Same-sex marriage laws and lending to same-sex couples

Jens Hagendorff, Duc Duy Nguyen, Vathunyoo Sila

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Abstract

We use the staggered adoption of same-sex marriage legalization across the U.S. to study its effects on same-sex couples' access to credit. Following the legalization of same-sex marriage, same-sex couples are *more* likely to be denied mortgage credit when compared to different-sex couples. Our data do not support opinion backlash as an explanation for the increasing denial gap. Instead, our results suggest that information frictions between loan officers and same-sex borrowers play a role in explaining the disparate treatment of same-sex and different-sex applicants. Our findings suggest that mortgage lending decisions may not be as automated as widely thought.

JEL classifications: G21, I28, J15, K36
Key words: Banks, mortgages, same-sex marriage

1. Introduction

The residential mortgage market is the largest consumer finance market in the U.S. Mortgage credit facilitates homeownership and is linked to the near-universal aspirations for a family life, wealth creation, and upward mobility. Successive U.S. administrations have embraced the expansion of housing credit and the principle of equitable access to housing finance. However, studies show that minority applicants face hurdles when accessing mortgage credit (Bayer, Ferreira, and Ross, 2018; Munnell et al., 1996; Ross and Yinger, 2002). This includes homosexual couples who, controlling for various characteristics, are more likely to be denied mortgage loans than heterosexual couples (Sun and Gao, 2019). Motivated by work demonstrating that the legalization of same-sex marriage (SSM) is accompanied by improved public attitudes toward sexual minorities (Aksoy et al., 2020; Bishin et al., 2016; Ofosu et al., 2019), our paper investigates whether the legalization of SSM affects access to credit for same-sex couples.

We examine detailed mortgage application data from 2004 to 2017 and classify applications as having been made by a same-sex couple if the main applicant and co-applicant are of the same sex. We find that following the recognition of SSM, the mortgage "denial gap" between same-sex and different-sex applicants *increases*. Before SSM legalization, same-sex couples are 4.07% more likely to be denied credit than different-sex couples. After SSM legalization, the denial gap increases to 4.95%. Importantly, the denial rate of applications made by different-sex applicants is not affected by SSM laws, which implies that the increase in the denial rate is confined to same-sex applicants.[1]

[1] We follow Sun and Gao's (2019) approach of inferring sexual orientation from application data published under the Home Mortgage Disclosure Act (HMDA). Sun and Gao demonstrate that their method accurately tracks the sexual orientation of the U.S. population by contrasting their estimates of the number of homosexual households against estimates derived from Gallup and Census Bureau surveys over several decades. A key advantage of Sun and Gao's approach is its comprehensive coverage. The coverage of other indicators of sexual orientation are patchy because they are confined to the geographic areas and time periods covered by surveys. While our indicator of same-sex households is estimated with error, surveys that rely on respondents' self-identification also suffer from measurement

To identify how SSM legalization affects the mortgage denial gap for same-sex applicants, our estimations exploit the staggered state-level introduction of SSM legislation. This setup allows us to contrast loan denial rates along two dimensions: (i) applications submitted in states that recognize SSM and applications submitted in states that do not recognize SSM; and (ii) applications submitted by same-sex and different-sex applicants. The rich data set allows us to match applications along all observable covariates across same-sex and different-sex couples, as well as before and after SSM legalization. Additionally, we saturate the models with bank*county*year fixed effects to absorb time-varying credit supply factors (e.g., banks' underwriting standards) and time-varying demand-side factors (e.g., local demographic, social, and economic factors). Conceptually, our analysis compares mortgage outcomes before and after SSM legislation in the same bank, county, and year between two otherwise identical couples: one that is different-sex and one that is same-sex.

We further sharpen the identification of the effects of SSM by focusing on states in which SSM was implemented via court orders and state legislatures. Arguably, these implementation methods are less influenced by public opinion and therefore make a stronger case for the exogeneity of SSM laws with respect to mortgage underwriting.[2] We show that the denial gap increases when SSM laws are implemented via court orders and state legislatures but not when SSM laws are introduced via referenda.

errors when respondents are reluctant to engage with surveys asking about their sexual orientation. In our data, we confirm the measure is a reasonable indicator for applications by homosexual couples. We show high correlation between the state-level share of same-sex mortgage applications and the share of homosexual households reported in the American Community Survey. Our results also hold when we restrict the sample to applications in which the applicant and co-applicant are of different races. This reduces the concern that family members could be misclassified as homosexual couples.

[2] In unreported analyses, we estimate a Cox hazard model and find no significant relation between the passage of SSM laws and macroeconomic factors (e.g., GDP per capita and GDP growth at both national and state levels) or the state-level proportion of votes cast for Republicans candidates in Presidential elections.

Our results hold when we control for state-level attitudes toward sexual minorities (e.g., previous bans on SSM or antidiscrimination laws that include sexual orientation) and when we use even tighter model specifications that allow each bank to have different underwriting models for different counties in different years. The latter alleviates concerns that our results capture differences between same-sex and different-sex applications in how they are matched with lenders with different lending standards (Ross and Yinger, 2002).

In a more detailed analysis, we explore the origins of the increasing denial gap between same-sex and different-sex applicants. The first channel that we examine is opinion backlash, which posits that SSM legalization causes greater disapproval of same-sex relationships (Flores and Barclay, 2016; Ofosu et al., 2019) and implies that loan officers deny applications made by same-sex couples for noneconomic reasons. To test this channel, we analyze whether loan officers impose stricter standards on same-sex applicants in the post-SSM period and only approve the highest-quality same-sex applicants. If so, the loans made to same-sex couples would be of higher quality than the loans made to different-sex applicants.

We find no relation between SSM legalization and the quality of the loans originated to same-sex borrowers (measured by applicants' FICO scores, loan-to-value ratios, and defaults). Additionally, we do not find that the effects of SSM laws on the denial gap stem from more socially conservative regions (based on state-level religiosity and antidiscrimination laws). Therefore, our data do not support opinion backlash as an explanation for the higher mortgage denial rates for same-sex borrowers.

Instead, our evidence lends support to a second channel: information frictions between loan officers and same-sex borrowers. While decisions on mortgage originations rely primarily on credit scores and other "hard" information (Stein, 2002), some lenders also process "soft" information on applicants such as data on employment stability, the quality of the data submitted, or the applicants' emotional attachment to the property (Arentsen et al., 2015; Keys et al., 2010).

We argue that if loan officers are less familiar with applications from same-sex couples, they will find it more challenging to process soft information on this group of applications. In particular, when demand for mortgage finance from same-sex couples increases post-SSM legalization (Miller and Park, 2018), loan officers may struggle to expend the additional effort required to process soft information on same-sex couples. If soft information are less likely to move the needle toward positive lending decisions for same-sex couples, mortgage decisions for this group will more likely be based on hard information.[3]

Our data offer broad support for this conjecture. First, by exploring loan officers' reasons for rejection (as entered into the application registry), we find that following SSM legalization, same-sex borrowers face a significantly higher likelihood of being denied a loan over less tangible "unverifiable information." Second, loan decisions that involve same-sex borrowers become increasingly standardized after SSM legalization and contain less soft information. Third, we show that the increase in the rate of denial of same-sex mortgage applications is more pronounced among large banks and national banks, which are less inclined to collect and act on soft information than small banks and less willing to lend to "informationally difficult" borrowers as a result (Berger et al., 2005). Finally, we find that when loan officers have more exposure to applications from same-sex borrowers, the dispersion in lending outcomes between same-sex and different-sex couples is

[3] Our arguments around the role of soft versus hard information in mortgage originations to minority applicants follow those presented in Calomiris, Kahm, and Longhofer (1994). The authors develop a model around how racial differences between loan officers and applicants cause a cultural disconnect that leads lenders to place more of an emphasis on hard and less of an emphasis on soft information (rather than engage in the costly collection of soft information).

reduced. In counties and at banks that receive a higher share of applications from same-sex couples, increases in mortgage denial rates are lower.

Our analysis is related to a long line of existing research that studies differential lending practices and minority groups. While this body of literature mainly focuses on differences in lending practices along racial and ethnic lines (e.g., Bayer et al., 2018; Calomiris et al., 1994; Munnell et al., 1996; Ross and Yinger, 2002), Sun and Gao (2019) show that same-sex mortgage applicants also experience lower approval rates. We contribute to this work by exploring the reasons for this denial gap. In particular, we use the increase in demand for housing finance generated by the extension of marriage rights to same-sex couples to test for the impact of information processing frictions on the denial gap.

Second, our analysis is related to the literature on information production and monitoring between borrowers and lenders (for a review, see Liberti and Petersen, 2019). Residential mortgage originations are predominantly based on hard borrower information. The view that mortgages are hard information products underpins massive securitization markets (Stein, 2002) as well as the rise of FinTech lenders that rely on hard information to make instant underwriting decisions (e.g., Stulz, 2019; Berg et al., 2020, for consumer lending). To date, evidence on the soft information content in mortgages is mainly restricted to the mortgages of low-income borrowers (Arentsen et al., 2015; Ergungor, 2010; Keys et al., 2010). We contribute to this work by presenting results that suggest routine mortgages contain a non-negligible soft information element. We do so by showing that when banks experience an increase in applications from a group whose soft information they are less familiar with, they reject more applications from that group.[4] Our results imply that routine mortgage lending is less automated than some of the literature assumes.

[4] Similarly, evidence from the corporate lending literature suggests that lenders focus on known corporate borrowers with whom they have existing relationships over new unknown borrowers. Dell'Ariccia et al. (2020) show that banks

Finally, we also contribute to the literature that examines whether SSM legislation shapes attitudes toward sexual minorities. The economics and political science literature has produced mixed evidence on whether "laws change minds" and improve public attitudes or generate an opinion backlash (Aksoy et al., 2020; Bishin et al., 2016; Flores and Barclay, 2016; Ofosu et al., 2019). However, questions remain over how accurate polling evidence is if individuals are reluctant to respond honestly about antigay views (Coffman, Coffman, and Ericson, 2017). While our paper also addresses whether laws change minds, it does so by drawing on the observed behavior of agents in a financial market. Our findings question the extent to which the changes in attitudes reported in the literature translate into changes in the economic treatment of same-sex couples.

2. The road to marriage equality for same-sex couples

The road to marriage equality for same-sex couples in the U.S. was bumpy. Crucial for the eventual legalization of SSM was the interplay between state and federal courts and state legislatures. Owing to this institutional interplay, the introduction of SSM was piecemeal and staggered across time and states, which aids our identification of the effects of SSM laws on loan origination to same-sex couples.

After initial campaigns for marriage equality met little success,[5] Massachusetts became the first state to legalize SSM. In 2003, the Massachusetts Supreme Judicial Court in *Goodridge v.*

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shy away from informationally difficult corporate borrowers (as measured by their use of intangible assets). Similarly, De Jonghe et al. (2020) show that banks allocate more funding to sectors and borrowers with which they are familiar following funding shocks.

[5] In 1972, the Supreme Court dismissed the appeal of a ruling by the Minnesota Supreme Court (*Baker v. Nelson*) that a state statute limiting marriage to heterosexual couples "did not offend" the U.S. Constitution. Following this, various states introduced explicit bans on SSM (e.g., Maryland in 1973, California and Florida in 1977, and New Hampshire in 1987). This culminated in the 1996 Defense of Marriage Act, which prohibited recognition of SSM at a federal level and allowed states to refuse recognition of SSM granted in other states.

Department of Public Health required Massachusetts to recognize SSM from May 17, 2004. This was followed by the legalization of SSM in 13 other states, although the timing and methods of implementation differed between them. SSM was legalized through state court decisions (in California,[6] Connecticut, and Iowa), state legislative changes (in Delaware, District of Columbia, Minnesota, New Hampshire, New York, Rhode Island, and Vermont), or public state referenda on the issue (in Maine, Maryland, and Washington).

In its landmark ruling in *United States v. Windsor* on June 26, 2013, the Supreme Court declared Section 3 of the Defense of Marriage Act (DOMA) unconstitutional. In Section 3, DOMA's definition of marriage as "a legal union between one man and one woman" had effectively prohibited the recognition of SSM at the federal level. Consequently, the *United States v. Windsor* decision forced the federal government to recognize the validity of SSM licenses issued by some states. The decision also ushered in a new wave of SSM legalization in 22 states through either court decisions or changes to state legislation.

In a final key step, in *Obergefell v. Hodges*, the Supreme Court ruled on June 26, 2015 that SSM is a constitutional right. This introduced SSM to the remaining 15 states that had not yet legalized SSM at that point.[7] Therefore, *Obergefell v. Hodges* introduced nationwide access to marriage for same-sex couples regardless of their state of residence.

Table A2 (in the Appendix) summarizes the dates and methods by which SSM was legalized in each state. In many states, SSM legalization hinged on court decisions, which are less

[6] California changed its view on legalizing SSM several times. The state first issued marriage licenses to same-sex couples in June 2008 after the Supreme Court of California ruled that barring same-sex couples from marriage violated the state's constitution. However, the issuance of such licenses was halted between November 2008 and June 2013 due to a state constitutional amendment barring SSM.

[7] The states that had not legalized SSM prior to *Obergefell v. Hodges* were Alabama, Arkansas, Georgia, Kansas, Kentucky, Louisiana, Michigan, Mississippi, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Tennessee, and Texas.

likely to be influenced by public opinion than other adoption methods (Sansone, 2020; Trandafir, 2015). Further, many of the key rulings were narrow (e.g., the Supreme Court ruled 5–4 in *Obergefell v. Hodges*) and thus difficult to predict. This allows us to argue that the changes to SSM laws and their timing are plausibly exogenous to macroeconomic or state-level characteristics that could influence credit decisions. For example, some of the most socially liberal states, such as California and New York, were not among the first to legalize SSM.

3. Data and methodology

3.1. Loan origination data

Our primary source of data is the Home Mortgage Disclosure Act (HMDA) loan application registry. This repeated cross-sectional loan-level data set is based on the mandatory reporting of all mortgage applications by qualified financial institutions. Institutions are required to report HMDA data to regulators if they have at least one branch office in a metropolitan statistical area and meet a minimum size threshold.[8] Because the reporting threshold is relatively low, HMDA data cover the majority of lenders and nearly 90% of mortgage applications in the United States (Cortés, Duchin, and Sosyura, 2016).

Our sample includes mortgage applications from 2004 to 2017.[9] For each loan application, we obtain borrower demographics (e.g., income, sex, and race), loan characteristics (e.g., the amount of loan applied for and its purpose), property type and location, the decision on the

[8] In 2010, the median year in our sample, the reporting threshold is $39 million in book assets. HMDA's reporting criteria can be found at https://www.ffiec.gov/hmda/reporterhistory.htm.

[9] Our sample starts in 2004 to ensure consistency in how the information on applicants is recorded over the sample period. In 2004, the HMDA recategorized how race and ethnicity are recorded and changed the definitions of mortgages that are classified as refinancing and home improvement loans. Additionally, the HMDA significantly increased the coverage by revising the reporting threshold to include all institutions with at least $25 million in mortgage loans. See https://www.minneapolisfed.org/article/2003/hmda-changes-are-on-the-way-new-rules-take-effect-in-2004.

application (e.g., approved, denied, or withdrawn), the year in which the application decision is made, and a lender identifier.

We apply the following screening procedure. First, we exclude applications that were closed for incompleteness, withdrawn by the applicant before a decision was made, or contain missing loan or demographic information. Second, because identifying same-sex applicants requires having gender information for a main applicant and a co-applicant, we drop observations without a co-applicant.[10] Third, we drop mortgage applications from the sample if the mortgage property is non-owner occupied. Most non-owner-occupied mortgages finance investments in property (Robinson, 2012), and borrower information will be less important for the lending decisions for these applications (compared to property characteristics, e.g., the expected rental income).

Finally, following Cortés et al. (2016), we match the HMDA loan data with the summary of deposits data (maintained by the FDIC) on the location of all bank branches. We exclude loan applications that are filed with banks that do not have a branch in the same county as the mortgage property. These loans are broker-originated applications sent to external processing centers for which we cannot infer the location of the loan officers or the SSM laws that apply to that location.

In some analyses, we use the McDash data set from Black Knight Financial Services Group. This data set contains information on approved mortgages, including interest rates, applicants' risk characteristics, and loan performance.

[10] Observations without a co-applicant may include applications by both homosexual and heterosexual borrowers. Therefore, the inclusion of these applications makes the sexual orientation of borrowers undistinguishable to us and could bias our estimate of same-sex applications in the population of borrowers.

3.2. *Identifying applications from same-sex couples*

We cannot directly identify same-sex couples in our sample because the sexual orientation of applicants is not reported in the HMDA data set. To identify potentially homosexual borrowers, we follow Sun and Gao (2019) and classify applications in our sample as having been made by a same-sex couple if the main applicant and co-applicant are of the same sex.

To demonstrate that our measure provides a reasonable identification of homosexual couples in our sample period, Figure 1 plots the share of same-sex applicants derived from the HMDA data set with the share of same-sex households reported in the American Community Survey (ACS) in 50 states. Because the ACS allows household members to report their relationship status, it provides a benchmark for us to compare our measure against.[11] The figure shows a high correlation between the share of same-sex mortgage applicants and the share of same-sex households (the correlation coefficient is just under 70%). This increases our confidence in our ability to identify mortgage applications from homosexual couples.

[Figure 1 around here]

Generally, it is comforting to note that if our approach were to misclassify some same-sex applications, it would probably cause us to underestimate the true effect of SSM laws. Our identification compares the rejection rate among same-sex applications relative to the rejection rate among different-sex applications. It is not obvious why the rejection rate among misclassified (heterosexual) same-sex applications should change relative to that of different-sex applications after the passage of SSM legislation. Therefore, any measurement error that arises from

[11] The ACS identifies same-sex households based on responses from householders in which a spouse or unmarried partner is reported to be of the same sex as the respondent. Our estimation of the correlation is conservative because we exclude the District of Columbia from the estimation. Since the District of Columbia has a high representation of same-sex households in both data sets, the correlation coefficient becomes very high (89%) when we include it. See the Census Bureau's "Frequently asked questions about same-sex couple households," available at https://www2.census.gov/topics/families/same-sex-couples/faq/sscplfactsheet-final.pdf.

misclassifying applicants is likely to be uncorrelated with the regression error term and result in an attenuation bias of the coefficients toward zero.

Finally, we show in Section 4.2.2 that our results hold when we restrict the sample to applications in which the applicant and co-applicant are of difference races and/or ethnicities. This suggests that our main results do not merely capture the effect of applications from family members (e.g., siblings who live together).

3.3. Empirical model

To examine how the legalization of SSM affects loan originations to same-sex borrowers, we need to account for changes in loan originations that would have occurred in the absence of SSM. This is particularly pressing because credit origination is shaped by various demand- and supply-side factors that range from a lender's underwriting standards to local economic growth. To account for these challenges, we employ a difference-in-difference model for all mortgage applications with a co-applicant (same- and different-sex co-applicants):

$$y_{ibsct} = \alpha \times \mathit{Same\text{-}Sex}_{it} + \beta \times \mathit{Same\text{-}Sex}_{it} \times \mathit{SSM}_{st} + \mathbf{c}'_{it}\boldsymbol{\gamma} + \boldsymbol{\delta}_{bct} + \varepsilon_{ibsct}, \qquad (1)$$

where y_{ibsct} is the outcome of loan application *i* submitted to bank *b* in county *c* of state *s* in year *t*. For most of our analysis, y_{ibsct} equals one if the application is denied, and zero if it is approved. $\mathit{Same\text{-}Sex}_{it}$ equals one when the main applicant and co-applicant are of the same gender, and zero otherwise (see Section 3.2). SSM_{st} equals one if the mortgage application is submitted in a state during or after the year in which SSM is legalized in that state and zero in other years. Finally, $\mathbf{c}$ and $\boldsymbol{\delta}$ represent loan characteristics and bank*county*year fixed effects, respectively.

Mortgage applicants by different-sex couples serve as the control group in our empirical setting because evidence shows that the enactment of SSM laws does not influence the behavior of heterosexual couples in terms of their marriage and divorce rates, workforce participation, and (most importantly for us) mortgage demand (see, e.g., Miller and Park, 2018; Sansone, 2020; Trandafir, 2015). It is also worth stressing that our model estimates the impact of SSM legalization on lending decisions, not the impact of whether or not applicants are married, which we cannot observe.

The main coefficient of interest in (1) is β, which is a difference-in-differences coefficient. The first difference is between applications submitted in states that recognize SSM and applications submitted in states that do not recognize SSM when the application is made. The second difference is between same-sex and different-sex applicants.

The rich data set allows us to saturate the models with bank*county*year fixed effects to remove confounding demand- and supply-side effects. Conceptually, we identify the outcomes of applications from same-sex and different-sex couples before and after SSM legislation in the same bank-county-year. The fixed effects absorb banks' time-varying credit supply factors (e.g., underwriting standards) as well as time-varying demand-side factors (e.g., local demographic, social, and economic factors). For instance, where y_{ibsct} measures the mortgage denial rate, a positive β would indicate that after SSM legalization, same-sex borrowers face a higher mortgage denial rate compared to different-sex borrowers who apply for mortgages at the same bank, in the same county, and in the same year.

For robustness, our subsequent analyses in Section 4.2.3 also allow banks to place different weights on different loan and borrower characteristics by interacting bank*county*year fixed effects with various loan and borrower characteristics, such as applicant income and loan type.

Finally, we follow Sun and Gao (2019) and control for several observable loan characteristics, including *Ln Applicant Income*, *Loan/Income*, and indicator variables for whether the applicant is *Male*, *Hispanic*, *African American*, *Asian*, or *Other Races*, whether the purpose of the loan is *For Refinance* or *For Home Improvement*, and whether the loan is Federal Housing Administration-insured (*FHA Loan*), Veterans Administration-guaranteed (*VA Loan*), or Farm Service Agency or Rural Housing Service-insured (*FSA/RHS Loan*). All variables are defined in Table A1 in the Appendix.

3.4. Controlling for changes in borrower characteristics around SSM legalization

As the HMDA data set is a repeat cross-sectional data set, one challenge behind our inferences is that we cannot observe our treated observations in their untreated states. That is, we cannot observe whether the outcome of a particular mortgage application after SSM legalization would have been different if it had been submitted before SSM legalization. Further, as shown in this section, SSM legalization encourages more applications from same-sex borrowers, especially those from lower income and ethnic minority groups. Therefore, our results could be confounded by the compositional change in our sample after SSM legalization.

To alleviate these concerns, we use matched-sample regressions in all our analyses. Specifically, we use Mahalanobis distance kernel matching to match mortgage applications in our treatment group to observations in our three control groups (same-sex applications before SSM, different-sex applications after SSM, and different-sex applications before SSM) that are similar along all observable covariates (Cochran and Rubin, 1973; Jann, 2017).[12] We then calculate three

[12] Kernel distance matching gives more weight to control observations that are more similar to treated observations. The Mahalanobis scaling metric standardizes the distance between two observations using the sample variance-covariance matrix. Therefore, the distance between two observations along a covariate takes into account the standard deviation of that covariate. We find similar results when we instead perform a three-way matching using propensity scores calculated from the same set of covariates.

sets of weights for observations in our three control groups and incorporate these three sets of weights into our difference-in-difference estimator:[13]

$$\{E[y_{ist}|\, Same\text{-}Sex_i = 1, SSM_{st} = 1] - w_{SSM=1}^{Same\text{-}Sex=0} \cdot E[y_{ist}|Same\text{-}Sex_i = 0, SSM_{st} = 1]\} - \{w_{SSM=0}^{Same\text{-}Sex=1} \cdot E[y_{ist}|Same\text{-}Sex_i = 1, SSM_{st} = 0\,] - w_{SSM=0}^{Same\text{-}Sex=0} \cdot E[y_{ist}|Same\text{-}Sex_i = 0, SSM_{st} = 0]\}, \tag{2}$$

where $w_{SSM=1}^{Same\text{-}Sex=0}$ contains the weights for different-sex applications after SSM, $w_{SSM=0}^{Same\text{-}Sex=1}$ for same-sex applications before SSM, and $w_{SSM=0}^{Same\text{-}Sex=0}$ for different-sex applications before SSM. We calculate the three weights independently using same-sex applications after SSM as our treatment group and then separately match these observations to the three control groups.

Our matching covariates include the main applicant's income, sex, race, and ethnicity as well as the loan amount, loan type (whether the loan is a conventional loan or whether it is insured by the Federal Housing Administration, Veterans Administration, or Farm Service Agency or Rural Housing Service), and loan purpose (for home purchase, refinancing, or home improvement). We impose exact matches on categorical variables.[14] Thus, our matched applications are from applicants of the same sex, race, and ethnicity with similar incomes who

[13] Our analysis compares the average denial rate of same-sex loan applications (*Same-Sex*=1) to the average denial rate of different-sex loan applications (*Same-Sex*=0) before and after SSM ($SSM_{it} = 0/1$). The main estimation can therefore be specified as follows:

$$\{E[y_{ist}|\,\text{Same-Sex}_i = 1, SSM_{st} = 1] - E[y_{ist}|\text{Same-Sex}_i = 0, SSM_{st} = 1]\} - \{E[y_{ist}|\text{Same-Sex}_i = 1, SSM_{st} = 0\,] - E[y_{ist}|\text{Same-Sex}_i = 0, SSM_{st} = 0]\}$$

[14] In unreported analyses, we impose the matching criteria more aggressively by matching treatment applications to control applications made to the same bank. Comparing loans made to the same bank by same- or different-sex applicants before/after SSM laws further alleviates the concern that the results are driven by the compositional change in risk profile of the applicants at the bank level. We find that our main findings remain the same.

apply for loans of similar amounts of the same loan type and for the same purpose. Furthermore, to ensure common support, our final matched sample excludes treated observations that lack matched observations in any of the three control groups (Atanasov and Black, 2016, 2019).[15]

Table 1 displays the summary statistics of our covariate-balanced sample of 14,581,079 credit applications. On average, 22.85% of the mortgage applications in our sample are denied. The average applicant earns $101,504 gross and applies for a loan of $161,531.[16]

[Tables 1 & 2 around here]

To demonstrate the need for matching in our data, we show SSM recognition is associated with changes in the demand for credit by same-sex couples. First, in Panel A of Table 2, we use all applications submitted by joint applicants between 2004 and 2017 and regress *Same-Sex* on *SSM*. We include bank*year fixed effects to allow *Same-Sex* to vary across states. Consistent with Miller and Park (2018), we find that SSM legalization is associated with a 1.07% increase in the share of same-sex applications (from 3.9% before SSM was recognized). Consequently, applications by co-applicants of the same sex increased by a substantial 27% relative to applications in which the co-applicants are of a different sex.

[15] Another concern is the that after SSM laws, same-sex couples with lower credit quality self-select into co-applying for a mortgage rather than submit a solo application. Because credit quality also influences different-sex couples' decisions to apply for a joint mortgage, this self-selection only becomes a threat to our interpretation when the self-selection among same-sex borrowers is so severe that only the lowest quality homosexual borrowers apply for a joint mortgage. In unreported results, we do not find that the passage of SSM laws affects the composition of solo versus joint applicants. Therefore, while this self-selection could exist, it does not seem to change around the passage of SSM laws and is thus unlikely to explain our main findings.

[16] Table A3 in the Internet Appendix presents the breakdown and the summary statistics of both the initial sample and the final matched sample. Our initial HMDA sample (Panel A) comprises 18,335,970 mortgage applications from the HMDA data set for the period from 2004 to 2017. In Panel B, Columns (5)–(8) present the mean of the same variables when mortgage applications are divided into four groups: same-sex applications after the passage of state-level SSM laws; same-sex applications before the passage of state-level SSM laws; different-sex applications after the passage of state-level SSM laws; and different-sex applications before the passage of state-level SSM laws. Panel B presents the summary statistics after a three-way covariate balancing using Mahalanobis distance kernel matching.

Second, Panel B of Table 2 demonstrates that the characteristics of same-sex applicants changed following the recognition of SSM. We regress several applicant characteristics on *SSM*Same-Sex* and bank*county*year fixed effects. Compared to different-sex borrowers, same-sex borrowers who apply for a mortgage after SSM legalization have a lower income and request larger loan amounts; thus, they have a higher loan-to-income ratio. Therefore, recognizing SSM encourages more same-sex applicants, especially from lower income groups, to co-apply for a mortgage.

4. Main analysis

4.1. Baseline results

Table 3 presents our baseline loan-level regressions that examine the effect of SSM legalization on the likelihood that same-sex borrowers' mortgage applications are denied. The dependent variable is *Denied*, which equals one if a loan is denied, and zero otherwise. All regressions include bank*county*year fixed effects.

[Table 3 and Figure 2 around here]

We find that after SSM legalization, same-sex borrowers face a higher likelihood of mortgage denial compared to different-sex borrowers. The coefficients on *Same-Sex*SSM* are positive and statistically significant below the 1% level across all columns. The magnitude of the coefficient estimates on *Same-Sex*SSM* is stable as we progressively include more control variables in the model.

Further, the results are economically meaningful. Before SSM legalization, same-sex applicants are 4.07% more likely to be denied credit. After SSM legalization, this denial gap increases by 88 basis points to 4.95% (= 0.0407 + 0.0088). Considering the average denial rate in our sample is 22.85%, the increase in the denial gap corresponds to a substantial marginal effect of 3.85% (= 0.0088 / 0.2285). Figure 2 displays the denial gap between same-sex and different-sex applicants around SSM legalization.[17]

As our models include bank*county*year fixed effects, the estimated effects of *Same-Sex*SSM* compare the change in denial rates between same-sex and different-sex applicants who apply for mortgages at the same bank, in the same county, and in the same year. Finally, the coefficients on the control variables have the expected signs. For instance, lower income, female, non-white, and Hispanic applicants are more likely to have their mortgage applications denied. The previous literature argues that these applicants tend to have a less detailed credit history and thus face a higher likelihood of loan denial (Ergungor, 2010).

4.2. Robustness of the baseline results

Are the results due to different-sex applications? One concern with our results is that they could be driven by different-sex applicants experiencing a lower denial rate after SSM legalization. While the previous literature reports no evidence that SSM laws affect different-sex households (e.g., Sansone, 2020; Trandafir, 2015), we further address this concern by running separate regressions for same-sex and different-sex borrowers.[18] The results in Panel A of Table 4 indicate that while same-sex borrowers face a significant 1.63% higher mortgage denial rate after the state permits SSM (Column (1)), the effect is statistically insignificant and is much smaller (0.49%) for different-sex borrowers (Column (2)). This implies that our main results can be attributed to an

[17] We exclude California and Massachusetts from this analysis because of the reversal of SSM laws in California and because Massachusetts passed the law before the start of the sample period.

[18] We run one regression that includes only loans submitted by same-sex borrowers and one that includes only loans submitted by different-sex borrowers. The main coefficient of interest is *SSM*, which compares the mortgage denial rate faced by same-sex and different-sex borrowers before and after SSM legalization. Because there is no variation within each bank-county-year, we cannot include bank*county*year fixed effects.

increase in mortgage denials for same-sex borrowers and not to unobserved differences between same-sex and different-sex borrowers.

Do we correctly identify same-sex couples? To alleviate the concern that the same-sex measure could misidentify family members (e.g., fathers and sons, mothers and daughters, or siblings) as same-sex couples, Panel B of Table 4 re-estimates our main regressions using only applications in which the main applicant and the co-applicant are from different races or ethnicities, and we find that our results continue to hold.

Variations in underwriting models based on loan and borrower characteristics. Another concern is that the main coefficient (*Same-Sex*SSM*) possibly captures the differences in how applicant groups match with lenders with different lending standards (see Ross and Yinger, 2002). To alleviate this concern, we present several analyses that allow for variation in underwriting models across banks, geographical areas, and times.

[Table 4 around here]

Specifically, in Panel C of Table 4, we progressively alter our baseline specification (Column (5) of Table 3) by interacting loan and borrower characteristics with various fixed effects. Firstly, Column (1) adds the interactions between all control variables and *SSM*. This alleviates the concern that the estimate on *Same-Sex*SSM* picks up changes in banks' underwriting models before and after SSM legalization. Column (2) then includes the interactions between all control variables and bank*year fixed effects. This allows each bank to assign different weights to different borrower and loan characteristics in different years.

Column (3) replaces the interactions between the control variables and *SSM* with the interactions between the control variables and the county*year fixed effects. This allows for the possibility that lenders take into account time-varying economic and credit risks at the local level.

Finally, Column (4) presents our tightest specification. We interact all control variables with bank*county*year fixed effects.[19] Consequently, we allow each bank to have different underwriting models for different counties in different years. Across all specifications in Panel C, we find that the coefficients on *Same-Sex*SSM* are positive and statistically significant with fairly similar economic magnitude to our baseline results.

Other robustness tests. Panel D shows that our results are not driven by any particular time periods, particular banks, or particular areas. Columns (1) and (2) divide the sample into 2004–2012 and 2013–2017. Because the Supreme Court's *United States v. Windsor* decision in 2013 resulted in several states legalizing SSM in short succession, this could hinder the measurement of the effect of SSM legalization. We do not find this to be the case. Instead, the coefficients on *Same-Sex*SSM* are positive and statistically significant in both time periods. Column (3) shows that our results are not driven by the inclusion of mortgage applications submitted during the 2008–2009 financial crisis.

We also show that our results are not driven by the largest lenders in the sample. Columns (4) and (5) show that our results continue to hold after excluding the largest five and ten lenders (based on the number of mortgage applications in our sample), respectively. In Columns (6) and (7), we show that credit decisions are not driven by extreme house price movements (e.g., Brueckner, Calem, and Nakamura, 2012). Using a county-level house price index from Zillow,[20] we exclude observations that are in the top and bottom 10% of house price appreciation in the county. Finally, Column (8) restricts the sample to observations in counties adjacent to state

[19] For the results in Panel C of Table 4, we replace the continuous control variables (*Ln Applicant Income* and *Loan/Income*) with decile indicator variables. These further allow for the possibility that the relations between these variables and the lending outcome are nonlinear.

[20] Zillow's housing data is available at: https://www.zillow.com/research/data/. We use the Zillow Home Value Index for Single-Family Homes as a time series at the county level.

borders to alleviate the concern that our results capture unobserved differences in borrowers' creditworthiness across different states. We find that the coefficients on *Same-Sex*SSM* are similar to our baseline results.

4.3. Different implementation modes of SSM

The implementation of SSM laws varies by state. Specifically, the introduction of SSM can be traced back to court decisions, statutory changes, or public referenda. This variation in the mode of implementation helps sharpen our identification strategy. Since SSM legislation that hinges on a court decision is less likely to be influenced by public opinion, changes in loan underwriting to same-sex applicants following court decisions help us make a stronger case for policy exogeneity.

Similarly, SSM legislation instigated by state legislatures was often unexpected and contrarian to contemporary public opinion on the topic. For instance, some of the most socially liberal states, including California and New York, were not among the first states to legalize SSM. By contrast, a referendum is likely to be a response to increasing awareness and changes in attitude toward SSM within the state that could also correlate with banks' lending policies.

[Table 5 around here]

In line with our expectation, Table 5 indicates that while SSM implemented via court orders and state legislation are associated with an increase in the likelihood that same-sex borrowers are denied credit, the effect is insignificant in the states that pass SSM via a referendum.

4.4. Mortgage cost

Next to mortgage underwriting, we also test whether SSM legalization affects the cost of credit (conditional on mortgages being approved). Bayer et al. (2018) show that racial and ethnic differences in the price of mortgage credit can be explained by certain borrowers matching with high-cost lenders. Similarly, high-profile U.S. Department of Justice cases were brought against various banks over differentials in the mortgage credit prices they charge to different ethnic groups.[21]

[Table 6 around here]

We obtain the contractual interest rates for a subsample of approved mortgages from the McDash database.[22] Table 6 shows that the coefficient for *Same-Sex*SSM* is not statistically significant, suggesting that SSM laws only affect the likelihood of mortgage approval but not the interest rates charged to borrowers of approved mortgages. Further, the results also suggest that lenders do not offset the higher denial rate by offering same-sex applicants lower interest rates on their approved loans.

5. Economic channels

In this section, we attempt to shed light on the underlying causes for the increasing denial gap between same-sex and different-sex borrowers after SSM is recognized. We examine two potential channels: (1) opinion backlash, and (2) information frictions.

5.1. Channel 1: Opinion backlash

Is the increasing denial gap due to greater antigay sentiment? The political science literature argues that legislation on salient events can cause an opinion backlash, resulting in greater disapproval of an issue (Bishin et al., 2016).[23] Consistent with this, Ofosu et al. (2019) find

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[21] See, for instance, "Justice Department reaches settlement with Wells Fargo resulting in more than $175 million in relief for homeowners to resolve fair lending claims", the US Department of Justice: https://www.justice.gov/opa/pr/justice-department-reaches-settlement-wells-fargo-resulting-more-175-million-relief.

[22] We note that contractual interest rates do not fully reflect the actual borrowing cost, as they ignore the impact of loan fees and other costs charged by the lender, which we do not observe in our data set.

[23] To date, public opinion research suggests that backlash caused by the recognition of SSM is rare (Aksoy et al., 2020; Bishin et al., 2016). However, there are questions over the accuracy of polls if individuals are reluctant to respond honestly about their antigay views (Coffman et al., 2017). Our study draws on actual behavior in a marketplace and

that antigay sentiment increases in states that were "forced" to recognize SSM following the 2015 U.S. Supreme Court ruling. More negative attitudes toward same-sex applicants could lead loan officers to deny applications for noneconomic reasons. In our data, that means loan officers would impose stricter standards on same-sex applicants relative to different-sex applicants following SSM recognition.

Inferring bias from lending data is challenging. How applicants perform on each of the determinants of a loan's expected profitability (e.g., the probability of late payments) is not observable to us. However, our data on originated loans allow us to infer bias should banks finance only the highest quality loans for same-sex applicants. That is, if opinion backlash explains the increasing denial gap, our data would show that loans to same-sex applicants are of higher quality than loans to different-sex applicants.[24] In contrast, if the data were to show same-sex and different-sex loans are of equal quality, it is unlikely that opinion backlash explains our results.

We use three proxies to contrast the quality of loans to same-sex and different-sex applicants: the couple's *FICO* score, the *Loan/Value* ratio (both supplied at the time of the application), and loan defaults. Similar to Cortés et al. (2016), *Default* equals one if a loan becomes 90-day delinquent or enters foreclosure during the first three years of its life, and zero otherwise.[25] The credit quality data come from Black Knight Financial Services Group and cover approximately two-thirds of the U.S. mortgage market with monthly loan-level status updates. All

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should therefore be particularly suitable to isolate backlash based on observed behavior (rather than based on what respondents tell pollsters).

[24] Since the compensation of most loan officers is partly tied to the volume of originated loans and their repayment, our arguments are consistent with Becker's (1957) taste-based discrimination model in which individuals voluntarily relinquish income to cater to a prejudice. For a more detailed discussion of this approach and the general challenge of inferring bias from lending data, see Gary Becker, "The Evidence Against Banks Doesn't Prove Bias" *Business Week*, April 19, 1993.

[25] The advantage of focusing on the early years of a loan's life is that the borrower characteristics will more closely resemble those at the time the application was submitted for review (Rajan, Seru, and Vig, 2015).

regressions include bank*county*year fixed effects and control variables similar to those in Table 3. The mortgage default regressions also control for borrowers' ex-ante risk characteristics (*FICO* score and *Loan/Value* ratio).

Table 7 displays the results. Across all outcome variables, the coefficients on *Same-Sex*SSM* are statistically insignificant and economically indistinguishable from zero. Thus, there is no relation between SSM legalization and the quality of loans originated to same-sex borrowers. The coefficients on other loan and borrower characteristics highlight the main drivers of loan denial rates. Since same-sex borrowers after SSM legalization do not exhibit superior credit quality compared to different-sex borrowers, the results are at odds with a backlash-based explanation.[26]

[Table 7 around here]

As a second test of the backlash channel, we examine how our main results vary by local attitudes. We interact *Same-Sex*SSM* with various proxies for *Local Attitudes*: (1) *Religiosity*, which is the number of religious adherents divided by a county's population:[27] (2) *Social Capital*, which is the first principal component of a principal component analysis based on the percentage of eligible voters who voted in presidential elections, the county-level response rate to the Census Bureau's census, and the per capita number of social organizations and nonprofit organizations; (3) *Antidiscrimination Law*, which is a dummy variable that equals one if the state has antidiscrimination policies with respect to sexual orientation in effect for employment and

[26] Admittedly, this test cannot completely rule out a backlash-based explanation because if the "true" default rate in the population was different between majority and minority groups (see Ross, 1996), there would be scenarios that are consistent with both our finding that same-sex and different-sex borrowers have similar observable credit quality and opinion backlash. For instance, assuming that (1) same-sex borrowers are on average more likely to default than different-sex borrowers; (2) loan officers are not aware of the higher default likelihood of same-sex borrowers; and (3) loan officers are biased against same-sex applicants (due to opinion backlash). Under these assumptions, biased loan officers could unintentionally cause same-sex borrowers to have similar default rates to different-sex borrowers.

[27] The data are collected by the Association of Religion Data Archives (ARDA) for 2000 and 2010. Following Callen and Fang (2015), we interpolate the data for the remaining years.

housing;[28] and (4) *Same-Sex Marriage Ban*, which is a dummy variable that equals one for states that passed an SSM ban through ballot initiatives (McVeigh and Maria-Elena, 2009).

Table 8 displays the results. The main coefficient of interest is *Local Attitudes*Same-Sex*SSM*, which captures the heterogeneity in the increase in the denial gap across different proxies for local attitudes. In all four columns, we do not find that the coefficient on the triple interaction is statistically significant. This suggests that none of the four proxies for local attitudes can explain variation in the same-sex denial gap. The fact that the increased mortgage denial gap for same-sex couples is unrelated to local attitudes is also at odds with the backlash explanation.

[Table 8 around here]

It is also worth pointing out that the interaction terms between *Same-Sex*Antidiscrimination Law* (Column (3)) and *Same-Sex*Same-Sex Marriage Ban* (Column (4)) are both statistically insignificant. This indicates that the effect of SSM laws on the denial gap does not appear to be driven by preexisting attitudes toward homosexual relationships.

5.2. Channel 2: Information frictions

Information frictions between loan officers and same-sex borrowers could explain the higher mortgage denial rates for same-sex borrowers. Stiglitz and Weiss (1981) show that a lack of information about a borrower's credit quality leads to credit rationing. To mitigate information frictions, decisions over mortgage originations are known to rely on credit scores and other hard information that is easy to collect and verify (Stein, 2002). However, Arentsen et al. (2015), Keys et al. (2010), and others show that it is beneficial for some mortgage lenders to process soft information (e.g., on employment stability, the emotional attachment of the borrowers to the

[28] The data on state-level antidiscrimination policies is from the Center for American Progress Action Fund, see https://www.americanprogress.org/wp-content/uploads/issues/2012/06/pdf/state_nondiscrimination.pdf.

property, or the quality of the documentation provided by the borrower) as well. Unlike hard information, soft information is not easy to codify and requires a conscious effort by lenders to collect and process.

If the average loan officer is less familiar with applications from same-sex couples, they will find it more difficult to process their soft information. This argument is based on Calomiris et al.'s (1994) "cultural affinity" hypothesis. The authors use racial differences between loan officers and applicants to argue that when loan officers are culturally disconnected from the applicants, they will place a greater emphasis on hard information when evaluating borrowers. Minority applicants could then face higher loan rejection rates because (absent loan officers engaging in additional and costly collection of information on minority applicants) the hard information requirements for loan approvals might be relatively higher for them.

Our data show a large spike in demand for mortgages by same-sex couples following the recognition of SSM (see Table 2). We argue that lenders might not be able to expend the additional effort to process soft information on same-sex borrowers due to their lack of familiarity with these borrowers. To test for the role of information frictions, we perform three tests that explore the role of soft information in mortgage decisions.

First, we examine the reasons why mortgage applications are denied. While loan officers do not need to report their reasons for approving loans, they do report their reasons for denying loans in 82% of rejected loans. The reasons for loan denials range from "hard" risk characteristics (e.g., an unfavorable credit history or debt-to-income ratio) to less tangible reasons such as "unverifiable information." We argue that if loan officers struggle to obtain information on same-sex applicants relative to different-sex applicants, we should observe a higher prevalence of loans denied due to "unverifiable information" for same-sex couples post-SSM recognition.[29]

To test for this, we examine all denied mortgage applications in our sample and show in Table 9 that same-sex borrowers face a significantly higher likelihood of being denied a loan following SSM legalization because of "unverifiable information." The effect is statistically significant and economically meaningful. The estimate in the full model in Column (2) indicates that after SSM legalization, same-sex borrowers are 0.3 percentage points (63% relative to the mean) more likely to have their mortgage applications denied because of "unverifiable information" when compared to different-sex couples who apply for mortgages at the same bank in the same county and in the same year.

[Tables 9 & 10 around here]

As a second test for the information channel, Table 10 reports that loan officers incorporate less soft information into lending decisions that involve same-sex couples when compared to different-sex couples. More importantly, following the legalization of SSM, lending decisions involving same-sex borrowers incorporate even less soft information. This is consistent with the view that as loan officers process more applications from same-sex couples in the post-SSM period, existing information frictions between loan officers and same-sex borrowers mount and cause elevated denial rates for the latter.

To estimate the importance of soft information in loan decisions, we employ a methodology similar in spirit to that of Skrastins and Vig (2019). We first split our observations into same-sex and different-sex applications. For each bank-county-year, we then estimate a loan-level regression in which the mortgage denial decision is a function of all observable loan and

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[29] Table A4 lists the reasons for loan denials. In our sample, 4.76% of loans are denied because of "unverifiable information."

borrower characteristics and collect the R^2 from each regression. Thus, for each bank-county-year, we have an R^2 for same-sex applications and one for different-sex applications. Since the R^2 captures the extent to which loan officers rely on observable hard information to make approval decisions, $1–R^2$ denotes the use of soft information. Each observation is weighted by the number of applications employed in the lending decision regression. The unit of analysis is at the bank-county-year level.

Consistent with the information frictions explanation, Table 10 demonstrates that the passage of SSM laws is associated with a reduction in the use of soft information in mortgage lending decisions involving same-sex applicants. The estimated coefficient on *Same-Sex* is negative and significant, suggesting that loan officers employ less soft information to make a lending decision on same-sex applications before the passage of SSM laws. More importantly, in the post-SSM period, the use of soft information involving same-sex applicants further decreases by 32% (= 0.0071 / 0.0213).

An alternative interpretation of the results in Tables 9 and 10 is that biased loan officers are unwilling (rather than unable) to incorporate soft information on same-sex applications after SSM. To further support our interpretation, we perform various tests that exploit cross-sectional variation in loan officers' ability to incorporate soft information on same-sex borrowers after the passage of SSM laws.

First, if the results in Table 10 reflect loan officers' initial struggle to collect and process soft information involving same-sex couples, the effects should be more salient in the immediate years after SSM laws pass. To test this, we estimate the dynamic effect of SSM laws on the incorporation of soft information for same-sex and different-sex applications. The results in Figure 3 indicate that the reduction in soft information incorporated into loan decision is indeed concentrated in the first two years following the passage of SSM laws. This is consistent with the view that the increase in the rejection rates for same-sex applications is due to loan officers being overwhelmed by the increase in the number of same-sex applications.

[Figure 3 around here]

Second, we condition our mortgage denial regressions on the size and charter of lenders. Berger et al. (2005) show that large banks have a competitive disadvantage in collecting and acting on soft information relative to small banks. Similarly, soft information is less likely to be utilized by national banks. If information frictions are the main drivers of the increased denial gap after the passage of SSM laws, the effect of SSM laws on the denial gap should be more pronounced among large banks and national banks.

Table 11 presents the results that are consistent with this view. In Column (1), *Large Bank* is a dummy which equals one for banks with total assets above $1 billion. In Column (2), *National Bank* is a dummy which equals one for banks that are chartered and supervised by the federal government. In both columns, the estimated coefficients on the triple interaction terms are positive and significant, indicating that the increased denial gap faced by same-sex borrowers after the passage of SSM laws is stronger for large and nationally chartered banks.

[Tables 11& 12 around here]

Finally, we examine whether increased exposure to applications from same-sex couples mitigates the impact of information frictions. For instance, loan officers in states with a higher share of applications from same-sex couples should have an informational advantage when making lending decisions.[30] Similarly, loan officers who work for banks that receive more applications

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[30] This is consistent with prior research showing that neighborhood characteristics play a crucial role in shaping mortgage outcomes (e.g., Bayer et al., 2018; Ergungor, 2010).

from same-sex borrowers should also have an advantage in collecting and processing soft information on same-sex borrowers.

To test this idea, we include *% Same-Sex Applications* and its interactions with *Same-Sex*SSM* in the regressions and display the results in Table 12 in which *% Same-Sex Applications* is the annual percentage of same-sex applications received in each county (Column (1)) and bank (Column (2)), respectively. Across all specifications in Table 12, the interaction terms between *SS Share*Same-Sex*SSM* are negative and statistically significant at the 1% level. Again, the results are consistent with the information-based explanation that loan officers with more exposure to same-sex borrowers are less likely to deny applications by same-sex borrowers.

6. Conclusions

We analyze a large sample of applications for housing finance by same-sex and matched different-sex couples. We show that following the extension of SSM to same-sex couples, the loan denial gap faced by same-sex couples increases. Our analyses find no support for explanations that the increasing loan denial gap is due to public opinion backlash or banks applying higher standards to same-sex applicants than different-sex applicants. Rather, our results suggest that information frictions between loan officers and same-sex borrowers play a role in the disparate treatment of same-sex and different-sex applicants.

Overall, our results are consistent with the view that even in the highly integrated and standardized U.S. mortgage finance market, routine underwriting decisions rely on non-negligible soft information elements on borrowers. Furthermore, our results do not indicate that increasing antigay sentiment explains the disparate application outcomes between same- and different-sex couples. Therefore, attempts by policymakers and financial regulators to improve access to housing finance need to start by focusing on information issues faced by lenders when processing applications from minority groups. Finally, while a large body of literature suggests that SSM improves public opinion on sexual minority groups, our results question the extent to which the changes in attitudes that respondents report to pollsters lead to changes in behavior toward minority groups. Our analysis of observed behavior in a financial market suggests that respondents might not necessarily “do as they say.”

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Figure 1 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) data set (vertical axis) and the percentage of same-sex mortgage applications at the state level in the HMDA data set (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 sex as the respondent. The data cover 50 states between 2005 to 2017 since ACS data start in 2005. District of Columbia is excluded from this scatter plot, because it has a very high representation of same-sex households in both data sets. The dotted line represents the predicted values from an OLS regression.

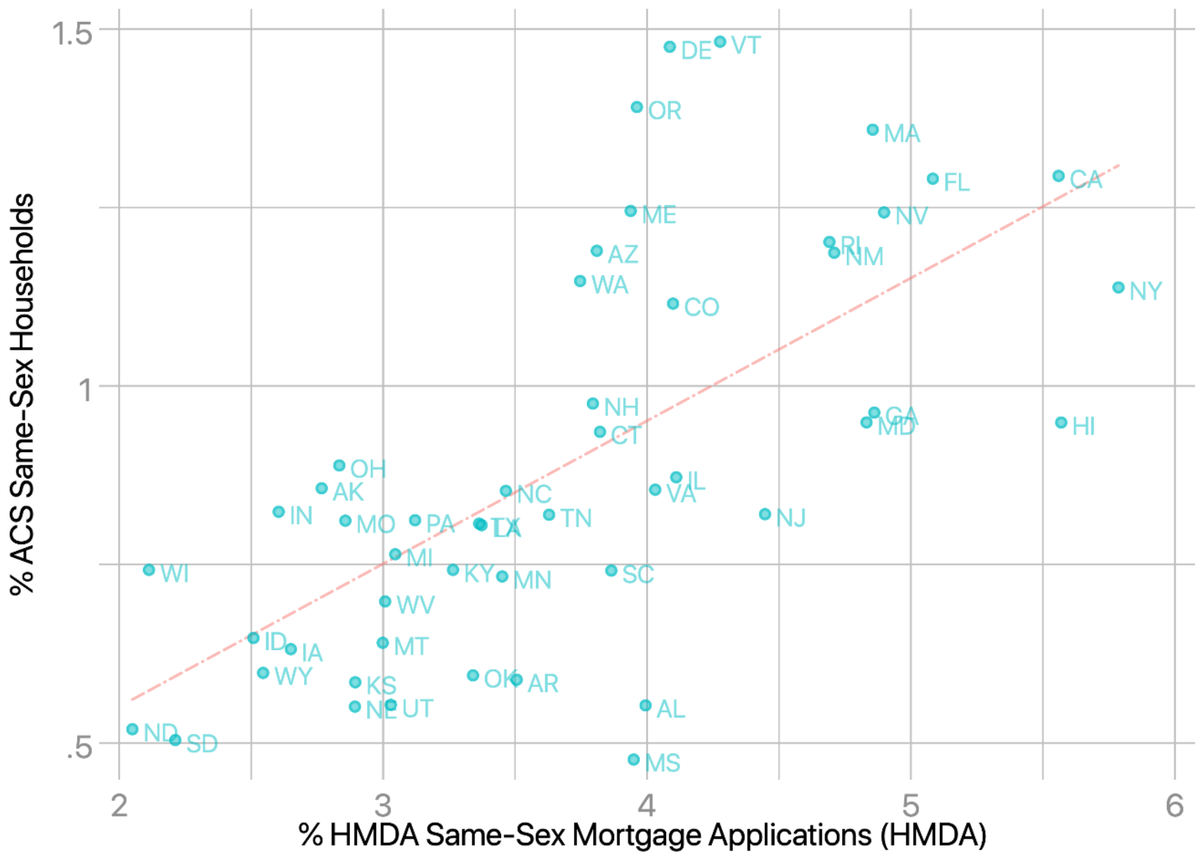

Figure 2 Dynamic effects of same-sex marriage laws on the mortgage denial gap

This figure plots the coefficient of the interaction between *Same-Sex* and time dummies for years [-5; ≥+5] relative to the passage of same-sex marriage (SSM) 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 Column (5) in Table 3. Bank*County*Year fixed effects are included in this analysis. We exclude mortgage applications for properties in California and Massachusetts. The legends indicate the 95% and 99% confidence intervals of the coefficient estimates.

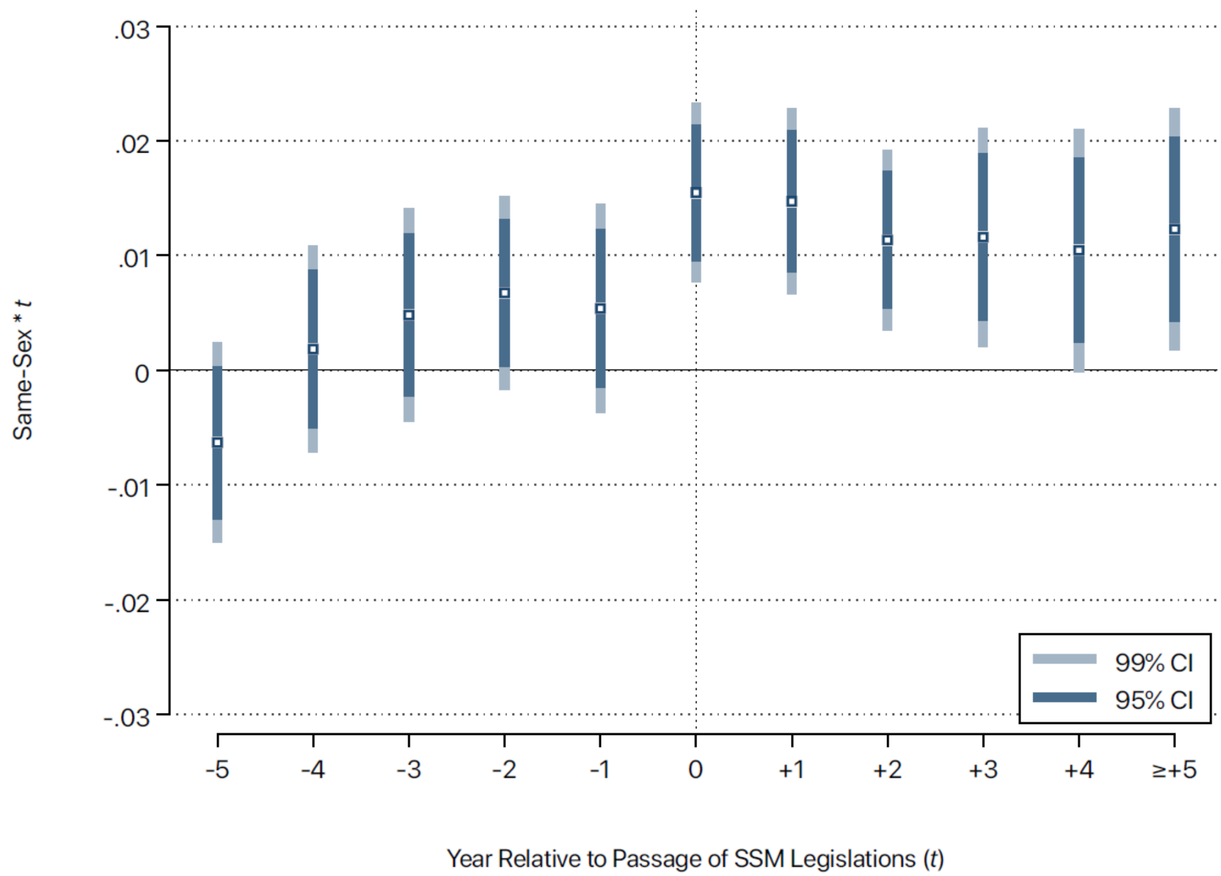

Figure 3 Dynamic effects of the soft information content in the mortgage decisions for same-sex couples

This figure plots the coefficient of the interaction between *Same-Sex* and time dummies for years [-5; ≥+5] in relation to the passage of SSM legislations. The dependent variable is 1-R^2 from the estimations of a lending decision model at the bank-county-year-same-sex level. Each observation is weighted by the number of applications employed in the lending decision regression. The control variables are the same as Column (2) in Table 8. County*Year and Bank*Year fixed effects are included in this analysis. We exclude mortgage applications for properties in California and Massachusetts. The legends indicate the 95% and 99% confidence intervals of the coefficient estimates.

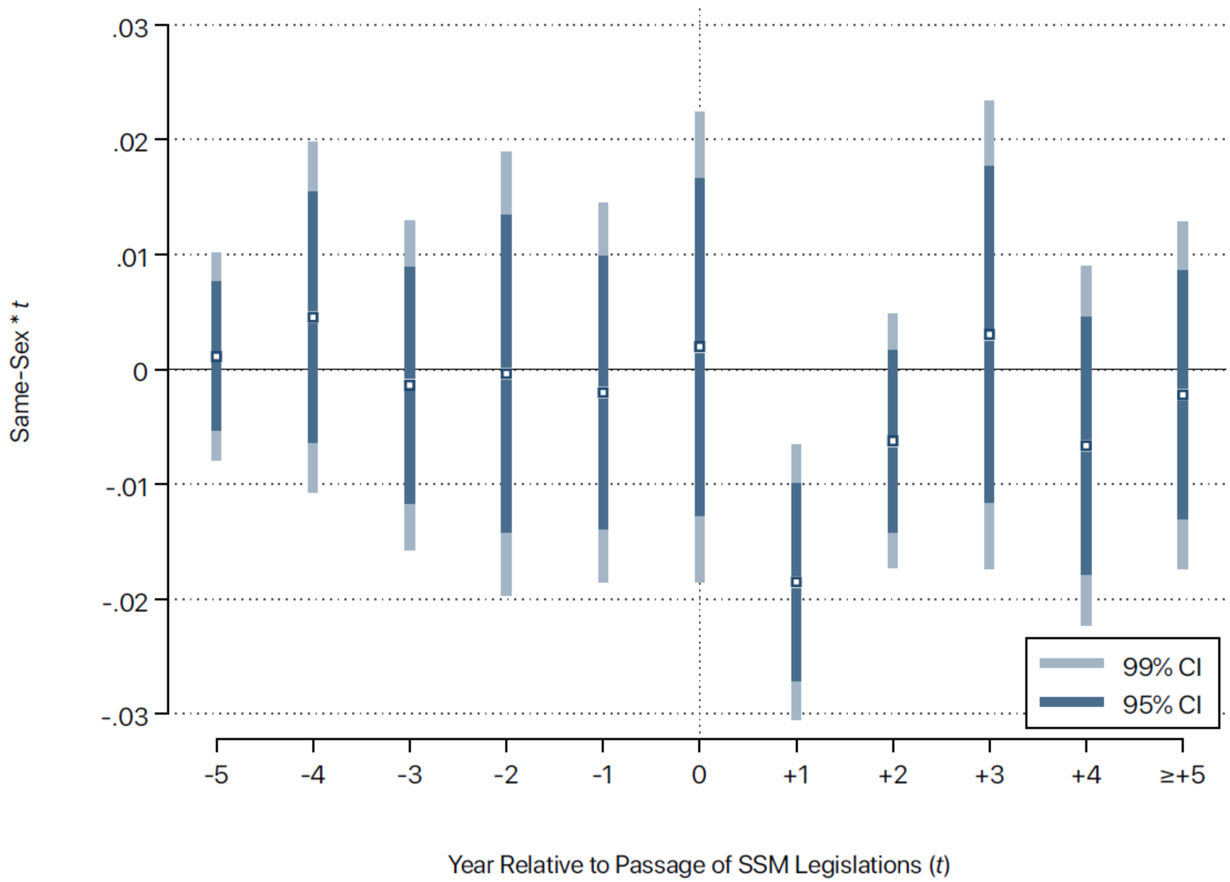

Table 1: Summary statistics

This table presents the summary statistics on key variables. The sample comprises 14,581,079 residential mortgage applications from HMDA between 2004 and 2017. We match same-sex applications, defined as applications in which the main applicant and the co-applicant are of the same reported sex, in a state following the state's recognition of SSM to three control groups. The control groups are same-sex applications before SSM, different-sex applications after SSM, and different-sex applications before SSM. We employ three-way covariate balancing using Mahalanobis distance kernel matching. Kernel matching does not alter the number of applications in the treatment and control groups but gives larger weight to control observations that are more similar to treated observations. Details on the unmatched sample and control groups are in Table A3. Variable definitions are listed in Table A1.

	Mean	Standard Deviation	Min	Percentiles 25th	50th	75th	Max
Denial	0.2285	0.4199	0.000	0.000	0.000	0.000	1.000
Same-Sex	0.0390	0.1936	0.000	0.000	0.000	0.000	1.000
SSM	0.3104	0.4626	0.000	0.000	0.000	1.000	1.000
Ln Applicant Income	4.6201	0.6261	3.045	4.174	4.595	5.024	6.554
Ln Loan Amount	5.0847	0.9644	1.609	4.644	5.220	5.720	7.003
Loan/Income	2.0759	1.2829	0.075	1.100	1.905	2.865	6.367
Male	0.5211	0.4996	0.000	0.000	1.000	1.000	1.000
Hispanic	0.1245	0.3302	0.000	0.000	0.000	0.000	1.000
Black	0.0418	0.2001	0.000	0.000	0.000	0.000	1.000
Asian	0.0925	0.2897	0.000	0.000	0.000	0.000	1.000
Other Races	0.0115	0.1068	0.000	0.000	0.000	0.000	1.000
FHA Loan	0.1053	0.3070	0.000	0.000	0.000	0.000	1.000
VA Loan	0.0071	0.0840	0.000	0.000	0.000	0.000	1.000
FSA/RSH Loan	0.0028	0.0532	0.000	0.000	0.000	0.000	1.000
Home Improvement	0.1103	0.3132	0.000	0.000	0.000	0.000	1.000
Refinance	0.4365	0.4959	0.000	0.000	0.000	1.000	1.000
% Same-Sex (State-Year)	3.7809	1.1298	1.2384	2.9871	3.5730	4.5683	15.3846
% Same-Sex (Bank-Year)	3.7640	1.7861	0.0000	2.8986	3.8945	4.5308	100.000

Table 2: Mortgage applications following the recognition of same-sex marriage

Same-Sex is a dummy that equals one if the reported sex of the main applicant is the same as the reported sex of the co-applicant, and zero otherwise. *SSM* is a dummy that equals one in a state during or after the year in which same-sex marriage is legalized in that state, and zero otherwise. Panel A estimates the change in the propensity of a loan application being from same-sex applicants after SSM laws pass. The dependent variable in Panel A is *Same-Sex*. In Panel B, the coefficients *Same-Sex*SSM* estimate the change in the differences in a couple's income, loan amount, loan-to-income ratio, sex, race, and ethnicity between same-sex and different-sex applicants after SSM laws pass. Variable definitions are listed in Table A1. In brackets are standard errors clustered at the bank-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: SSM legalization and the propensity that an application is from same-sex borrowers

Dependent variable = *Same-Sex*	(1)
SSM	0.0107***
	(0.0013)
Bank*Year fixed effects	Yes
Observations	16,086,529
Adjusted R-squared	0.006

Panel B: SSM legalization and the composition of same-sex applicants

Dependent variable =	*Ln Applicant Income* (1)	*Ln Loan Amount* (2)	*Loan/ Income* (3)	*Non-White* (4)
*Same-Sex*SSM*	-0.0172***	0.0071*	0.0200***	0.0009
	(0.0027)	(0.0038)	(0.0061)	(0.0016)
Same-Sex	-0.0503***	-0.1592***	-0.1162***	0.0230***
	(0.0017)	(0.0032)	(0.0043)	(0.0010)
Bank*County*Year fixed effects	Yes	Yes	Yes	Yes
Observations	16,073,089	16,073,089	16,073,089	16,073,089
Adjusted R-squared	0.201	0.379	0.230	0.130

Table 3: Same-sex marriage laws and loan-level mortgage decisions

Same-Sex is a dummy that equals one if the reported sex of the main applicant is the same as the reported sex of the co-applicant, and zero otherwise. *SSM* is a dummy that equals one in a state during or after the year in which same-sex marriage is legalized in that state, and zero otherwise. The dependent variable is *Denial*, a dummy that equals one if the mortgage application is denied, and zero otherwise. The coefficient on *Same-Sex*SSM* estimates the change in the denial rate after SSM laws faced by same-sex applicants compared to different-sex applicants. Variable definitions are listed in Table A1. In brackets are standard errors clustered at the bank-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable = *Denial*				
	(1)	(2)	(3)	(4)	(5)
*Same-Sex*SSM*	0.0090***	0.0078***	0.0084***	0.0089***	0.0088***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0015)
Same-Sex	0.0342***	0.0422***	0.0377***	0.0381***	0.0407***
	(0.0013)	(0.0012)	(0.0013)	(0.0013)	(0.0013)
Loan/Income	-0.0017				0.0110***
	(0.0010)				(0.0007)
Ln Applicant's Income	-0.0955***				-0.0578***
	(0.0018)				(0.0018)
Male		-0.0258***			-0.0087***
		(0.0010)			(0.0008)
Hispanic		0.1328***			0.0961***
		(0.0026)			(0.0025)
Black		0.1776***			0.1498***
		(0.0032)			(0.0029)
Asian		0.0539***			0.0482***
		(0.0025)			(0.0023)
Other Races		0.0751***			0.0606***
		(0.0065)			(0.0063)
FHA Loan			0.0334***		0.0451***
			(0.0029)		(0.0027)
VA Loan			-0.0278***		-0.0019
			(0.0044)		(0.0042)
FSA/RSH Loan			0.0192***		0.0348***
			(0.0072)		(0.0072)
For Refinance				0.1778***	0.1873***
				(0.0042)	(0.0038)
For Home Improvement				0.0778***	0.0882***
				(0.0020)	(0.0019)
Bank*County*Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	14,621,261	14,621,261	14,621,261	14,621,261	14,621,261
Adjusted R-squared	0.162	0.161	0.147	0.160	0.184

Table 4: Additional analyses

Panel A estimates the effect of *SSM* legalization on separate samples of same-sex and different-sex mortgage applications. Panel B estimates the baseline model on a subsample of mortgage applications in which the main applicant and the co-applicant have a different race and/or ethnicity. Panel C presents results with additional interactions between all control variables and various fixed effects. Panel D presents additional robustness checks on various subsamples. *Same-Sex* is a dummy that equals one if the reported sex of the main applicant is the same as the reported sex of the co-applicant, and zero otherwise. *SSM* is a dummy that equals one in a state during or after the year in which same-sex marriage is legalized in that state, and zero otherwise. Variable definitions are listed in Table A1. In brackets are standard errors clustered at the bank-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Separate regressions for same-sex and different-sex applications

Dependent variable = *Denial*	Same-Sex (1)	Different-Sex (2)
SSM	0.0084**	0.0067
	(0.0038)	(0.0063)
Control Variables	Yes	Yes
Bank fixed effects	Yes	Yes
County fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	569,950	15,483,322
Adjusted R-squared	0.116	0.093

Panel B: Different race and/or ethnicity

Dependent variable = *Denial*	(1)
*Same-Sex*SSM*	0.0175***
	(0.0065)
Same-Sex	0.0252***
	(0.0045)
Bank*County*Year fixed effects	Yes
Control Variables	Yes
Observations	574,282
Adjusted R-squared	0.267

Panel C: Interacting control variables with fixed effects

Dependent variable = *Denial*	(1)	(2)	(3)	(4)
*Same-Sex*SSM*	0.0076***	0.0077***	0.0077***	0.0058***
	(0.0016)	(0.0017)	(0.0018)	(0.0020)
Same-Sex	0.0406***	0.0410***	0.0398***	0.0394***
	(0.0013)	(0.0014)	(0.0014)	(0.0016)
Controls**SSM*	Yes	Yes	No	No
Controls*Bank*Year fixed effects	No	Yes	Yes	No
Controls*County*Year fixed effects	No	No	Yes	No
Controls*Bank*County*Year fixed effects	No	No	No	Yes
Bank*County*Year fixed effects	Yes	Yes	Yes	Yes
Observations	14,540,656	14,349,256	14,224,095	13,417,516
Adjusted R-squared	0.189	0.231	0.303	0.261

Panel D: Other robustness checks

Dependent variable = *Denial*	2004-2012 (1)	2013-2017 (2)	Excl. 2008-2009 (3)
*Same-Sex*SSM*	0.0132***	0.0131***	0.0082***
	(0.0027)	(0.0041)	(0.0017)
Same-Sex	0.0406***	0.0339***	0.0401***
	(0.0017)	(0.0035)	(0.0013)
Bank*County*Year fixed effects	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes
Observations	8,288,371	4,532,295	12,467,523
Adjusted R-squared	0.151	0.211	0.186

Dependent variable = *Denial*	Excluding 10 Largest Lenders (4)	Excl. 10% Counties with Highest House Price Growth (5)	Exl.10% Counties with Lowest House Price Growth (6)	Only counties adjacent to state borders (7)
*Same-Sex*SSM*	0.0090***	0.0088***	0.0099***	0.0113***
	(0.0023)	(0.0017)	(0.0016)	(0.0025)
Same-Sex	0.0379***	0.0409***	0.0384***	0.0392***
	(0.0016)	(0.0013)	(0.0013)	(0.0020)
Bank*County*Year fixed effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Observations	7,205,061	12,544,469	12,566,460	4,885,445
Adjusted R-squared	0.278	0.190	0.185	0.197

Table 5: Different modes of SSM implementation

This table modifies the model in Column (5) of Table 3 by replacing the *SSM* indicator variable with four indicator variables: *State Court Decisions*, *Federal Court Decisions*, *State Legislations*, and *Referendums*, which equal one when same-sex marriage is legalized through state court decisions, federal court decisions, state legislations, and state referendum respectively, and zero otherwise. The control variables include *Loan/Income, Ln Applicant's Income, Male, Hispanic, Black, Asian, Other Races*, *FHA Loan*, *VA Loan*, *FSA/RHS Loan and For Refinance*, *For Home Improvement*. *Same-Sex* is a dummy that equals one if the reported sex of the main applicant is the same as the reported sex of the co-applicant, and zero otherwise. *SSM* is a dummy that equals one in a state during or after the year in which same-sex marriage is legalized in that state, and zero otherwise. Variable definitions are listed in Table A1. In brackets are standard errors clustered at the bank-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable = *Denial*	(1)
*Same-Sex * State Court Decisions*	0.0071**
	(0.0029)
*Same-Sex * Federal Court Decisions*	0.0101***
	(0.0019)
*Same-Sex * State Legislations*	0.0094***
	(0.0030)
*Same-Sex * Referendums*	0.0054
	(0.0046)
Same-Sex	0.0401***
	(0.0013)
Bank*County*Year fixed effects	Yes
Control Variables	Yes
Observations	14,581,079
Adjusted R-squared	0.188

Table 6: Same-sex marriage laws and mortgage costs

The dependent variable, *Interest Rate (%)*, is the contractual interest rate of approved loans. Control variables include *Loan/Income, Ln Applicant's Income, Male, Hispanic, Black, Asian, Other Races*, *FHA Loan*, *VA Loan*, *FSA/RHS Loan and For Refinance*, *For Home Improvement*. *Same-Sex* is a dummy that equals one if the reported sex of the main applicant is the same as the reported sex of the co-applicant, and zero otherwise. *SSM* is a dummy that equals one in a state during or after the year in which same-sex marriage is legalized in that state, and zero otherwise. Variable definitions are listed in Table A1. In brackets are standard errors clustered at the bank-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Interest Rate (%) (1)
*Same-Sex*SSM*	0.0046
	(0.0060)
Same-Sex	0.0009
	(0.0047)
Loan/Income	-0.0873***
	(0.0030)
Ln Applicant's Income	-0.1556***
	(0.0052)
Male	-0.0060**
	(0.0028)
Hispanic	0.0175***
	(0.0047)
Black	0.0407***
	(0.0077)
Asian	-0.0266***
	(0.0065)
Other Races	0.0049
	(0.0199)
FHA Loan	-0.0723***
	(0.0061)
VA Loan	-0.1365***
	(0.0076)
For Refinance	0.4609***
	(0.0406)
For Home Improvement	-0.0487***
	(0.0047)
Bank*County*Year fixed effects	Yes
Observations	1,102,710
Adjusted R-squared	0.814

Table 7: Same-sex marriage legalization and the credit quality of mortgage applicants

The dependent variables are *FICO/100*, the FICO score reported in the application divided by 100; *Loan/Value,* the application's loan-to-value ratio; *Default*, a dummy variable which equals one if the mortgage becomes 90 days delinquent or enter foreclosure during the first three years of its life. *Same-Sex* is a dummy that equals one if the reported sex of the main applicant is the same as the reported sex of the co-applicant, and zero otherwise. *SSM* is a dummy that equals one in a state during or after the year in which same-sex marriage is legalized in that state, and zero otherwise. Variable definitions are listed in Table A1. In brackets are standard errors clustered at the bank-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable =	*FICO/100*	*Loan/Value*	*Default*
	(1)	(2)	(3)
*Same-Sex*SSM*	-0.0060	-0.0026	-0.0024
	(0.0062)	(0.0016)	(0.0019)
Same-Sex	-0.0018	0.0084***	0.0027
	(0.0051)	(0.0011)	(0.0016)
Loan/Income	0.0213***	0.0755***	0.0005
	(0.0020)	(0.0015)	(0.0006)
Ln Applicant's Income	0.1045***	0.1102***	-0.0033***
	(0.0040)	(0.0022)	(0.0010)
Male	0.0214***	-0.0029***	-0.0005
	(0.0029)	(0.0007)	(0.0009)
Hispanic	-0.0836***	0.0201***	0.0093***
	(0.0051)	(0.0014)	(0.0017)
Black	-0.1757***	0.0200***	0.0115***
	(0.0076)	(0.0019)	(0.0030)
Asian	-0.0111*	0.0027	-0.0000
	(0.0059)	(0.0017)	(0.0015)
Other Races	-0.0355*	0.0017	0.0100*
	(0.0183)	(0.0046)	(0.0058)
FHA Loan	-0.6354***	0.2038***	-0.0110***
	(0.0044)	(0.0015)	(0.0014)
VA Loan	-0.3511***	0.1624***	-0.0139***
	(0.0105)	(0.0024)	(0.0018)
For Refinance	0.0432***	-0.2406***	0.0006
	(0.0125)	(0.0051)	(0.0038)
For Home Improvement	-0.0450***	-0.0890***	-0.0024**
	(0.0040)	(0.0015)	(0.0011)
FICO/100			-0.0268***
			(0.0010)
Loan/Value			0.0084***
			(0.0032)
Bank*County*Year fixed effects	Yes	Yes	Yes
Observations	1,103,104	1,103,104	1,103,104
Adjusted R-squared	0.514	0.719	0.281

Table 8: The same-sex borrower denial gap and local attitudes

This table presents cross-sectional results on four geographical proxies for local attitudes as indicated at the top of each column. *Religiosity* is the number of religious adherents divided by a country's population. *Social Capital* is the first principal component of the following variables: the percentage of eligible voters who voted in presidential elections; the county-level response rate to the Census Bureau's decennial census; the number of social organizations in the county divided by populations; and the total number of tax-exempt non-profit organizations with a domestic focus in the county divided by populations. *Anti-discrimination Laws* is an indicator variable which equals 1 for states in which the law explicitly prohibits discrimination based on sexual orientation and gender identity. *Same-Sex Marriage Ban* is an indicator variable which equals 1 for states that passed a same-sex marriage ban through ballot initiatives (McVeigh and Maria-Elena, 2009). *Same-Sex* is a dummy that equals one if the reported sex of the main applicant is the same as the reported sex of the co-applicant, and zero otherwise. *SSM* is a dummy that equals one in a state during or after the year in which same-sex marriage is legalized in that state, and zero otherwise. Variable definitions are listed in Table A1. In brackets are standard errors clustered at the bank-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable = *Denial*			
Proxy for *Local Attitudes* =	*Religiosity* (1)	*Social Capital* (2)	*Anti-discrimination Laws* (3)	*Same-Sex Marriage Ban* (4)
*Local Attitudes*Same-Sex*SSM*	-0.0069	0.0005	0.0017	0.0016
	(0.0135)	(0.0011)	(0.0031)	(0.0032)
*Local Attitudes*Same-Sex*	0.0152	-0.0030***	0.0011	-0.0018
	(0.0104)	(0.0009)	(0.0025)	(0.0027)
*Same-Sex*SSM*	0.0124*	0.0105***	0.0081***	0.0082***
	(0.0068)	(0.0016)	(0.0024)	(0.0025)
Same-Sex	0.0327***	0.0388***	0.0394***	0.0412***
	(0.0051)	(0.0012)	(0.0019)	(0.0022)
Bank*County*Year fixed effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Observations	14,540,432	14,506,093	14,540,657	14,540,656
Adjusted R-squared	0.184	0.184	0.184	0.184

Table 9: Loan rejections due to unverifiable information

The sample includes all denied mortgage applications between 2004 and 2017 in which the loan officer includes at least one reason for denial. The dependent variable is *Unverifiable Information*, a dummy variable which equals one if the loan officer indicates that the application was denied due to unverifiable information. *Same-Sex* is a dummy that equals one if the reported sex of the main applicant is the same as the reported sex of the co-applicant, and zero otherwise. *SSM* is a dummy that equals one in a state during or after the year in which same-sex marriage is legalized in that state, and zero otherwise. Variable definitions are listed in Table A1. In brackets are standard errors clustered at the bank-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable = *Unverifiable Information*	(1)
*Same-Sex*SSM*	0.0060**
	(0.0027)
Same-Sex	-0.0014
	(0.0018)
Loan/Income	0.0017**
	(0.0007)
Ln Applicant's Income	0.0069***
	(0.0014)
Male	0.0035***
	(0.0013)
Hispanic	0.0007
	(0.0025)
Black	-0.0106***
	(0.0024)
Asian	0.0142***
	(0.0027)
Other Races	0.0068
	(0.0066)
FHA Loan	0.0089***
	(0.0031)
VA Loan	0.0114
	(0.0110)
FSA/RSH Loan	-0.0174*
	(0.0094)
For Refinance	-0.0380***
	(0.0022)
For Home Improvement	-0.0250***
	(0.0019)
Bank*County*Year fixed effects	Yes
Observations	1,035,200
Adjusted R-squared	0.139

Table 10: How important are soft information in mortgage denials?

We split our observations into same-sex and different-sex applications. For each bank-county-year, we then estimate a loan-level regression in which the mortgage denial decision is a function of all observable loan and borrower characteristics and collect the R^2 from each regression. Thus, for each bank-county-year, we have an R^2 for same-sex applications and one for different-sex applications. Since the R^2 captures the extent to which loan officers rely on observable hard information to make approval decisions, 1– R^2 denotes the use of soft information. Each observation is weighted by the number of applications employed in the lending decision regression. *Same-Sex* is a dummy that equals one if the reported sex of the main applicant is the same as the reported sex of the co-applicant, and zero otherwise. *SSM* is a dummy that equals one in a state during or after the year in which same-sex marriage is legalized in that state, and zero otherwise. Variable definitions are listed in Table A1. In brackets are standard errors clustered at the bank-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable =	Soft information (1-R^2)	
	(1)	(2)
*Same-Sex*SSM*	-0.0071***	-0.0071***
	(0.0022)	(0.0023)
Same-Sex	-0.020500***	-0.0213***
	(0.0021)	(0.0000)
Bank fixed effects	Yes	No
County * Year fixed effects	Yes	Yes
Bank * Year fixed effects	No	Yes
Observations	73,840	61,592
Adjusted R-squared	0.251	0.304

Table 11: Mortgage denials among large banks and national banks

In Column (1), *Large Bank* is a dummy that equals one for bank-years with total assets above $1 billion, and zero otherwise. In Column (2), *National Bank* is a dummy that equal one for banks that are chartered and supervised by the federal government and 0 otherwise. The *Large Bank* and *National Bank* dummy variables are centered at the sample mean so that all the coefficients represent the marginal effects of the relevant variables on an average mortgage application in the sample. *Same-Sex* is a dummy that equals one if the reported sex of the main applicant is the same as the reported sex of the co-applicant, and zero otherwise. *SSM* is a dummy that equals one in a state during or after the year in which same-sex marriage is legalized in that state, and zero otherwise. Variable definitions are listed in Table A1. In brackets are standard errors clustered at the bank-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable = *Denial*	(1)	(2)
*Large Bank * Same-Sex * SSM*	0.0106***	-
	(0.0030)	-
*Large Bank * Same-Sex*	-0.0032	-
	(0.0023)	-
*National Bank * Same-Sex * SSM*	-	0.0096***
	-	(0.0031)
*National Bank * Same-Sex*	-	-0.0020
	-	(0.0023)
*Same-Sex * SSM*	0.0078***	0.0084***
	(0.0015)	(0.0015)
Same-Sex	0.0406***	0.0416***
	(0.0012)	(0.0017)
Bank*County*Year fixed effects	Yes	Yes
Control Variables	Yes	Yes
Observations	14,538,240	14,538,240
Adjusted R-squared	0.184	0.184

Table 12: How familiar are banks with mortgage application from same-sex couples?

In Column (1), *% Same-Sex Applications by State-Year* is the number of same-sex mortgage applications divided by the total number of mortgage applications in each state-year. In Column (2), *% Same-Sex Applications by Bank-Year* is the number of same-sex mortgage applications divided by the total number of mortgage applications in each bank-year. *Same-Sex* is a dummy that equals one if the reported sex of the main applicant is the same as the reported sex of the co-applicant, and zero otherwise. *SSM* is a dummy that equals one in a state during or after the year in which same-sex marriage is legalized in that state, and zero otherwise. Variable definitions are listed in Table A1. In brackets are standard errors clustered at the bank-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable = *Denial*	% Same-Sex Applications by State-Year (1)	% Same-Sex Applications by Bank-Year (2)
*% Same-Sex Applications * Same-Sex * SSM*	-0.0037***	-0.0022***
	(0.0012)	(0.0008)
*Same-Sex Share * Same-Sex*	0.0044***	0.0009
	(0.0010)	(0.0006)
*Same-Sex * SSM*	0.0096***	0.0105***
	(0.0017)	(0.0016)
Same-Sex	0.0391***	0.0396***
	(0.0012)	(0.0012)
Bank*County*Year fixed effects	Yes	Yes
Control Variables	Yes	Yes
Observations	14,540,656	14,540,656
Adjusted R-squared	0.184	0.184

Table A1: Variable definitions

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.
SSM	= 1 if the mortgage application is submitted in a state in the year or after the year in which same-sex marriage is legalized in that state; and 0 otherwise.
State Court Decisions	=1 if same-sex marriage is legalized through a state court decision; and =0 otherwise
Federal Court Decisions	=1 if same-sex marriage is legalized through a federal court decision; and =0 otherwise
State Legislations	=1 if same-sex marriage is legalized through a state legislation; and =0 otherwise
Referendums	=1 if same-sex marriage is legalized through a public referendum; 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/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 nor 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	if the loan's purpose is for refinancing; and = 0 otherwise.
FICO/100	The FICO score reported in the application divided by 100
Loan/Value	The application's loan-to-value ratio
Default	=1 if the mortgage becomes 90 days delinquent or enter foreclosure during the first three years of its life; and = 0 otherwise
Religiosity	The number of religious adherents divided by a country's population.
Social Capital	The first principal component of the following variables: the percentage of eligible voters who voted in presidential elections; the county-level response rate to the Census Bureau's decennial census; the number of social organizations in the county divided by populations; and the total number of tax-exempt non-profit organizations with a domestic focus in the county divided by populations.
Anti-discrimination Laws	=1 for states in which the law explicitly prohibits discrimination based on sexual orientation and gender identity; and = 0 otherwise
Same-Sex Marriage Ban	=1 for states that passed a same-sex marriage ban through ballot initiatives (McVeigh and Maria-Elena, 2009); and =0 otherwise
Unverifiable Information	= 1 if the loan officer indicate that the application was denied due to unverifiable information; and = 0 otherwise.
Soft information (1–$R^{2)}$	1-R^2 from the estimations of a lending decision model regressions at the bank-county-year-same-sex level
% Same-Sex Applications by State-Year	The number of same-sex mortgage applications divided by the total number of mortgage applications in each state-year.
% Same-Sex Applications by Bank-Year	The number of same-sex mortgage applications divided by the total number of mortgage applications in each bank-year.

Table A2: Same-sex marriage legalization by state

Table A2 reports the date and method by which same-sex marriage was legalized in each state.

State	Method of Enactment	Date of Enactment
Alabama	Federal court decision	June 26, 2015
Alaska	Federal court decision	October 12, 2014
Arizona	Federal court decision	October 17, 2014
Arkansas	Federal court decision	June 26, 2015
California	State court decision	May 15, 2008
	Federal court decision	August 4, 2010
Colorado	State court decision	July 9, 2014
Connecticut	State court decision	October 10, 2008
Delaware	Legislative statue	May 7, 2013
District of Columbia	Legislative statue	December 18, 2009
Florida	Federal court decision	August 21, 2014
Georgia	Federal court decision	June 26, 2015
Hawaii	Legislative statue	November 13, 2013
Idaho	Federal court decision	October 7, 2014
Illinois	Legislative statue	November 20, 2013
Indiana	Federal court decision	September 4, 2014
Iowa	State court decision	April 3, 2009
Kansas	Federal court decision	June 26, 2015
Kentucky	Federal court decision	June 26, 2015
Louisiana	Federal court decision	June 26, 2015
Maine	Referendum	November 6, 2012
Maryland	Referendum	March 1, 2012
Massachusetts	State court decision	November 18, 2003
Michigan	Federal court decision	June 26, 2015
Minnesota	Legislative statue	May 14, 2013
Mississippi	Federal court decision	June 26, 2015
Missouri	Federal court decision	June 26, 2015
Montana	Federal court decision	November 19, 2014
Nebraska	Federal court decision	June 26, 2015
Nevada	Federal court decision	October 7, 2014
New Hampshire	Legislative statue	June 3, 2009
New Jersey	State court decision	September 27, 2013
New Mexico	State court decision	December 19, 2013
New York	Legislative statue	June 24, 2011
North Carolina	Federal court decision	October 10, 2014
North Dakota	Federal court decision	June 26, 2015
Ohio	Federal court decision	June 26, 2015
Oklahoma	Federal court decision	July 18, 2014
Oregon	Federal court decision	May 19, 2014
Pennsylvania	Federal court decision	May 20, 2014
Rhode Island	Legislative statue	May 2, 2013
South Carolina	Federal court decision	November 12, 2014
South Dakota	Federal court decision	June 26, 2015
Tennessee	Federal court decision	June 26, 2015
Texas	Federal court decision	June 26, 2015
Utah	Federal court decision	June 25, 2014
Vermont	Legislative statue	April 7, 2009
Virginia	Federal court decision	July 28, 2014
Washington	Referendum	February 13, 2012
West Virginia	Federal court decision	October 9, 2014
Wisconsin	Federal court decision	September 4, 2014
Wyoming	Federal court decision	October 17, 2014

Table A3: Distance kernel matching

Panel A presents the mean and standard deviation of key variables from the unmatched full HMDA sample. The full HMDA sample comprises 16,088,706 mortgage applications filed between 2004-2017. Panel B presents the mean and standard deviation of key variables after a three-way covariate balancing using the Mahalanobis distance kernel matching (Cochran and Rubin, 1973; Jann, 2017). The covariate balanced sample comprises 14,581,079 mortgage applications. Both panels also present the breakdown of the applications into four groups: same-sex applications after the passage of the state-level same-sex marriage laws; same-sex applications before the passage of the state-level same-sex marriage laws; different-sex applications after the passage of the state-level same-sex marriage laws; different-sex applications before the passage of the state-level same-sex marriage laws.

Panel A: Before matching

	Full HMDA Sample		Same-Sex Applications				Different Sex-Applications			
			Pre SSM Laws		Post SSM Laws		Pre SSM Laws		Post SSM Laws	
	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Denial	0.183	0.387	0.269	0.443	0.261	0.439	0.182	0.386	0.176	0.381
Ln Applicant Income	4.527	0.598	4.441	0.613	4.636	0.633	4.464	0.581	4.672	0.605
Ln Loan Amount	4.913	0.951	4.694	0.992	5.137	0.964	4.783	0.932	5.215	0.916
Loan/Income	1.908	1.190	1.769	1.233	2.150	1.317	1.802	1.156	2.148	1.218
Male	0.837	0.369	0.526	0.499	0.523	0.499	0.856	0.351	0.835	0.371
Hispanic	0.071	0.256	0.130	0.336	0.137	0.344	0.065	0.247	0.075	0.264
Black	0.034	0.180	0.058	0.234	0.043	0.203	0.035	0.184	0.028	0.164
Asian	0.050	0.218	0.058	0.233	0.108	0.311	0.037	0.188	0.077	0.266
Other Races	0.012	0.107	0.021	0.142	0.016	0.127	0.012	0.107	0.011	0.103
FHA Loan	0.057	0.232	0.134	0.341	0.114	0.318	0.057	0.233	0.048	0.214
VA Loan	0.018	0.133	0.005	0.070	0.009	0.095	0.016	0.125	0.024	0.154
FSA/RSH Loan	0.005	0.072	0.003	0.054	0.003	0.056	0.005	0.071	0.006	0.075
Home Improvement	0.110	0.313	0.115	0.319	0.107	0.309	0.113	0.316	0.105	0.306
Refinance	0.582	0.493	0.462	0.499	0.447	0.497	0.603	0.489	0.551	0.497
Observations		16,088,706		392,764		212,480		10,734,563		4,748,899

Panel B: After matching

	Matched HMDA Sample		Same-Sex Applications				Different Sex-Applications			
			Pre SSM Laws		Post SSM Laws		Pre SSM Laws		Post SSM Laws	
	Mean (1)	St Dev (2)	Mean (3)	St Dev (4)	Mean (5)	St Dev (6)	Mean (7)	St Dev (8)	Mean (9)	St Dev (10)
Denial	0.229	0.420	0.250	0.433	0.256	0.436	0.207	0.405	0.204	0.403
Ln Applicant Income	4.632	0.627	4.628	0.624	4.629	0.625	4.634	0.630	4.637	0.628
Ln Loan Amount	5.138	0.956	5.133	0.953	5.134	0.954	5.137	0.960	5.147	0.957
Loan/Income	2.148	1.303	2.143	1.297	2.145	1.300	2.146	1.307	2.157	1.309
Male	0.525	0.499	0.524	0.499	0.524	0.499	0.525	0.499	0.526	0.499
Hispanic	0.132	0.339	0.131	0.337	0.131	0.337	0.133	0.340	0.133	0.340
Black	0.039	0.194	0.038	0.192	0.038	0.192	0.041	0.197	0.040	0.195
Asian	0.105	0.307	0.103	0.305	0.103	0.304	0.107	0.309	0.107	0.309
Other Races	0.012	0.109	0.011	0.102	0.011	0.102	0.014	0.117	0.013	0.114
FHA Loan	0.109	0.311	0.108	0.311	0.108	0.311	0.109	0.312	0.109	0.312
VA Loan	0.007	0.081	0.005	0.072	0.005	0.072	0.008	0.089	0.008	0.091
FSA/RSH Loan	0.003	0.050	0.002	0.048	0.002	0.048	0.003	0.052	0.003	0.053
Home Improvement	0.104	0.305	0.102	0.303	0.102	0.303	0.106	0.307	0.105	0.307
Refinance	0.451	0.498	0.451	0.498	0.452	0.498	0.450	0.497	0.450	0.497
Observations		14,540,656		364,787		203,821		9,527,172		4,444,876

Table A4: Reasons for mortgage denials
This table presents possible reasons for denial that loan officers can report in the HMDA data set, and the percentage of applications denied due to these reasons.

Code	Reasons	%
1	Debt-to-income ratio	27.56
2	Employment history	1.85
3	Credit history	42.42
4	Collateral	24.69
5	Insufficient cash (down payment, closing costs)	4.97
6	Unverifiable information	4.76
7	Credit application incomplete	9.94
8	Mortgage insurance denied	0.18
9	Other	12.46