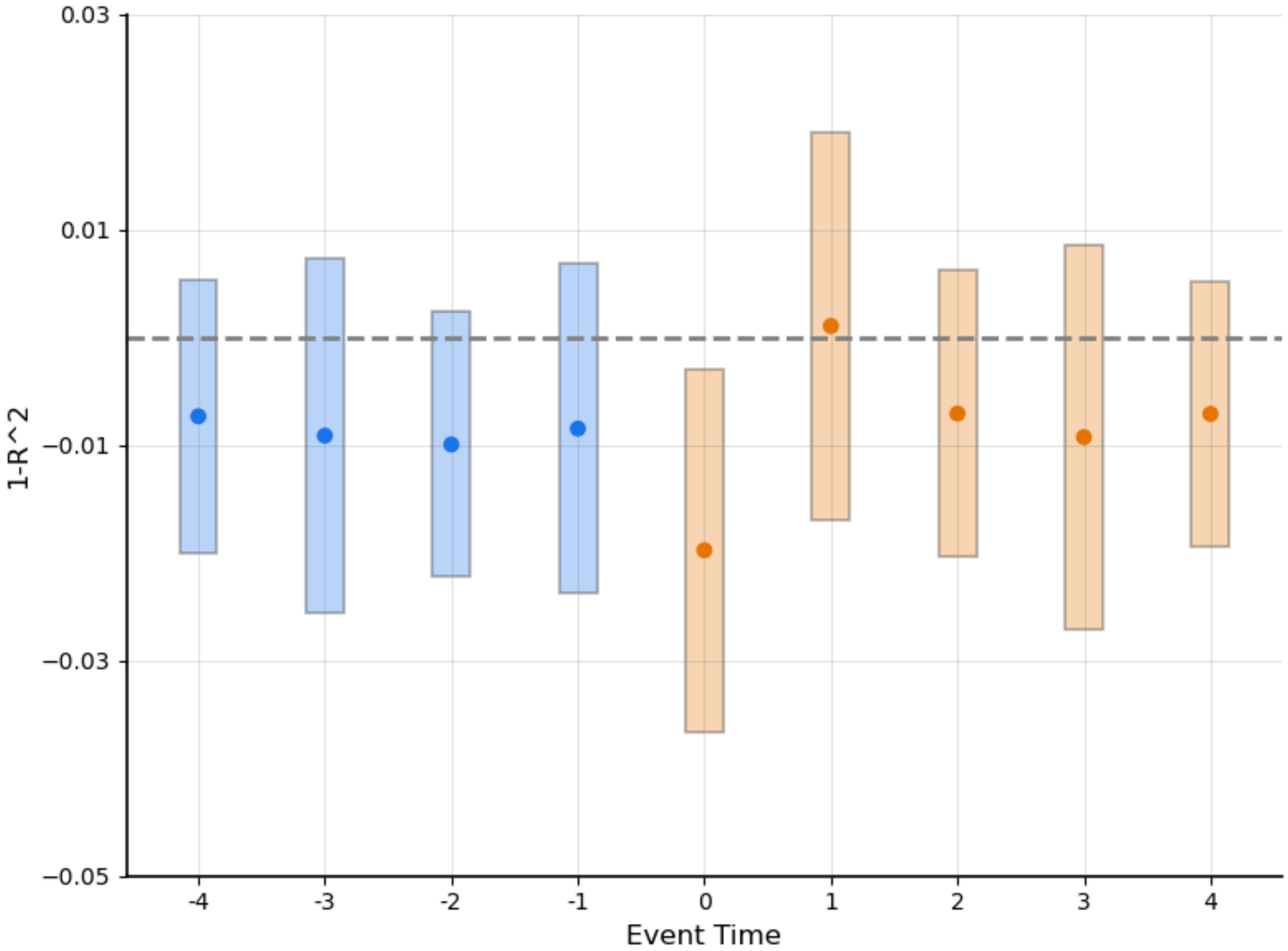

Figure 5: Dynamic effects of non-discrimination laws on the soft information utiliztion.
This figure plots the coefficient of the interaction between Same-Sex and time dummies for [−4, +4] years relative to the passage of non-discrimination law (NDL) legislation. The dependent variable is $1 - R^2$, which captures the soft information utilized by loan officers. Because our analysis is at the Bank*County*Year level, we incorporate Bank*County and Year fixed effects instead.

Appendices Containing Supplemental Details

1. Variable Description

Table A1: Variable Description

Variable	Definition
Denial	= 1 if the application is denied by the financial institution, and = 0 if the application is approved and the mortgage is originated.
Same-Sex	= 1 if the reported sex of the main applicant is the same as the reported sex of the co-applicant, and = 0 otherwise.
Different-Sex	= 1 if the reported sex of the main applicant is different from the reported sex of the co-applicant, and = 0 otherwise.
NDL	= 1 if the mortgage application is submitted in a state in the year or after the year in which non- discrimination law is legalized in that state, and 0 otherwise.
Ln Applicant Income	Natural logarithm of applicant's gross annual income the lender relies on when making the credit decision (in thousands of dollars).
Ln Loan Amount	Natural logarithm of loan amount (in thousands of dollars).
Loan Amount/Income	Loan amount divided by gross annual income the lender relies on when making the credit decision.
Male	= 1 if the main applicant's reported sex is male, and = 0 if the main applicant is female.
Hispanic	= 1 if the main applicant's reported ethnicity is Hispanic or Latino, and = 0 if the main applicant is not Hispanic or Latino.
Black	= 1 if the main applicant's reported race is Black of African American, and = 0 otherwise.
Asian	= 1 if the main applicant's reported race is Asian, and = 0 otherwise.
Other Races	= 1 if the main applicant's reported race is American Indian, Alaska Native, Native Hawaiian, Other Pacific Islander, and = 0 otherwise.
FHA Loan	= 1 if the loan is insured by the Federal Housing Administration, and = 0 otherwise.
VA Loan	= 1 if the loan is guaranteed by the Veterans Administration, and = 0 otherwise.
FSA/RSH Loan	= 1 if the loan is guaranteed by the Farm Service Agency or the Rural Housing Service, and = 0 otherwise.
Home Improvement	= 1 if the loan's purpose is for home improvement, and = 0 otherwise.
Refinance	= 1 if the loan's purpose is for refinancing, and = 0 otherwise.

Table A1: Variable Description (continued)

Variable	**Definition**
Male Same-Sex	= 1 if both main applicant and co-applicant are male, and = 0 otherwise.
Female Same-Sex	= 1 if both main applicant and co-applicant are female, and = 0 otherwise.
Risk_75	= 1 if loan-to-income ratio is greater than the 75th percentile, and = 0 otherwise.
Risk_90	= 1 if loan-to-income ratio is greater than the 90th percentile, and = 0 otherwise.
$\ln\left(\mathrm{IQR}_{b,c,t}\right)$	Natural logarithm of the interquartile range of loan amounts for each bank-county-year.
$\ln\left(\sigma_{\mathrm{loan}_{b,c,t}}\right)$	Natural logarithm of the standard deviation of loan amounts for each bank-county-year.
National Bank	= 1 if banks that are chartered and supervised by the federal government, and = 0 otherwise.
SSM	= 1 if The mortgage application is submitted in a state in the year or after the year in which same-sex marriage law is legalized in that state, and 0 otherwise.
Local Complaints	The logarithm of the number of mortgage complaints in a given county.
LGBTQ+ Percentage	The proportion of same-sex households in a given state-year.
Loan-officer Experience	The number of same-sex mortgage applications received by a specific bank-county-year.
State Loan-officer Experience	The number of same-sex mortgage applications divided by the total number of loan officers in each state-year.
Total number of loan officers	The overall count of loan officers within a given state.
Jobs per 1,000	The number of loan officers employed per 1,000 jobs in the state.
Competition	A county is considered to have high competition if its Herfindahl-Hirschman Index (HHI) exceeds that of the state.
SF-Imbalance	The deviation in $1-R^2$ between same-sex and different-sex applicants.

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2. State Non-discrimination Laws on Sexual Orientation

Table A2: State Non-discrimination Laws on Sexual Orientation

State	Fair Credit	Fair Housing	Status
AL	2021	2021	
AK	2020	2020	
AZ	2021	2021	
AR	2021	2021	
CA	2005	1999	Exclude
CO	2008	2008	Exclude
CT	1991	1991	Exclude
DE	2021	2009	Exclude
DC	1973	1973	Exclude
FL	2021	2020	
GA	2021	2021	
HI	2021	2005	Exclude
ID	2021	2021	
IL	2006	2006	Exclude
IN	2021	2021	
IA	2007	2007	Exclude
KS	2021	2020	
KY	2021	2021	
LA	2021	2021	
ME	2005	2005	Exclude
MD	2021	2001	Exclude
MA	2011	2011	
MI	2021	2018	
MN	1993	1993	Exclude
MS	2021	2021	
MO	2021	2021	
MT	2021	2021	
NE	2021	2020	
NV	2019	2011	
NH	2021	1997	Exclude
NJ	1992	1992	Exclude
NM	2003	2003	Exclude
NY	2002	2002	Exclude
NC	2021	2021	
ND	2020	2020	
OH	2021	2021	
OK	2021	2021	
OR	2021	2007	Exclude
PA	2021	2018	
RI	1995	1995	Exclude
SC	2021	2021	
SD	2021	2021	
TN	2021	2021	

Continued on next page

State	Fair Credit	Fair Housing	Exclude
TX	2021	2021	
UT	2021	2015	
VT	1992	1992	Exclude
VA	2020	2020	
WA	2006	2006	Exclude
WV	2021	2021	
WI	2021	1982	Exclude
WY	2021	2021	

3. Summary statistics after mahalanobis distance matching across treatment group and control groups

Table A3: Summary statistics after Mahalanobis distance matching

Variable	**NDL=1, Same-Sex=0**	**NDL=0, Same-Sex=1**	**NDL=1, Same-Sex=1**	**NDL=0, Same-Sex=0**
Denial	0.1633	0.2159	0.2118	0.1779
NDL	1.0000	0.0000	1.0000	0.0000
Same-Sex	0.0000	1.0000	1.0000	0.0000
Ln Loan Amount	5.1430	5.1094	5.1089	5.1398
Ln Applicant Income	4.7068	4.6802	4.6726	4.7147
Loan-to-Income Ratio	2.0740	1.9946	2.0852	1.9861
Male	0.4945	0.4924	0.4925	0.4958
Hispanic	0.1036	0.1009	0.0998	0.1035
Black	0.0572	0.0549	0.0542	0.0568
Asian	0.0606	0.0569	0.0564	0.0607
Other Races	0.0094	0.0082	0.0077	0.0096
FHA Loan	0.0634	0.0645	0.0624	0.0627
VA Loan	0.0050	0.0047	0.0045	0.0052
FSA RSH Loan	0.0025	0.0025	0.0024	0.0026
Home Improvement	0.1659	0.1650	0.1655	0.1656
Refinance	0.3556	0.3577	0.3587	0.3557

4. Mortgage applications following the enactment of non-discrimination law

Table A4: Mortgage applications following the enactment of non-discrimination law

	(1) Risk_75	(2) Risk_90
Same-Sex	-0.0170***	0.0042**
	(0.0037)	(0.0020)
*Same-Sex*NDL*	0.0211***	0.0105***
	(0.0049)	(0.0036)
Bank*County*Year fixed effects	Yes	Yes
Adjusted R-squared	0.0659	0.0371
Observations	9,059,616	9,059,616

This table presents the changes in demand and characteristics following the implementation of the non-discrimination law. Following Chu *et al.* (2021), we use the 75th and the 90th of the loan-to-income ratio as the threshold to define two risk measures. Risk_75 is a dummy variable, equal to 1 if loan-to-income ratio is greater than the 75th percentile. Risk_90 is a dummy variable, equal to 1 if loan-to-income ratio is greater than the 90th percentile. Definitions of variables are listed in the internet appendix Table A1. In parentheses are standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Different fixed effects controls

Table A5: Non-discrimination law and same-sex borrowers loan level mortgage decision.

	Dependent variable = *Denial*		
	(1)	(2)	(3)
Same-Sex	0.0305***	0.0298***	0.0298***
	(0.0028)	(0.0026)	(0.0026)
*Same-Sex*NDL*	0.0144***	0.0152***	0.0148***
	(0.0029)	(0.0023)	(0.0026)
Male	-0.0025	-0.0024	-0.0022
	(0.0023)	(0.0024)	(0.0023)
Hispanic	0.0593***	0.0591***	0.0581***
	(0.0021)	(0.0023)	(0.0022)
Black	0.1365***	0.1392***	0.1362***
	(0.0049)	(0.0050)	(0.0049)
Asian	0.0594***	0.0592***	0.0589***
	(0.0047)	(0.0046)	(0.0047)
Other Races	0.0881***	0.0906***	0.0882***
	(0.0108)	(0.0115)	(0.0107)
FHA Loan	-0.0046	-0.0127*	-0.0029
	(0.0053)	(0.0053)	(0.0053)
VA Loan	-0.0244***	-0.0270***	-0.0233***
	(0.0059)	(0.0063)	(0.0062)
FSA/RSH Loan	0.0397**	0.0387*	0.0382*
	(0.0161)	(0.0167)	(0.0166)
Home Improvement	0.2604***	0.2660***	0.2617***
	(0.0195)	(0.0209)	(0.0198)
Refinance	0.0865***	0.0871***	0.0865***
	(0.0071)	(0.0074)	(0.0071)
Ln Applicant Income	-0.0797***	-0.0799***	-0.0795***
	(0.0031)	(0.0032)	(0.0032)
Loan Amount/Income	0.0019	0.0019	0.0020
	(0.0012)	(0.0011)	(0.0012)
Bank fixed effects	No	Yes	No
County fixed effects	Yes	No	No
Bank*Year fixed effects	Yes	No	Yes
County*Year fixed effects	No	Yes	Yes
Adjusted R-squared	0.1785	0.1753	0.1948
Observations	7,525,620	7,525,620	7,525,620

6. Robustness: Controlling for Time-Varying State-Level Characteristics

Location is a key factor that may confound the relationship between the passage of NDL and lending outcomes. For instance, states with larger LGBT populations may be more likely to enact such laws. To address this concern, we incorporate a set of observable state-level characteristics into our regression analysis.

Table A6 reports the results. In addition to the standard set of control variables, we include several time-varying state-level covariates: the logarithm of annual state population, GDP, unemployment rate, and the proportion of the LGBT population. These data are obtained from the U.S. Bureau of Economic Analysis. Importantly, after controlling for these factors, we continue to observe a statistically significant increase in the denial gap following the adoption of NDL.

Table A6: Additional state controls

	Denial (1)
Same-Sex	0.0285***
	(0.0027)
*Same-Sex*NDL*	0.0154***
	(0.0025)
Log GDP	-0.4032
	(1.4801)
Log State Income	3.7067
	(2.5424)
Log Population	-3.2283**
	(1.2908)
Rate Adjusted	-0.6447
	(27.0429)
LGBT percentage	-1.0995
	(1.5805)
Control variables	Yes
Bank*County*Year fixed effects	Yes
Adjusted R-squared	0.2443
Observations	7,525,620

7. ML out-of-sample performance metrics

Table A7: Default ML model performance

Sampling Method	Accuracy	Precision	Recall	F1 Score	ROC AUC Score
Hybrid Sampling	0.7479	0.0119	0.5000	0.0232	0.6813
Under Sampling	0.6817	0.0143	0.7701	0.0282	0.7447
Over Sampling	0.7177	0.0095	0.4483	0.0187	0.6328

8. Loan officer departure

Another piece of evidence supporting the hypothesis of insufficient soft information collection is the significant decline in the number of loan officers following the implementation of NDL. Drexler and Schoar (2014) suggest that when loan officers leave, they generate a cost to the bank. As the departing loan officers have no incentives to voluntarily transfer the soft information, borrowers are less likely to receive new loans from the bank in their absence. To test this conjecture, we employ two metrics: the total number of loan officers and the number of loan officers per 1,000 jobs, to observe changes in loan officer employment following the implementation of the NDL.

The first metric, the total number of loan officers, captures the overall count of loan officers within a given state. The second metric, jobs per 1,000, represents the number of loan officers employed per 1,000 jobs in the state. To account for potential variations in loan officer employment across states, we include Bank*Year fixed effects in our analysis.

Table A8 provides further evidence supporting information friction channel. Both the number of loan officers and the number of loan officers per 1,000 jobs declined after the implementation of NDL. The results suggest that the implementation of the NDL may lead to information frictions, potentially driven by the departure of loan officers.[1]

Table A8: Information friction and Loan Officer Departure

	Dependent Variable	
	Number of Loan Officers	Loan Officer Jobs per 1000 Workers
NDL	-0.4318***	-0.0977***
	(0.0010)	(0.0008)
Bank*Year Fixed Effects	Yes	Yes
Adjusted R-squared	0.4775	0.4487
Observations	7,525,620	7,525,620

Note: This table reports the effect of NDL on loan officer employment outcomes. Column 1 uses the raw number of loan officers, and Column 2 scales by the local labor force. Standard errors are clustered at the state level. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

[1] Despite limited growth in loan officer employment, approximately 22,900 openings for loan officers are projected each year, on average, over the decade. Most of these openings are expected to result from the need to replace workers who transfer to different occupations or exit the labor force, such as to retire. For more details, see https://www.bls.gov/ooh/business-and-financial/loan-officers.htm#tab-6.

9. Alternative matching method

Table A9: Alternative matching method: PSM(1-NN)

	Denial (1)
Same-Sex	0.0311***
	(0.0032)
*Same-Sex*NDL*	0.0136***
	(0.0029)
Log Income	-0.0774***
	(0.0036)
Loan-to-Income	0.0060***
	(0.0018)
Male	-0.0038
	(0.0026)
Hispanic	0.0596***
	(0.0031)
Black	0.1309***
	(0.0059)
Asian	0.0517***
	(0.0052)
Other Races	0.0792***
	(0.0135)
FHA Loan	-0.0008
	(0.0049)
VA Loan	-0.0320***
	(0.0076)
FSA/RHS Loan	0.0231
	(0.0212)
Home Improvement	0.2712***
	(0.0204)
Refinance	0.0880***
	(0.0070)
Control variables	Yes
Bank*County*Year fixed effects	Yes
Adjusted R-squared	0.2724
Observations	2,800,194

10. Average denial rates change overtime

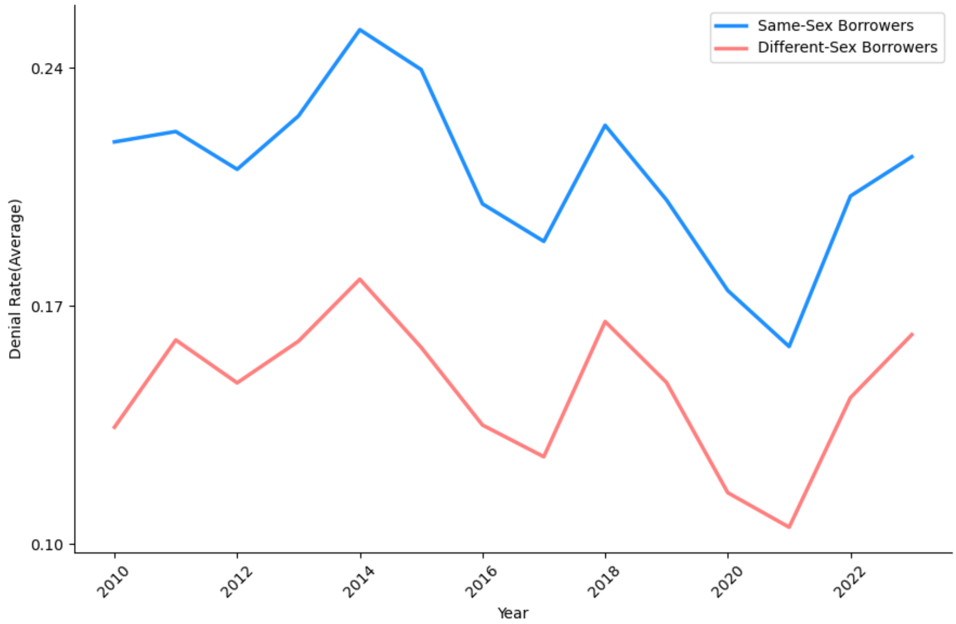

Figure A1: Average denial rates change overtime

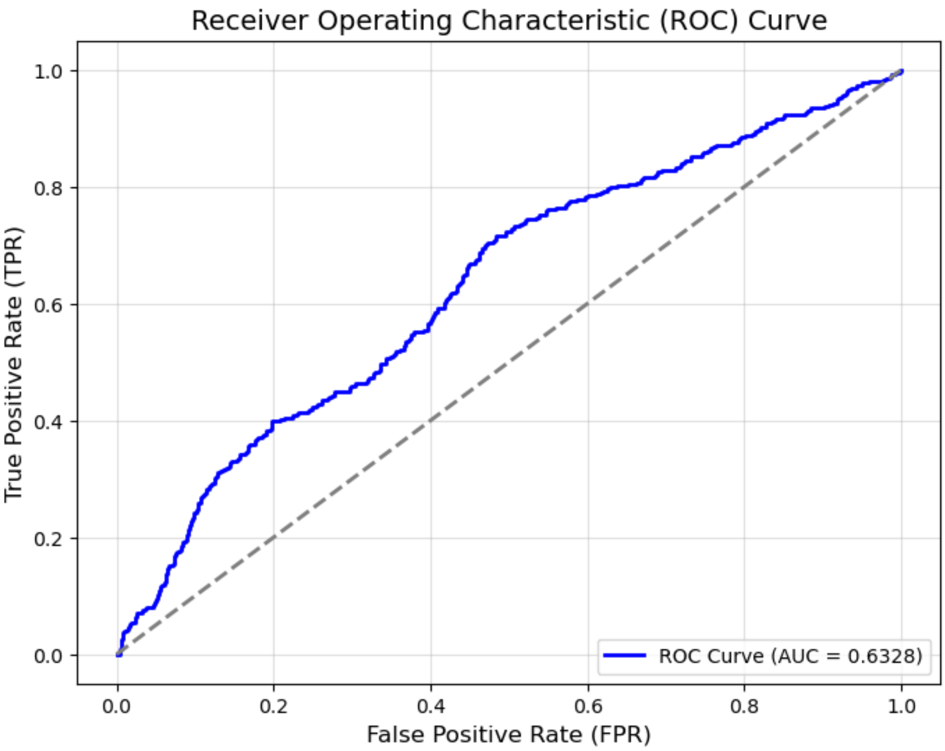

Figure A2: AUC Curve: Prediction on default probabilities

References

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