The Rainbow of Credit:

Same-sex Mortgage Discrimination and Two-sided Spillover Effect *

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Abstract

Using the Home Mortgage Disclosure Act (HMDA) national data from 1990 to 2015, we propose a method to identify potentially homosexual borrowers without requiring any self-disclosure on sexual orientation. Augmenting the HMDA data with the classical 1990 Boston Fed data and Fannie Mae Loan Performance data, we test whether their perceived homosexual status affects the approval, cost, and performance of the mortgages for which they apply. The results reveal that, in contrast with otherwise comparable loan applicants, the average approval rate for potentially homosexual applicants is about 3% to 8% lower. Furthermore, conditional on being approved, their financing cost is about 0.02% to 0.2% higher. This is equivalent to an annual total of $8.6 million to $86 million in additional interest/fees paid by same-sex borrowers nationwide. Meanwhile, we find no evidence that homosexual status is associated with higher default risk. Finally, we document evidence of a two-sided spillover effect. That is, holding other factors constant, when a neighborhood's same-sex population increases, although same-sex applicants still experience lower approval rate and higher financing cost, the treatment discrepancy between same-sex and straight applicants narrows from both sides.

Key words: Credit Rationing, Discrimination, Mortgage, LGBT

JEL Class: G21, J1

1. Introduction

In the U.S, owning a home has long been associated with achieving the American Dream. Based on the U.S. Bureau of the Census, as of 2016, the national homeownership rate is 63.7%, despite the decline since its peak value of 69.2% in 2004. One important vehicle that makes it possible for Americans to become homeowners is through a mortgage. As of 2016, the total U.S. residential loan balance is $11.45 trillion,[1] in contrast to $19.98 trillion[2] of the national debt at the same time. Due to the heavy involvement of and reliance on U.S households on the mortgage market, an economically sound and fair lending mechanism is crucial to sustaining and promoting the welfare of society.

One disturbing concern in the credit market is the likely practice by some lenders of denying loans to selected groups of people for non-economic reasons. Since the influential seminal work of Black et al. (1978), many researchers have studied lending discrimination based on skin color, gender, and race over the last four decades. For instance, minority lending discrimination has been extensively studied in consumer markets, such as the mortgage market (Ladd, 1982; Munnell et al., 1996; Ross and Yinger, 2002; Cheng et al., 2011; Bayer et al., 2016), rental housing market (Ahmed and Hammarstedt, 2008; Ahmed et al., 2008), and auto loan market (Ayres, 1991; Ayres and Siegelman, 1995; Goldberg, 1996; Morton et al., 2003).

The above studies on discrimination are echoed by many high-profile cases reported to the general public. For example, there have been numerous lawsuits alleging discrimination by auto loan lenders (and the affiliated auto manufactures, if any) against minority borrowers for overcharging them on interests. Most of these bias suits ended with multi-million dollar settlements. An incomplete list of the auto loan minority bias suit settlements includes GM (1989), Nissan (2003), Ford (2006), Ally (2013), Honda (2015), and Toyota (2016)[3].

Potentially discriminatory practices are also found in the labor market. In 2009, Walmart agreed to an $11.7 million settlement in response to an accusation of denying jobs to female applicants from

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[1] Source: Federal Reserve (https://www.federalreserve.gov/econresdata/releases/mortoutstand/current.htm).
[2] Source: U.S. Department of the Treasury (https://treasurydirect.gov/govt/reports/pd/pd_debttothepenny.htm).
[3] Sources: GM (1989) http://articles.latimes.com/1989-09-06/business/fi-1773_1_gm-suit-settlement; Nissan (2003) http://www.nytimes.com/2003/02/21/business/nissan-settles-bias-suit-by-minority-buyers.html; Ford (2006) http://articles.latimes.com/2006/nov/09/business/fi-ford9; Ally (2013) https://dealbook.nytimes.com/2013/12/20/ally-in-98-million-settlement-on-bias-in-auto-loans; Honda (2015) https://www.bloomberg.com/news/articles/2015-07-14/honda-finance-unit-agrees-to-pay-25-million-in-u-s-loan-case; Toyota (2016) http://www.latimes.com/business/la-fi-toyota-settlement-20160202-story.html.

1998 through February 2005.[4] Costco also settled an $8 million bias suit in 2013 for the claim of discriminating against women in promotions to management jobs.[5]

Despite the ample archival evidence on discrimination regarding race and gender in consumer and labor markets, fewer cases of potential discrimination on sexual orientation have been reported. According to Washington Blade, a popular LGBT news outlet, it was not until 2016 that the U.S. Equal Employment Opportunity Commission (EEOC) reached its first settlement in history in an anti-gay bias case,[6] which was against Pallet Companies for firing a lesbian employee after she complained about being harassed by her supervisor due to her sexual orientation.[7]

Motived by the huge stake that U.S. households have on the mortgage market and the lack of systematic investigations on sexual orientation-based discrimination, this paper examines potential lending discrimination on homosexual mortgage applicants. Although the federal Fair Housing Act (FHA) of 1968 and the Equal Credit Opportunity Act (ECOA) of 1974 prohibit any lending discrimination based on a borrower's race, gender, marital status, religion, and so on, they do not specifically include sexual orientation as a prohibited basis. To the best of the authors' knowledge, there is no previous academic study examining whether mortgage lenders systematically provide less access to credit (e.g., higher denial rates) or unfavorable terms (e.g., charging higher interest) for lesbian, gay, bisexual, and transgender (LGBT) borrowers, possibly due to the difficulty of identifying these types of borrowers.[8] Accompanying the wake of human rights equality for the LGBT community in recent decades, study of this specific topic of mortgage lending discrimination for LGBT borrowers is very timely.

Our study begins by investigating whether mortgage lenders are more likely to deny applicants who are potentially homosexual than other applicants with similar backgrounds. Following past research, such as Munnell et al.'s (1996) Boston Fed study and Ross and Yinger (2002), we first apply the settings similar to previously studied racial- and gender-based discrimination to our research question. This way, our results are as robust as those from previous literature and the discrimination level is contextualized. We start our test with a national sample of data from the Home Mortgage

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[4] See https://www.eeoc.gov/eeoc/newsroom/release/3-1-10.cfm.
[5] See http://www.sfgate.com/nation/article/Costco-to-pay-8-million-to-settle-gender-bias-5083273.php.
[6] See http://www.washingtonblade.com/2016/06/29/eeoc-reaches-first-ever-settlement-anti-gay-discrimination-case/.
[7] Walmart also settled a bias suit with a $7.5 million in 2016, after being claimed for denied spousal health insurance benefits to same-sex employees between 2011 and 2013. See http://money.cnn.com/2016/12/02/news/companies/walmart-discrimination-settlement/.
[8] Sexual orientation disclosure is not required for mortgage applications.

Disclosure Act (HMDA) from 1990 to 2015, and we confirm the homosexual discrimination results within the large dataset. What is more, the longer period and wider scope of the national level data allows us to study the trend of homosexual mortgage discrimination over time and geographic variation. We find that the pattern of potential lending discrimination is persistent over time.

However, due to the limited coverage of borrower information in HMDA, it misses some important information such as a borrower's credit worthiness, employment history, and other factors. As a result, we cross-validate our findings by using the classical Boston Fed dataset, which includes an extensive list of property, neighborhood, borrower, and lender characteristics for a random sample of borrowers in Boston in 1990. Our results are qualitatively consistent and quantitatively stronger when we use the Boston Fed data, indicating the lack of borrower's characteristic controls in HMDA data is unlikely to bias us toward finding a pseudo discrimination pattern. Instead, much the opposite seems to be true. That is, HMDA estimation without extensive controls on borrower's characteristics seems to provide a conservative lower bound on the magnitude of lending discrimination to same-sex borrowers.

Overall, when compared with otherwise similar loan applicants, we find the gross approval rate for potentially homosexual applicants to be from 3% (HMDA) to 8% (Boston Fed) lower. The results based on the Boston Fed data further show that homosexual applicants are about 73.12% more likely to be denied a mortgage application than heterosexual applicants with similar characteristics. In contrast, using the same data and a similar methodology, Munnell et al.'s (1996) find that compared to similar white applicants, minority applicants are about 40% more likely to be denied a mortgage.

However, studying loan approval rates alone does not establish a complete, convincing case for lending discrimination. As Gary Becker points out in his 1993 Nobel Prize speech, while commenting on minority lending discrimination, "If banks discriminate against minority applicants, they should earn greater profits on the loans actually made to them than on those to whites." Inspired by this observation, we further merge the HMDA data with Fannie Mae Single-Family Loan Performance data, which provides us more information on borrower characteristics, mortgage terms, and performance. Our results show that, after controlling for a list of loan and borrower characteristics, lenders charge 0.02% to 0.2% higher interest expenses to potentially homosexual borrowers. Based on our inferred loan balance of $43 billion from same-sex borrowers in the U.S., this is equivalent to about $8.6 million to $86 million more interest/fees paid by homosexual borrowers nationwide every year. Finally, we find no evidence that borrowers' homosexual status is associated with higher default risk.

Another striking finding from this study is a two-sided spillover effect. We use a county's (or tract's) percentage of same-sex population each year as a proxy for the friendliness of the neighborhood to LGBT people. Compared to neighborhoods of low LGBT presence and ceteris paribus, same-sex loan applicants living in more LGBT-friendly neighborhood are treated less "unfairly," as evidenced by lower approval rate drop and narrower financing cost markup. Surprisingly, hetero-sex loan applicants living in more LGBT-friendly neighborhood are treated more "unfairly," as their loan approval rates decline and financing costs increase.

Over the course of this study, we make several contributions to discrimination study literature. First, we find significant evidence that there is discrimination against LGBT group mortgage applications, and we quantify the degree of the discrimination. This important mortgage loan discrimination problem has been overlooked in the existing literature and has led to erroneous assumptions on the financial equality among groups based upon their sexual orientation. Hence our study fills in the gap by testing same-sex applicants to shed light on the existence and degree of lending discrimination against the homosexual group.

Second, our findings have strong implications for policy makers. There is no term in federal fair lending laws that explicitly forbids mortgage discrimination based on sexual orientation. We provide empirical evidence that the buyers' perceived homosexuality is an under-investigated factor in monitoring creditors' lending practices.

Last but not least, using the free and publicly available HMDA data, we propose a straightforward method to identify potentially homosexual borrowers (households) without self-disclosure requirement. As shown in section 4.1, when we compare our measured state-level percentage of homosexual borrowers with the 2012 Gallup survey on the adult LGBT population percentage, the correlation is remarkably high at 0.76. A further demonstration using Washington D.C data shows that, up to the tract level, our measure accurately matches the LGBT population percentage survey released by the U.S. Bureau of Census. As HMDA data is compiled and released annually, we can construct accurate measures of LGBT population distribution across the country every year, in contrast to 10-year release of similar information from the census data. Although this study focuses on lending discrimination against homosexual borrowers, our method suggests that researchers can also merge HMDA with other data sets, such as the Panel Study of Income Dynamics (PSID), to study a wider range of topics regarding LGBT society at the individual level that can be otherwise difficult to identify.

We proceed as follows: in section 2, we provide literature background on mortgage lending, discrimination in credit and labor markets, and relevant regulations; in sections 3 and 4, we describe the data and our research design; in section 5, we summarize our results; and in section 6, we offer conclusions.

2. Literature Review and Hypothesis Development

Though the federal Fair Housing Act (FHA) of 1968 and Equal Credit Opportunity Act (ECOA) of 1974 are in place to regulate lenders against discriminations, researchers have found strong evidence of lending discriminations against gender, racial, or ethnic groups. Using Boston Fed data, Munnell et al. (1996) reveal that minority applicants face significant discrimination on lending approval decisions. Colman (2000), using National Survey of Small Business (NSBF) data, finds that female applicants are more likely to be asked to pledge collateral and pay high interest rates than males. Cavalluzoo et al. (2002) finds that with a lack of lender competition, female-owned businesses tend to be denied credit applications more often than businesses owned by males. Such gender-based discrimination evidence has also been documented internationally; Bellucci et al. (2010) and Alesian et al. (2013) both report supportive evidence that banks discriminate against female credit applicants in Italy. In field studies, Hanson et al. (2015) finds that lenders offer more information and assistance in response to borrower inquiries and are more likely to follow up on initial contact from white borrowers.

In contrast, existing literature is silent about lending discrimination based on sexual orientation. We suspect this is mostly because of a data availability issue. Unlike gender, race, etc., a loan applicant's sexual orientation is not required to be disclosed and hence is impossible to be measured directly.

Despite the vacuum in literature on lending discrimination by sexual orientation, there is some research in other markets/fields on LGBT community that may shed light on the possible existence of such discrimination in mortgage market. Using experimental data of faked resumes with listed sexual orientation, Weichselbaumer (2003) shows that lesbians are less likely to be hired. Using questionnaires to 119 LGBT students, Schneider and Dimmito (2010) find that majority of the respondents experienced anti-LGBT discrimination in the past. Almeida et al. (2009) use survey data to show LGBT youth experience more depression, higher tendency to self-harm, or to commit suicide. The authors find that perceived discrimination is a significant contributor to the observed pattern.

The LGBT community faces discrimination in many different aspects for complex historical reasons. Notably, in the United States, the majority of citizens support the legal recognition of same-sex marriage in the recent decade.[9] This support has increased steadily for more than a decade, and has consistently remained above 50% in opinion polls since 2010.[10] However, there is significant opposition to same-sex marriage in different groups and states. This homophobia is especially associated with conservatives, many members of the Tea Party movement, people with religious beliefs conflicting with homosexuality, people who attend religious services at least weekly, some members of the Republican Party, and many people living in the Southern United States and the Bible Belt. On June 26, 2015, the U.S. Supreme Court held, in *Obergefell v. Hodges*, that the Fourteenth Amendment requires states to offer same-sex marriage and recognize same-sex marriages performed elsewhere in the country, and that state-level bans on same-sex marriage are unconstitutional. However, officials of fourteen counties in three states were still unwilling to issue licenses to same-sex couples as of October 2015.[11]

Due to the significant opposition to same-sex marriage, we should not be surprised to find discrimination against homosexual couples in mortgage applications. However, little research is available on this topic in academia. This paper attempts to fill the void. In particular, we construct a reliable proxy for homosexual orientation based on publicly available dataset to shed light on this important topic. Overall, anecdotal evidence and other results suggest lending discrimination against homosexuals is very likely to exist, and this hypothesis is the precise focus of this study.

3. Data

The Home Mortgage Disclosure Act (HMDA), a federal law enacted in 1975, requires certain financial institutions to provide mortgage data to the public. HMDA data covers information such as the applicant's race, gender, income, loan purpose, loan approval, and so on.[12] We collect HMDA

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[9] http://www.pewforum.org/2016/05/12/changing-attitudes-on-gay-marriage/
[10] http://www.gallup.com/poll/162398/sex-marriage-support-solidifies-above.aspx
[11] Alabama judges use segregation-era law to avoid gay marriage http://www.al.com/news/index.ssf/2015/10/alabama_judges_use_segregation.html#incart_river_home , and https://ballotpedia.org/Local_government_responses_to_Obergefell_v._Hodges#tab=Alabama
[12] The details of the data can be found at the FDIC website (https://www.fdic.gov/regulations/laws/rules/6500-3030.html#6500hmda1975).

national data from 1990 to 2015. The data from 1990 to 2012 is available from the National Archives' website. HMDA national data from 2013 to 2015 is likewise available from Federal Financial Institutions Examination Council's (FFIEC) website. We also collect the matching census data from these sources.

One significant limitation of the original HMDA data is their omission of important information on loan applicants, which is crucial to lenders' approval decisions and to any credible investigation of lending discrimination.[13] In response, in 1990, the Federal Reserve Bank of Boston conducted a survey of a sample of lenders in Boston Metropolitan Statistical Area (MSA) and collected detailed information on the borrowers' financial and credit strength, employment, other demographic and property characteristics. The data were later used by Munnell et al. (1996) to generate the famous Boston Fed Study, which is classic research on minority lending discrimination. The Boston Fed data was made public by the authors and have since been used by numerous researchers.

Although our major loan analysis findings are derived from HMDA national data, we cross-validate our results by using Boston Fed data. Because the public use version of the Boston Fed data does not include lender identification information, Ross and Yinger (2002) merge it with the HMDA data, and correct some coding errors in the original data. The details of the merging process are available in the data appendix of Ross and Yinger (2002).[14] The adjusted sample size from Boston Fed data is 2,316. To be consistent with the Boston Fed study and to facilitate understanding of the degree of homosexual discrimination compared to other discrimination found in earlier literature, for HMDA data we follow Munnell et al. (1996) by omitting incomplete or withdrawn loan applications. We also omit all observations from borrowers who have missing values for the variables we use in this analysis; see Table 1 for a complete list of these variables. Furthermore, as identifying same-sex borrowers requires gender information for both the main applicant and co-applicant, we drop observations that have only the main applicant on record for ease of comparison.[15] Because our HMDA data covers 1990 to 2015 and is for the whole nation—a very large sample size—we draw a 20% random sampling

[13] Lenders with information advantage practice price discrimination by charging high prices in residential mortgage market, see Gan and Riddiough (2008).
[14] The cleanup version of the Boston Fed data is downloadable from John Yinger's website (http://faculty.maxwell.syr.edu/jyinger/datasets/index.html).
[15] In an earlier draft, we also include the main applicant only observations and add a dummy control, and the findings are similar. The results are available upon request.

from the full data. The total number of observations that we use for loan approval analysis from HMDA national data is 28,988,939.

To investigate loan costs and performances, we merge HMDA's full sample with Fannie Mae Loan Performance data. This public-use Fannie Mae data includes all 30-year, fully amortizing, full documentation, single-family, conventional fixed-rate mortgages that Fannie Mae purchased since 2000. In addition to the loan performance record, the Fannie Mae data provide crucial information that is not reported in HMDA, such as borrowers' credit scores, contractual interest rates, loan-to-value ratios, debt-to-income ratios, and mortgage insurance premiums, if any, etc. Regarding the HMDA data, since 2004, HMDA has included additional information on approved loan characteristics, such as property type (e.g., single-family, manufactured homes, etc.), lien status (first, second, or non-secured), and rate spread. To take advantage of the expanded information in HMDA, we use 2004 as the starting point for our cost and performance analysis. When merging this data with Fannie Mae data, we keep all HMDA approval records regarding conventional loans that are secured by a first lien and are sold to Fannie Mae. We then merge these observations with Fannie Mae data based on the common variables available.[16] To minimize matching errors, we only retain the matched pairs that are unique from both ends. As all identified same-sex applicants from HMDA have a co-applicant present by construction, to make a meaningful comparison, we only keep the merged non-same-sex applicants that also have a co-applicant on record. After the merge, we omit the unusual observations that have loan-to-value ratios over 80% but lack any mortgage insurance policy.[17] Finally, we drop the observations that are missing information on any baseline control variables in the loan performance analysis. The list of the variables in the baseline analysis is found in model 1 of Table 10. Our final sample in the cost and performance analysis consists of 425,239 loans acquired by Fannie Mae since 2004.

A list of the key variables used in this study is reported in Table 1.

[Insert Table 1 Here]

The summary statistics is reported in Table 2.

[16] We merge by state, MSA, county, year, loan amount, loan purpose (e.g. purchase, refinancing, etc), owner-occupancy, property type, and the presence of co-borrower. County information is inferred from Fannie Mae data via the first three digits of the reported zip codes.

[17] It accounts for less than 0.005% of the matched observations.

[Insert Table 2 Here]

4. Research Design

4.1 Identifying potentially homosexual loan applicants

Because sexual orientation is not a required disclosure item, it is impossible to identify homosexual loan applicants directly from the available data. A fair concern, therefore, is how to attribute any findings to homosexual discrimination if we cannot identify homosexual applicants. However, the definition of "discrimination" from the *Cambridge Dictionaries Online* is, "discrimination is treatment or consideration of, or making a distinction in favor of or against, a person or thing based on the group, class, or category to which that person or thing is *perceived to belong to* rather than on individual merit." Hence, it is the external perception, instead of the authenticity of an identity, which matters in discrimination identification. Fortunately, measuring such perception is possible. Almeida (2009) actually finds it is very likely perceived discrimination is a contributor to emotional distress among LGBT 9th–12th grade students. To comply with the FHA and ECOA, disclosing gender information of the applicant and the co-applicant, if available, is mandatory. Therefore, based on HMDA data, whenever we observe a joint presence of a loan applicant and co-applicant with the same gender, we identify them as a potential pair of homosexual applicants, and assign one on a dummy variable called "same-sex."

To verify we propose a sensible identification strategy for identifying homosexual loan applicants, for each state in 2012, we calculate the percentage of same-sex pairs out of all identifiable applicant-pairs from the full HMDA dataset and compare this percentage with the Gallup estimate of state-level adult LGBT population percentage of the same year.[18] The correlation between our measure and the Gallup LGBT estimate is 0.76. We plot this data in Figure 1a below. Given the remarkably high correlation between these two aggregate estimates, we are confident that our measure covers a significant portion of homosexual loan applicants.

[Insert Figure 1a Here]

[18] See http://www.gallup.com/poll/160517/lgbt-percentage-highest-lowest-north-dakota.aspx.

As the HMDA dataset allows us to map each observation up to the census tract level, we further choose Washington D.C. and calculate the percentage of same-sex applicants in each census tract, using post 2010 data. We then compare our measure with a well-known LGBT population survey from the Williams institute at UCLA which is based on recent 2010 U.S census data, and common sense with news and other anecdotal evidence on LGBT communities in Washington D.C. For example, Logan Circle and DuPont Circle areas are considered as the neighborhoods with the highest gay population.[19] We include the survey results of the Williams Institute in Figure 1b, and we plot the heat map of our estimated same-sex percentage in Figure 1c. We can see our measure is consistent with both the Williams institute survey and anecdotal evidence that the commonly perceived same-sex neighborhoods are the Logan Circle and DuPont Circle areas.

[Insert Figure 1b Here]

[Insert Figure 1c Here]

However, we acknowledge our measure has its flaws. For example, it is certainly possible that some of the identified pairs in our sample are merely family members. As a result, in section 5.3, a series of robustness checks are conducted to address the concern of potential measurement errors.

4.2 Model development

There is a vast literature for studies on lending discrimination, although the literature focuses primarily on racial-based discrimination. Ross and Yinger (2002) provide a comprehensive review on this literature. As pointed out by Ross and Yinger (2002), the key challenge facing scholars as they try to understand lending discrimination is that different lenders may use different underwriting standards. As a result, it is possible that at the individual lender level, there is a common underwriting standard for everybody and, therefore, no "discrimination". However, due to the fact that applicants might be sorted disproportionally to different lenders, the sorting might lead to the case that certain types of applicants are more (or less) likely to have their applications approved.

To address this concern, we follow the methodology used by Ross and Yinger (2002) by examining several kinds of variations of lenders' underwriting models. The logit model, seen in

[19] See https://www.borderstan.com/2012/05/30/the-winner-is-dcs-gay-neighborhood/.

equation 1, is the baseline model in which we assume all lenders share a common underwriting model. The details on variable definitions can be found at Table 1.

$$Approve = \beta_0 + \beta_1 Same\text{-}Sex + \beta_2 Male + \beta_3 RaceDummy + \beta_4 Occupied + \beta_5 LTI + \beta_6 \log \quad Income + \beta_7 purposeDummy + \beta_8 loanTypeDummy + \beta_9 DemographicCtrl + F.E. + \epsilon \tag{1}$$

To examine the potential spillover effect, we further expand our analysis from equation 1 by adding $\text{LG}\_CountyPct$ and $Same\text{-}Sex \times \text{LG}\_CountyPct$ interaction term, as well as various lender/state fixed effects to account for varied lenders' underwriting models in a simple, systematic way.

With the additional characteristics from the Boston Fed data, we next add a comprehensive list of variables that measure loan applicants' financial, employment, educational, and demographic backgrounds. This model is shown in equation 2. Similar to equation 1, we do not include the $\text{LG}\_TractPct$ dummy in the baseline equations:

$$\begin{aligned} Approve = {} & \beta_0 + \beta_1 Same\text{-}Sex + \beta_2 Minority + \beta_3 HETI + \beta_4 TDTI + \beta_5 NetWorth \\ & + \beta_6 Predicted\ Unemp + \beta_7 Self\text{-}employed + \beta_8 PMI\ Denial \\ & + \beta_9 Multi\ Family + \beta_{10} Fixed\ Rate + \beta_{11} Special\ Program + \beta_{12} Loan\ Term \\ & + \beta_{13} Gift + \beta_{14} Co\text{-}applicant + \beta_{15} Cosigner + \beta_{16} At\ least\ 50 + \beta_{17} Male \\ & + \beta_{18} Married + \beta_{19} Occupied + \beta_{20} Poor\ Tract + \beta_{21} Bankrupcy \\ & + \beta_{22} Credit\ History + \beta_{23} LTV + \beta_{24} Short\ Work\ Exp. + \beta_{25} High\ School \\ & + \beta_{26} Dependents + Other\ Controls + F.E. + \epsilon \end{aligned} \tag{2}$$

In addition to the lender/state fixed effects and the added control variables regarding applicants' characteristics, we further allow for variations in underwriting based on loan terms. That is, we allow lenders to put different underwriting weights on various loan and borrower characteristics depending upon the nature of the loan. Ross and Yinger (2002) provide a clear example that demonstrates the importance of controlling for this type of variation:

> Consider, for example, a lender that specializes in high LTV loans and a common underwriting process in which the weight placed on the debt-to-income ratio is higher for loans with a high LTV. Under these circumstances, this lender will appear to place a higher weight on the debt to income ratio than do other lenders, even though this is not the case. (p. 194)

In order to combat this potential problem, we first identify a list of key underwriting variables (i.e., house expense-to-income ratio, total debt expense-to-income ratio, loan-to-value ratio, bankruptcy history, and borrower's consumer and mortgage credit history). We then construct pair-wise interaction terms for these variables and add them into our model.

As discussed in Ross and Yinger (2002), if lenders indeed differ on their underwriting standards, and these variations are legitimate reflections of their perceived business necessity (hence, not indicative of discrimination), these variations should reflect either differences in the applications lenders receive or differences in lenders' past experiences. As a result, conformation that potential "discrimination" in loan approval disappears after accounting for the link between a lender's underwriting standards and their portfolio will satisfy a necessary condition for the business' necessity defense (Ross and Yinger, 2002). To address this and to further control for lender underwriting standard variations, we identify a list of key lender portfolio variables, which Ross and Yinger (2002) also use. These variables are the percentage of conventional loans sold to the secondary market, average loan size, average applicant's income, and average loan-to-income ratio; we also included the pair-wise interactions of the previously identified key underwriting variables and the lender portfolio variables. The resulting model is our most comprehensive model using Boston Fed data.

At this point, we have formed models to test the likelihood of loan approval for same-sex borrowers, controlling for other social economics features. To ensure convincing findings on lending discrimination, we go one step further to check the loan cost and performance for approved applicants, because if same-sex borrowers are not discriminated against due to perceptions of their homosexual orientation, we should not expect any significant difference from the average cost and loan performance for the approved loans. However, if discrimination is found within the results, aside from individual deviations due to fundamental economic reasons, we should expect that same-sex borrowers' loans are more profitable because same-sex borrowers are more qualified for the loans with comparable terms. Other evidence of discrimination might be if, in business practice, same-sex borrowers are charged extra fees to get a similar loan. We test the following situations for approved loans: the loan spread disclosure, the rate spread, the contractual rate, and the likelihood of a default.

After 2004, a rate spread for a loan must be reported if it is above a certain threshold as defined by HMDA. Between January 2004 and September 2010, a loan's rate spread is defined as the difference between the APR on a loan and the prevalent rate on treasury securities of comparable maturity. HMDA mandates disclosure of rate spread if it is at least 3%, for a loan secured by a first lien. To check if it is more likely that same-sex borrowers experience a higher spread than hetero-sex borrowers, meaning same-sex borrowers probably pay higher interest, we define a dummy variable as set to 1 if a loan has a reported spread, and 0 otherwise. We run the following logit model as in equation 3.

$$\begin{aligned} Disclosure = {} & \beta_0 + \beta_1 Same\text{-}Sex + \beta_2 Male + \beta_3 Hispanic + \beta_4 Black + \beta_5 Asian \\ & + \beta_6 Otherrace + \beta_7 Orignal\ Loan\ to\ Value + \beta_8 \log\ \ Income \\ & + \beta_9 Borrower\ Score + \beta_{10} Co\text{-}Borrower\ Score + \beta_{11} First\ Time \\ & + \beta_{12} Num_{unit} + \beta_{13} Mortgage\ Insurance_{pct} + \beta_{14} Loan\_Purp \\ & + \beta_{15} Occupancy\ Status + Other\ Controls + F.E. + \epsilon \end{aligned} \tag{3}$$

Alternatively, we can test the rate spread directly by regressing the rate spread on loan and borrower characteristics as the following Tobit model in equation 4.

$$\begin{aligned} RateSpread = {} & \beta_0 + \beta_1 Same\text{-}Sex + \beta_2 Male + \beta_3 Hispanic + \beta_4 Black + \beta_5 Asian \\ & + \beta_6 Otherrace + \beta_7 Orignal\ Loan\ to\ Value + \beta_8 \log\ \ Income \\ & + \beta_9 Borrower\ Score + \beta_{10} Co\text{-}Borrower\ Score + \beta_{11} First\ Time \\ & + \beta_{12} Num_{unit} + \beta_{13} Mortgage\ Insurance_{pct} + \beta_{14} Loan\_Purp \\ & + \beta_{15} Occupancy\ Status + Other\ Controls + F.E. + \epsilon \end{aligned} \tag{4}$$

Although the Tobit model handles censored data better, the extremely high rate of censoring might concern econometricians, given the strong normality assumption that the model makes. We use data from Fannie Mae to further analyze the original contractual rate using equation 5.

$$CtrtRate = \beta_0 + \beta_1 Same\text{-}Sex + \beta_2 Male + \beta_3 Hispanic + \beta_4 Black + \beta_5 Asian + \beta_6 Otherrace + \beta_7 Orignal\ Loan\ to\ Value + \beta_8 \log\ Income + \beta_9 Borrower\ Score + \beta_{10} Co\text{-}Borrower\ Score + \beta_{11} First\ Time + \beta_{12} Num_{unit} + \beta_{13} Mortgage\ Insurance_{pct} + \beta_{14} Loan\_Purp + \beta_{15} Occupancy\ Status + Other\ Controls + F.E. + \epsilon \quad (5)$$

After checking the contractual rates, we check the likelihood of a default on the loans for same-sex borrowers with the following logit model in equation 6.

$$Default = \beta_0 + \beta_1 Same\text{-}Sex + \beta_2 Male + \beta_3 Hispanic + \beta_4 Black + \beta_5 Asian + \beta_6 Otherrace + \beta_7 Orignal\ Loan\ to\ Value + \beta_8 \log\ Income + \beta_9 Borrower\ Score + \beta_{10} Co\text{-}Borrower\ Score + \beta_{11} First\ Time + \beta_{12} Num_{unit} + \beta_{13} Mortgage\ Insurance_{pct} + \beta_{14} Loan\_Purp + \beta_{15} Occupancy\ Status + Other\ Controls + F.E. + \epsilon \quad (6)$$

Finally, conditional on the loans that are already in default, we employ a Cox proportional hazard model on the duration before the default to check if it same-sex borrowers tend to default later than other comparable borrowers. Making more mortgage payments still mean less risk to the banks when we compare two defaults.

5. Results

5.1 Loan approval decision

5.1.1 Main results with HMDA data

We first use the 20% random sample of HMDA data from 1990 to 2015 to test lending discrimination on sexual orientation. Before we conduct the loan approval analysis, we calculate the raw distribution of hetero and same-sex applicants based on different loan types and programs. The results are reported in Table 3.

Table 3 reveals that applications filed by same-sex borrowers account for 4.03% of the total received. However, based on the approved loans, this percentage drops to 3.75%. Given the total residential loan balance of $11.45 trillion as of 2016, we infer that about $43 billion are borrowed by same-sex applicants. The raw approval rate for hetero-sex applicants is 82.74%, in contrast to only 76.82% for same-sex applicants. The lower approval rate for same-sex applicants is persistent among various loan purposes and programs, although the margins are smaller for government sponsored programs.

[Insert Table 3 Here]

The lower raw approval rate is not enough to establish a case of potentially unfair treatment to same-sex applicants, as we do not control for other confounding factors that affect lender's approval decision. As a result, we follow equation 1 in section 4.2 and run a serious of logit and linear probability models with available controls from the HMDA and census data. We report the results in Table 4. Column (1) reports the baseline results. The coefficient for same-sex applicants is -0.147 (at 1% level of significance), which indicates that the log odds are 14.7 % lower for homosexual applicants to be approved for a mortgage loan after controlling for a whole set of basic mortgage loan control variables, such as property type, natural log of applicants' income, loan purpose, and so on. We also find that the coefficients for minorities are negative and significant: Hispanic (-0.390), Black (-0.809), and Asian (-0.172), which are qualitatively consistent with previous studies, such as Munnell et al. (1996). The coefficient for county level market share of each lender (Lendershare_County), measured yearly, is positive but insignificant. Hence the relative size of lenders in local market does not play a significant role on their approval decision.

A consumer's mortgage lending approval and interest rates are impacted by neighborhoods. Bayer, Ferreira, and Ross (2016) find the cohort of the most recent purchase or refinancing is influential in predicting defaults. Before the subprime mortgage crisis, lenders targeted geographic areas with historically low rates of home ownership where loan sellers identified many underserved consumers. In Column (3), we include county-level percentages of same-sex applicants each year (LG_countypct), and its interaction with same-sex dummy as control variables, and the results become more negative for the main effects; we also report the average marginal effect in Column (4). The same-sex coefficient is -0.312, at a 1% significance level. The margin coefficient of -0.042 suggests that, relative to an otherwise similar hetero-sex applicant, the approval rate for a same-sex applicant is 4.2% lower on average. The coefficient of LG_Countypct is -0.0619, at 1% significance level. Its margin of -0.08 indicates that, when the share of a county's same-sex population increases by 1%, the loan approval rate to hetero-sex applicants reside in that county drops by 0.8%. The interaction term between same-sex dummy and LG_Countypct is 0.0343, at 1% significance level. The corresponding margin of 0.005 suggests that homosexual applicants' loan approval rate is increased by 0.5% if they choose to live in a county that has 1% higher same-sex population. It appears that in more LGBT presented neighborhoods, same-sex applicants are treated less unfavorably, in contrast to higher loan rejection rates for straight applicants. This finding hence suggests a two-sided spillover effect when a county's LGBT population density changes.

As we control for the census tract demographics plus county and year fixed effects, our findings in Column (3) are unlikely to be driven by the unobserved county-specific economic characteristics. This is further confirmed in Column (5), where we run a linear probability model with additional lender*county fixed effect plus other controls in Column (3). A nice feature of the linear probability model is the simple probabilistic interpretation on coefficients. The findings are qualitatively unchanged from Column (3). We again find significant evidence of lower approval rate for same-sex applicants, and the two-sided spillover effect as discussed above. In Column (6), we go one step further to include lender*county*year fixed effect. Under this specification, we can no longer estimate the spillover effect from LG_Countypct, but the other findings are otherwise consistent with earlier columns.

[Insert Table 4 Here]

5.1.2 Main results for the Boston Fed data

Due to lack of some important control variables on loan and borrower characteristics, HMDA data may suffer from biased estimates. Therefore, we further tested the Boston Fed data for sexual orientation discrimination. The results are reported in Table 5.

Table 5, Column (1) is the baseline result for which we assumed all lenders share a common underwriting model. Its coefficient for same-sex is -1.159 (with a standard error of 0.404), which indicates homosexual applicants are much less likely to be approved for a mortgage loan application after controlling for a rich set of variables from the Boston Fed data.

Because of the much narrower geographic coverage, we calculate the percentage of same-sex applicant at the census tract level (LG_Tractpct) using HMDA data in 1990, and include it in column

(2).[20] The result is about the same for the same-sex coefficient. We then introduce lender fixed effects to allow different lenders to vary in a simple, systematic way, and report the results in Column (3). The coefficient is actually lower than the coefficient of Column (1); it is -1.190 with a standard error of 0.415.

In Column (4), in addition to lender fixed effect, we also include variations in underwriting based on loan terms. That is, the model allows lenders to put different underwriting weights on various loan and borrower characteristics, depending upon the nature of the loan. Ross and Yinger (2002) provide a clear example to demonstrate the importance of controlling this type of variation. We first identify a list of key underwriting variables (i.e., house expense to income ratio, total debt expense to income ratio, loan to value ratio, bankruptcy history, and borrowers' consumer and mortgage credit history). We then construct pair-wise interaction terms for these variables, and add them into our model. After controlling for these variables, the approval rates further decrease, with a coefficient of -1.296 (standard error 0.487).

Column (5) is the result for our final attempt to control for variations on lenders' underwriting standards. We also report its average marginal effect in Column (6). To address the problem, we identify a list of key lender portfolio variables, including the percentage of conventional loans sold to secondary market, average loan size, average applicant's income, and average loan-to-income ratio. We also include the pair-wise interactions of the previously identified key underwriting variables and the lender portfolio variables. This model is our most comprehensive model. The coefficients for same-sex, however, fall even further than those of our previous tests (-1.285 with a standard error of 0.544). Its margin of -0.084 suggests that, ceteris paribus, the loan approval rate for homosexual applicant is 8.4% lower than straight applicant on average. Consistent with HMDA based findings from Table 4, we again find strong evidence of the negative spillover effect in more LGBT dense neighborhoods. The margin for LG_Tractpct is -0.002, suggesting that when the same-sex population percentage in a census tract increases by 1%, the straight applicant's loan approval rate declines by 0.2%.

[Insert Table 5 Here]

[20] Due to the small sample size with only 56 same-sex applicants, we do not add the interaction term between same-sex dummy and LG_Tractpct.

It is important to clarify that we have a limited focus in this analysis. It abstracts from discrimination that may occur in different areas of the economy. For example, if homosexual individuals are subject to discrimination in labor markets (see Weichselbaumer, 2003), they will have lower incomes and their higher denial ratio may actually reflect higher obligation ratios, greater loan-to-value ratios, or poorer credit histories. We did not try to study these discriminations. However, our results are robust, even when controlled for these social economic characteristics. Similarly, if homosexual couples are discouraged from moving into predominantly heterosexual areas, they will limit their search to neighborhoods sanctioned for homosexual families. These neighborhoods tend to be older central cities with high-density housing, and high-density housing might be associated with higher denial rates (see Black et al. [2002] for some potential reasons that why gay men like cities like San Francisco). Given the extensive controls of borrower's characteristics, census tract demographics, and county and lender fixed effects, it is unlikely our findings related to same-sex applicants are spuriously driven by the above factors.

5.1.3 Robustness check

One concern for the main findings is that the results might be driven by observations of early years or a few extreme years. We run the regressions year by year using the full sample of national HMDA data and report the estimates and confidence interval in Figure 2. The pattern of lower approval rate to same-sex applicants is persistent over time, except in 1996 and 2000, in which the coefficient is not significant from zero at 5%. Surprisingly, the extent of discrimination seems unmitigated in the last decade, when the Democratic Party is in power.

[Insert Figure 2 Here]

To rule out other explanations of the results such as the potentially inaccurate proxy for sexual orientation and estimation bias, we conduct a robustness check on both the HMDA and Boston Fed data. Table 6 reports the robustness check on the HMDA national data. Although it is very rare that fathers and sons or brothers/sisters will buy a house together, we still need to rule out such cases to check if our results hold. We further restrict our sample for same-sex co-applicants to different races. The results are essentially the same. For Column (1), the same-sex coefficient is -0.159 at 1% significant level, which is essentially the same as Column (1) of Table 4.

[Insert Table 6 Here]

In Table 7, we address the concern that same-sex borrowers are more likely to live in multi-family units than single-family units, and are more likely to have a cosigner than not. We restrict our sample to applicants for single-family units without a cosigner. The results are still similar to those results without the constraints (i.e., the results in Table 5). The Table 7 Column (1) same-sex coefficient is -1.525 at 1% significant level, which is very similar to Column (1) of Table 5. The following four columns are also very similar.

[Insert Table 7 Here]

To address the concern that same-sex mortgage applicants are younger on average, and to rule out potential parent-kid pairs, we restrict our Boston Fed sample to applicants over 50 years old and with no dependents. The finding of lower approval rate is even stronger when we compare them to the same-sex coefficients in Table 8. The Column (1) same-sex coefficient is -2.196 (standard error 0.708). The coefficients in the other four columns are also lower than corresponding coefficients in Table 5.

[Insert Table 8 Here]

Finally, following a process first suggested by Munnell et al. (1996), we first run a full logit regression (Logit (5) in table 5, but excluding same-sex as control variable, with Boston Fed Data) on non-same-sex observations. Then for the same-sex applicants, we plug in their attributes to the model pretending they are hetero-sexual, and compare the average predicted denial probability with the actual denial rate observed in data. Compared to otherwise similar non-same-sex applicants, same-sex applicant are 73.12% more likely to be rejected. The results are reported in Table 9.

[Insert Table 9 Here]

5.2 Mortgage cost

Measuring mortgage costs to borrowers can be tricky. One obvious choice is to use the contractual rate. Nevertheless, we shall be aware that the contractual rate is often not an accurate measure of the effective borrowing cost. Unlike annual percentage rate (APR), the contractual rate ignores the impact of loan fees and other closing costs charged by lender. As a simple example, consider a 30-year fixed rate mortgage for $200,000. Suppose a lender offers a 4.5% contractual rate with two discount points.[21] The terms observed from the merged HMDA-Fannie Mae data will have loan amount of $200,000 and a contractual rate of 4.5%. The monthly mortgage payment is $1013.37. Nevertheless, because of the two discount points, lenders will charge $4,000 fees upon closing. Assuming the borrower chooses to amortize the fees over the loan term, the actual monthly payment will be $1033.64, which is based on the principal value of $204,000. In another word, this borrower only receives $200,000 from the lender, but her mortgage payment will be calculated as if she had borrowed $204,000. The effective borrowing cost (hence the APR) is 4.67%, which is 0.17% higher than its contractual rate. This example demonstrates why contractual rate often underestimates the true financing cost when loan fees are present. In practice, lenders tend to maintain "sticky" mortgage rates and use loan fees and points to achieve the desired yield. Brueggeman and Fisher (2016) offer an excellent discussion on why lenders often prefer to use loan fee, rather than contractual rate, to adjust yield. Because APR measures the effective borrowing cost more accurately than contractual rates, we first conduct our mortgage cost analysis using APR measure in the next subsection.

5.2.1 Rate spread analysis

Under HMDA, since 2004, a rate spread for a loan must be reported if it is above a certain threshold. Between January 2004 and September 2010, the rate spread is defined as the difference between the APR on a loan and the prevalent rate for treasury securities of comparable maturity. HMDA mandates disclosure of such rate spread if it is at least 3% for a loan secured by a first lien. Due to this high threshold, only 3.89% of the loans in our usable sample have reported rate spreads. Since October 2010, HMDA changed its definition of rate spread as the difference between a loan's APR and a survey-based estimate of prevalent APR (instead of treasure rate) for comparable loans. Given this new definition, disclosure is required if a rate spread is above 1.5%. The new disclosure threshold is even higher than before, as only 1.01% of the loans in our sample are above this threshold, and hence, have reported spreads.

Because only loans with APRs well above average have disclosed rate spreads, we define a dummy variable called "Disclosure," which is set to 1 if a loan has a reported spread, and 0 otherwise. We then run a logit model by controlling an extensive set of loan and borrower characteristics. The results are reported in Table 10. Model 1 reports the baseline result, and we gradually add LG_Countypct, its interaction with same-sex dummy, and more fixed effects in subsequent models. We find consistently

[21] One point means a 1% upfront charge of a loan discount fee, applicable to the contractual loan amount.

across models that, compared with loans that are otherwise similar, loans granted to same-sex borrowers are more likely to have a reported rate spread. The same-sex coefficient in Model 3 is 0.112 (standard error 0.00411), which suggests that, holding other factors constant, same-sex borrowers are more likely to have a loan with a reported rate spread, and thus, a higher APR.

[Insert Table 10 Here]

As an alternative test for higher APRs for same-sex borrowers, we regress the rate spread directly on loan and borrower characteristics. One restriction, as discussed above, is that our sample is censored below by the threshold that triggers the rate spread disclosure. We therefore adopt a Tobit model to address the data censoring issue. Due to the 2010 change to the reporting threshold and the definition of rate spread, we split our sample into periods before and after 2010,[22] and report the Tobit regression results in Table 11. Models 1 and 4 correspond to the baseline model for pre- and post-2010 periods separately, and Models 3 and 6 are full models after controlling the interaction terms between same-sex and county level same-sex percentage variable, and additional fixed effects for the corresponding periods. We find significant evidence that same-sex borrowers are charged higher rate spreads. For example, the coefficient of same-sex borrowers for the full model before 2010 (Model 3) is 0.202 at a 1% significance level, which implies that, compared with otherwise similar borrowers, the base group same-sex borrowers, on average, pay 0.202% more on their mortgages, which is both statistically and economically significant. The same coefficient for post-2010 (Model 6) is smaller at 0.111, although it is still highly significant. However, we read this result with great caution; as for the post-2010 period, due to the higher reporting threshold, the rate spread information of almost 99% of the observations are censored out. This leaves us with only 115 reported rate spreads from same-sex borrowers out of 237,197 total observations and, thus, with little information to extract.

[Insert Table 11 Here]

5.2.2 Contractual rate analysis

Although the Tobit model is suitable to handle censored data, the extremely high censoring rate in our sample and the strong normality assumption made by the Tobit model can still be of

[22] Here we drop the loans originated in the last quarter of 2009 as it is the transitional period of the changing reporting rules.

concern. In response, in this section we examine the original contractual rate, which is available for all observations thanks to Fannie Mae data.

With the caveat that contractual rate tends to be sticky and usually underestimates the effective financing cost, we report the OLS regression results using it as our cost measure in Table 12. The model specifications are otherwise identical to Table 11. As the changing disclosure rule is no longer relevant, we first report the full sample result in Columns (1) to (3). Then, to facilitate comparison with Table 11, we break our sample into the same pre and post 2010 periods in Columns (4) and (5). The findings from contractual rate are qualitatively consistent with the previous APR based rate spread analysis. For example, in Colum (1), the coefficient for same-sex is 0.0195 (standard error 0.00298), which suggests same-sex borrowers on average pay 1.95 more basis points on contractual rate compared with otherwise similar hetero-sex borrowers. The pattern is persistent across different sub-periods, hence suggesting that overpricing to same-sex borrowers is a common business practice. Finally, the larger coefficient for same-sex after 2010 in Column (5) echoes the trend of increasing approval discrimination to same-sex applicants since 2004, as shown in Figure 2.

As far as the spillover effects, the coefficient for LG_Countypct is at least 10% significant across all model specifications, suggesting some evidence on rate markup to straight borrowers living in more LGBT dense counties. On the other hand, for same-sex borrowers living in these counties, there is evidence that rate markup for them tend to decline. Overall, consistent with loan approval analysis, we are able to find evidence of two-sided spillover effect on financing costs as well.

[Insert Table 12 Here]

5.3 Mortgage default

Our findings so far suggest same-sex borrowers are more likely to be rejected when they apply for loans, and, conditional on being approved, lenders tend to charge them higher financing costs, primarily through upfront fees. Although we have controlled for an extensive list of characteristics on both borrowers and their loans, it may still be plausible that there could be some unobserved characteristics that cause same-sex borrowers riskier and, therefore, more likely to default. In this case, the higher APRs charged to same-sex borrowers could simply reflect the premium of their higher default risk. To investigate whether the higher financing costs to same-sex borrowers can be justified by the risk premium and, hence, a reflection of financial necessity, we look at the loan performance using our merged HMDA-Fannie Mae samples.

We first estimate logit models for the mortgage defaults. The dependent variable is a dummy variable indicating when a mortgage becomes delinquent for at least 60 days within 5 years since its origination date. As the most recent performance updates in our data were from the end of 2015, we restrict our sample to loans originated before 2010 in order to generate a five-year observation window. The results are shown in Table 13. Model 1 is our baseline model. In Model 2 we add LG_Countypct. In Model 3, we add the interaction between same-sex and the LG_Countypct. Although there is no reason to associate subsequent loan performance with the original lender after loan characteristics are controlled, we still include the annually measured lender's county-level market share measured yearly and lender fixed effects in model 4. The coefficient of same-sex borrowers across all four models is highly insignificant. Hence we feel comfortable saying that same-sex status exhibits no greater risk of default.

[Insert Table 13 Here]

Finally, we investigate loan performance conditioning on loans that have experienced default. In particular, for all loans that have a record of at least 60 days' delinquency, we measure how long it has been since origination before they are in default. We then run a Cox proportional hazard model on the duration before default with a standard list of control variables. Our model specifications are identical to the previous logit analysis on default. The results are reported in Table 14. Interestingly, the coefficient for the same-sex is negative, although insignificant. A negative coefficient implies that, conditional on the loan's already default status, same-sex borrowers tend to postpone default from happening more often than non-same-sex borrowers. Obviously, conditional on loans being in default, lenders prefer to see default happening later than sooner. The lack of significance makes it unwarranted to claim that same-sex borrowers perform better. However, we shall not forget that our control of financing cost, i.e., contractual rate, is likely to underestimate the true cost markup for same-sex borrowers. It is obvious from Table 14 that financing cost exhibits a significant impact on triggering default. So once again, there is certainly no evidence that same-sex borrowers are riskier for lenders, and the findings from the duration model weakly suggest that it may be the opposite if we have better measures on borrowers' financing costs.

[Insert Table 14 Here]

5.4 The types of lending discrimination

We present evidence that, compared with otherwise similar loan applicants, same-sex borrowers are more likely to have their applications turned down by lenders and, conditional on being approved, they tend to be charged with higher interest rates. One issue that is yet to be investigated is the type of lending discrimination that our findings reveal. The courts implementing the federal fair lending laws broadly recognize two types of lending discrimination evidence: disparate treatment and disparate impact.[23]

Evidence on disparate treatment can be established by showing that during the lending practice, lenders explicitly use either prohibitory factors (overt evidence) or factors that are not justified by legitimate nondiscriminatory factors (comparative evidence).

Disparate impact, on the other hand, happens when a lender applies a factor "neutral" policy to all credit applicants, but the policy or practice disproportionately excludes or burdens certain group of people on a prohibited basis. One example, provided by the Federal Fair Lending Regulations and Statutes Overview,[24] states, "A lender's policy is to deny loan applications for single-family residences for less than $60,000. The policy has been in effect for ten years. This minimum loan amount policy is shown to disproportionately exclude potential minority applicants from consideration because of their income levels or the value of the houses in the areas in which they live." This type of discrimination is much harder to prove because, at the lender level of the decision model, discriminatory factor coefficients, such as sexuality or minority status, will be insignificant. Practically, the courts will then determine whether the policy or practice can be justified by "business necessity."

To begin to address this issue of discrimination type, we first examine whether same-sex applicants are distributed unevenly in lenders' customer pools, which can potentially lead to disparate impact. In particular, using HMDA 20% data, we computed the proportion of same-sex applicants within each lender-state pair. We then regressed the proportion based on lenders' overall size ranking in percentile and average loan characteristics for each lender, plus the state fixed effects. Please note that our definition of a "lender," which is identified by a unique combination of HMDA respondent ID and agency code, is somewhat narrower in scope due to data; because HMDA allows affiliated subsidiaries to use different respondent IDs, it is possible that multiple identified lenders actually belong to one parental financial institution. This is especially relevant for large financial institutions.

[23] See Ross and Yinger (2002) for a comprehensive discussion on this matter.
[24] https://www.federalreserve.gov/boarddocs/supmanual/cch/fair_lend_over.pdf.

Based on a report[25] from Mortgage Bankers Association (MBA), for 2010, 8,124 "lenders" reported data to HMDA. After adjusting for their parent companies, the list was narrowed down to 6,700 financial institutions.

We report the results in Table 15. The overall findings do provide evidence for disproportional clustering. It seems that same-sex applicants are more likely to choose lenders that also have a bigger share of minority applicants. Furthermore, the summary statistics in Table 2 reveal that same-sex applicants tend to have higher loan-to-income ratios (LTI). Hence, it is no surprise to see from Table 15 that same-sex applicants are more likely to choose a lender who is willing to offer larger LTI loans. Another notable difference from the summary statistics is that same-sex applicants tend to have higher income. Interestingly, Table 15 shows that same-sex borrowers are more likely to apply for a loan from a lender whose average customer has lower income. Shopping this way, the comparative income advantage for same-sex borrowers becomes bigger, which could strengthen their profiles in competing for a loan. Finally, there is no evidence that lender size matters when same-sex borrowers decide from whom to borrow.

[Insert Table 15 Here]

Next, to distinguish disparate treatment from disparate impact, we re-run the loan approval and credit cost regression at the lender level. A significant coefficient for our key variable, "same-sex," would support the conclusion of disparate treatment; an insignificant coefficient would suggest either no discrimination from that lender, or it can be subject to potential disparate impact investigation. To minimize the noise from the many small lenders, and for economic significance, we restrict our attention to the top 100 lenders identified in the merged HMDA-Fannie Mae data when we run the lender level OLS regression on mortgage cost in section 5.2. For the same lenders, we also refer back to the HMDA 20% sample and run the lender-level loan approval linear probability regression for all loans those lenders processed. Our model specifications are similar to the models used in Table 4 (Column 5) and Table 12 (Column 1), with the exception that we now use state fixed effect to maintain the degree of freedom. Because now we run lender-level regressions, we also remove all lender-related fixed effects. Given our primary interest on the coefficient of "same-sex," we plot its values for all top 100 lenders in Figure 3, in which lender size 1 is the largest.

[25] http://apps.mba.org/files/Research/HMDAFAQ.pdf.

[Insert Figure 3 Here]

We find significant evidence that many lenders internally treat "same-sex" status unfavorably. This is particularly true when lenders come to loan approval decisions. With respect to the mortgage cost, although we see fewer lenders "overcharge" same-sex borrowers on their interest rates upon approval, the incidence of this kind of business practice is still noticeable, especially among large lenders on the market.

Finally, for lenders with either 10% insignificant or unexpected signs on the "same-sex" coefficient, we pool them together to investigate whether unfavorable outcomes to same-sex borrowers emerge again. We adopt the full models used in Table 4 (Model 4) and Table 12 (Model 1). Although the results do not appear here to save space, for the coefficient on "same-sex," we again find negative 1% significant result in the loan approval model and positive 1% significant result in the mortgage rate model. Hence, for lenders who pass the individual disparately treatment test, there is collective evidence that same-sex borrowers are subject to unfavorable credit outcomes. This suggests that there is also potential disparate impact, due to the disproportional clustering of same-sex loan applicants among lenders.

6. Conclusion

This study examines avenues through which differential treatment could affect same-sex applicants' access to credit and opportunities for homeownership. The results indicate that homosexual mortgage applicants in the United States are more likely to be turned down than other applicants with similar characteristics. Following traditional approaches of estimating mortgage loan discrimination based on race, we study two samples—one from national loan applications from HMDA originating between 1990 and 2015, and one from classical Boston Fed loan application data with more extensive borrower characteristics in 1990. The results provide empirical evidence of lending discrimination concerning sexual orientation in U.S. loan applications. Homosexual applicants are 73.12% more likely than otherwise similar straight applicants to be denied a loan.

We further check the cost and performance of the approved loans, and we find lenders tend to charge higher financing costs to homosexual borrowers, primarily through upfront fees. After we merge the HMDA data with Fannie Mae data, we find no evidence that same-sex borrowers exhibit more risk of default.

Our analysis also provides evidence of a two-sided spillover effect. That is, holding other factors constant, when a neighborhood's same-sex population increases, although same-sex applicants still experience lower approval rate and higher financing cost, the treatment discrepancy between same-sex and straight applicants narrows from both sides.

Our research might suffer from omitted variable bias. For example, the original HMDA data suggest that differential treatment by sexual orientation is occurring in the mortgage market. There might be important confounding variables related to both loan approval and sexual orientation that are missing from the HMDA data. To cross-validate the reliability of our findings, we employ Boston Fed data that cover in detail on lenders' information set, including essentially all of the information the lenders use in their decision-making process, and find that sexual orientation still played a significant role in mortgage lending decisions.

Furthermore, our investigation on mortgage performance doesn't find that homosexual applicants default more often, or that their defaults are costlier to lenders. Given the absence of hard evidence suggesting sexual orientation may be a reliable signal for loan performance, this suggests that a serious discrimination problem may exist in the mortgage market. As a result, our findings have strong policy implications. Lenders, LGBT community groups, and regulators must work together to guarantee homosexual applicants are treated fairly.

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Table 1: Variable Definitions

Part A: Loan information

Variable Name	Meaning	Used at
Approve	Dummy if loan application is approved	HMDA&Boston Fed
Occupied	Dummy if Occupied as a principal dwelling	HMDA&Boston Fed
Loan Amount	Loan Amount on contract	HMDA
Loan Purpose	1: Home purchase 2: Home Improvement 3: Refinancing	HMDA
Loan Type	1: Conventional 2: FHA 3: VA 4: FSA/RHS	HMDA
Loan to Income	Loan to Income Ratio	HMDA
PMI Denial	Dummy if applicant applied PMI and was denied	Boston Fed
LTV	Loan to Value Ratio	Boston Fed
High LTV	Dummy if LTV is above 1	Boston Fed
Extreme LTV	Dummy if LTV is above 2	Boston Fed
Loan Term	Term in years	Boston Fed
Fixed Rate	Fixed rate mortgage dummy	Boston Fed
Multi-family	Dummy for multi-family unit	Boston Fed
Special Program	Dummy for special program loan	Boston Fed
Lendershare_County	Lenders' market share in a county	HMDA

Part B: Borrower information

Variable Name	Meaning	Used at
Same-Sex	Dummy, equals 1 if applicant and co-applicant are of the same sex	HMDA&Boston Fed
Annual Income	Total annual income (applicant + co-applicant)	HMDA&Boston Fed
Co-applicant	Dummy if co-applicant is present	HMDA&Boston Fed
LG_CountyPct	Percentage of Same Sex borrowers in a county	HMDA
LG_TractPct	Percentage of Same Sex borrowers in a tract	HMDA
Male	Dummy for Male Applicant	HMDA
Black	Dummy for Black applicant	HMDA
Hispanic	Dummy for Hispanic/Latino applicant	HMDA
Asian	Dummy for Asian applicant	HMDA
Other race	Dummy for other minority applicant	HMDA
Minority	Dummy for all minority applicant	Boston Fed
HETI	Housing expense-to-income ratio	Boston Fed
TDTI	Total debt expense-to-income ratio	Boston Fed
Net Worth	Net worth of applicant (in thousands)	Boston Fed
Cosigner	Dummy for Cosigner (other than co-applicant)	Boston Fed
Married	Dummy if applicant is married	Boston Fed
Consumer Credit History	Applicant's consumer credit history (See Boston Fed study for definition)	Boston Fed
Mortgage Credit History	Applicant's mortgage credit history (See Boston Fed study for definition)	Boston Fed
Bankruptcy	Dummy if applicant has public recorded bankruptcy	Boston Fed
Gift	Dummy for gift is used in down payment	Boston Fed
Predicted Unemp	Predicted unemployment probability for applicant (See Boston Fed Study)	Boston Fed
Short Work Experience	Dummy if applicant has less than two year's job experience	Boston Fed
Self-employed	Dummy if applicant is self-employed	Boston Fed
At Least 50	Dummy if applicant is over 50	Boston Fed
High School	Dummy if applicant has finished at least high school	Boston Fed
public records		Boston Fed

Dependent	# of dependent of applicant	Boston Fed

Part C: Census tract information

Variable Name	Meaning	Used at
Poor Tract	Dummy for poor tract (income below area median)	HMDA&Boston Fed
Minority Tract	Dummy if tract has over 30% Minority	HMDA&Boston Fed
LnPOP_tract	Log of total population in tract	HMDA
FMI_tract	Median family income in tract	HMDA
Unit/Pop	# of Occupied units per capital in tract	HMDA
Age_tract	Median age of residents in tract	HMDA
Houseage_tract	Median house age in tract	HMDA
Male_tract	Proportion of male in tract	HMDA
LnHV_tract	Log of median house vale in tract	HMDA

Part D: Lender's mortgage portfolio information (all in 1990)

Variable Name	Meaning	Used at
CONVshare	Percent of conventional loans sold at secondary market by lender	Boston Fed
Loansize_lender	Average loan size made by lender	Boston Fed
Income_lender	Average applicant's income by lender	Boston Fed
LTI_lender	Average loan to income ratio by lender	Boston Fed

Part E: Loan Cost and performance information

Variable Name	Meaning	Used at
Original rate	Original Interest Rate	Fannie Mae
Original Loan to value	Original Combined Loan-to-Value	Fannie Mae
Income	Log Income	Fannie Mae
Borrower Score	Borrower Credit Score	Fannie Mae
Co-Borrower Score	Co-Borrower Credit Score	Fannie Mae
First Time	First-Time Home Buyer Indicator	Fannie Mae
Num_unit	Number of Units,	Fannie Mae
Mortgage Insurance_pct	Mortgage Insurance Percentage,	Fannie Mae
Loan_purp	Loan Purpose,	Fannie Mae
Occupancy Status	Occupancy Status	Fannie Mae
Debt to Income	Debt-to-income Ratio	Fannie Mae

Table 2: Summary Statistics for Key Variables (Mean, Std)

Variables	Full Sample (STD)	Same-sex=0 (STD)	Same-sex=1 (STD)	Two Sample t test (p-level)
Approve	0.8250	08274	0.7682	***
(HMDA)	(0.3800)	(0.3779)	(0.4220)	(0.0000)
Same-Sex	0.0403	N/A	N/A	N/A
(HMDA)	(0.1966)			
LG_CountyPct	4.1523	4.1177	4.9746	***
(HMDA)	(1.8226)	(1.7914)	(2.3030)	(0.0000)
Lendershare_County	3.7578	3.7690	3.4903	***
(HMDA)	(4.8558)	(4.8642)	(4.6414)	(0.0000)
Loan to Income	1.8523	1.8514	1.8747	***
(HMDA)	(1.2774)	(1.2717)	(1.4065)	(0.0000)
Loan Amount ($000s)	159.3674	159.6204	153.3385	***
(HMDA)	(165.2771)	(165.6286)	(156.5490)	(0.0000)
Annual Income ($000s)	97.7372	97.4595	104.3517	***
(HMDA)	(125.5848)	(123.2398)	(172.1206)	(0.0000)
Occupied	0.9233	0.9250	0.8834	***
(HMDA)	(0.2661)	(0.2634)	(0.3209)	(0.0000)
Approve	0.8549	0.8567	0.7971	
(Boston Fed)	(0.3523)	(0.3505)	(0.4051)	(0.1663)
Income ($000s)	76.1072	75.9923	79.8398	
(Boston Fed)	(67.3506)	(67.4778)	(63.4164)	(0.6403)
HEI	25.2734	25.3116	24.0310	
(Boston Fed)	(9.7264)	(9.7274)	(9.6804)	(0.2815)
TDTI	33.1560	33.1569	33.1274	
(Boston Fed)	(11.0951)	(10.9940)	(14.0955)	(0.9826)
Net Worth ($000s)	0.2298	0.2311	0.1863	
(Boston Fed)	(0.9873)	(0.9999)	(0.3972)	(0.7105)
Predicted Unemp	3.7876	3.7853	3.8623	
(Boston Fed)	(2.0366)	(2.0342)	(2.1279)	(0.7571)
Self Employed	0.1231	0.1246	0.0725	
(Boston Fed)	(0.3286)	(0.3304)	(0.2612)	(0.1942)
LTV	0.7653	0.7650	0.7773	
(Boston Fed)	(0.2807)	(0.2827)	(0.2063)	(0.7194)
PMI Denial (Boston	0.0194	0.0200	0	
Fed)	(0.1381)	(0.1401)	(0)	(0.2354)
Multi-family	0.1403	0.1366	0.2609	***
(Boston Fed)	(0.3474)	(0.3435)	(0.4423)	(0.0034)
Fixed Rate	0.6576	0.6573	0.6667	
(Boston Fed)	(0.4746)	(0.4747)	(0.4749)	(0.8720)
Special Program	0.1718	0.1700	0.2319	
(Boston Fed)	(0.3773)	(0.3757)	(0.4251)	(0.1797)
Loan Term	28.7244	28.7694	27.2899	**
(Boston Fed)	(5.1376)	(5.0478)	(7.4065)	(0.0185)
Gift	0.1861	0.1918	0	***
(Boston Fed)	(0.3893)	(0.3938)	(0)	(0.0001)
Cosigner	0.0358	0.0338	0.1014	***
(Boston Fed)	(0.1859)	(0.1808)	(0.3041)	(0.0029)
At Least 50	0.4642	0.4747	0.2174	***
(Boston Fed)	(0.4988)	(0.4993)	(0.4155)	(0.0000)
Male	0.7794	0.7859	0.5652	***
(Boston Fed)	(0.4148)	(0.4103)	(0.4994)	(0.0000)
Married	0.5920	0.6101	0	***
(Boston Fed)	(0.4916)	(0.4878)	(0)	(0.0000)
Occupied	0.9598	0.9595	0.9710	
(Boston Fed)	(0.1964)	(0.1972)	(0.1690)	(0.6315)
Bankruptcy	0.0812	0.0801	0.1159	
(Boston Fed)	(0.2732)	(0.2715)	(0.3225)	(0.2832)
Mortgage Credit History	1.7453	1.7468	1.6957	
(Boston Fed)	(0.5330)	(0.5350)	(0.4635)	(0.4327)
Consumer Credit	2.1706	2.1709	2.1594	
History	(1.7161)	(1.7151)	(1.7625)	(0.9546)

(Boston Fed)				
High School	0.7409	0.7414	0.7246	
(Boston Fed)	(0.4382)	(0.4379)	(0.4500)	(0.7539)
Short Work Experience	0.0885	0.0859	0.1739	**
(Boston Fed)	(0.2841)	(0.2803)	(0.3818)	(0.0112)
Dependent	0.7845	0.8042	0.1449	***
(Boston Fed)	(1.1114)	(1.1193)	(0.4933)	(0.0000)
Original Loan-to-Value	74.2732	74.3010	73.6033	***
(Fannie Mae)	(15.6316)	(15.6324)	(15.5973)	(0.0000)
Borrower Score	753.8248	753.9804	750.0820	***
(Fannie Mae)	(48.4005)	(48.3368)	(49.7632)	(0.0000)
Co-Borrower Score	756.3145	756.3955	754.3646	***
(Fannie Mae)	(47.9988)	(47.9335)	(49.5047)	(0.0000)
First Time	0.1169	01144	0.1774	***
(Fannie Mae)	(0.3213)	(0.3182)	(0.3820)	(0.0000)
Num_unit	1.0778	1.0738	1.1740	***
(Fannie Mae)	(0.3798)	(0.3706)	(0.5487)	(0.0000)
Mortgage Insurance_pct	5.5181	5.5490	4.7733	***
(Fannie Mae)	(10.7624)	(10.7870)	(10.1243)	(0.0000)

Table 3: Loan Applications Sort by Purpose and Program

Panel A. Loan Applications sort by Purpose

# of Received Applicants	Same-Sex	Purchase	Improvement	Refinancing	Row Total
	No	10,372,452	2,453,051	14,995,533	27,821,036
		(94.57%)	(96.51%)	(96.88%)	(95.97%)
	Yes	595,487	88,833	483,583	1,167,903
		(5.43%)	(3.49%)	(3.12%)	(4.03%)
	Column Total	10,967,939	2,541,884	15,479,116	28,988,939
		(37.83%)	(8.77%)	(53.40%)	(100%)
# of Approved Applications	**Same-Sex**	**Purchase**	**Improvement**	**Refinancing**	**Row Total**
	No	9,005,866	1,814,448	12,197,951	23,018,265
		(94.95%)	(97.10%)	(97.10%)	(96.25%)
	Yes	479,279	54,218	363,702	897,199
		(5.05%)	(2.90%)	(2.90%)	(3.75%)
	Column Total	9,485,145	1,868,666	12,561,653	23,915,464
		(39.66%)	(7.81%)	(52.53%)	(100%)
Raw Approval Rate	**Same-sex**	**Purchase**	**Improvement**	**Refinancing**	**Row Total**
	No	86.82%	73.97%	81.34%	82.74%
	Yes	80.48%	61.03%	75.21%	76.82%

Panel B: Loan Applications sort by Loan Program

# of Received Applications	Same-Sex	Conventional	FHA	VA	Row Total
	No	25,116,803	1,931,534	685,816	27,821,036
		(96.22%)	(91.95%)	(98.75%)	(95.97%)
	Yes	987,633	169,101	8,698	1,167,903
		(3.78%)	(8.05%)	(1.25%)	(4.03%)
	Column Total	26,104,436	2,100,635	694,514	28,988,939
		(90.05%)	(7.25%)	(2.40%)	(100%)
# of Approved Applications	**Same-Sex**	**Conventional**	**FHA**	**VA**	
	No	20,729,860	1,619,381	595,654	23,018,265
		(96.52%)	(92.00%)	(98.80%)	(96.25%)
	Yes	747,153	140,847	7,211	897,199
		(3.48%)	(8.00%)	(1.20%)	(3.75%)
	Column Total	21,477,013	1,760,228	602,865	23,915,464
		(89.80%)	(7.36%)	(2.52%)	(100%)
Raw Approval Rate	**Same-Sex**	**Conventional**	**FHA**	**VA**	
	No	82.53%	83.84%	86.85%	82.74%
	Yes	75.65%	83.08%	82.90%	76.82%

Note: calculated based on 20% HMDA national data.

Table 4: HMDA National 20% Result (1990-2015)

	Logit (1) Approve	Logit (2) Approve	Logit (3) Approve	Average Marginal Effect Logit (3)	Linear Probability (4) Approve	Linear Probability (5) Approve
Same-Sex	-0.147*** (0.0243)	-0.140*** (0.0245)	-0.312*** (0.0281)	-0.042	-0.0300*** (0.00248)	-0.0296*** (0.00218)
LG_CountyPct		-0.0593*** (0.00942)	-0.0619*** (0.00953)	-0.008	-0.00223*** (0.000515)	N/A
Same*LG_CountyPct			0.0343*** (0.00523)	0.005	0.00136*** (0.000424)	0.000939*** (0.000256)
Lendershare_County	0.00935 (0.00959)	0.00945 (0.00936)	0.00942 (0.00936)	0.001	0.00164* (0.000870)	N/A
LTI	-0.0631*** (0.0166)	-0.0629*** (0.0166)	-0.0630*** (0.0166)	-0.008	-0.0188*** (0.00103)	-0.0213*** (0.00119)
Log Income	0.458*** (0.0513)	0.457*** (0.0510)	0.457*** (0.0509)	0.061	0.0290*** (0.00299)	0.0223*** (0.00314)
Male	0.431*** (0.0231)	0.430*** (0.0231)	0.429*** (0.0231)	0.057	0.0325*** (0.00186)	0.0285*** (0.00170)
Occupied	0.0198 (0.0480)	0.0191 (0.0479)	0.0185 (0.0479)	0.003	0.0274*** (0.00304)	0.0299*** (0.00308)
Hispanic	-0.390*** (0.0218)	-0.389*** (0.0218)	-0.389*** (0.0218)	-0.052	-0.0503*** (0.00442)	-0.0500*** (0.00449)
Black	-0.809*** (0.0219)	-0.805*** (0.0223)	-0.806*** (0.0222)	-0.107	-0.0934*** (0.00320)	-0.0908*** (0.00304)
Asian	-0.172*** (0.0213)	-0.172*** (0.0214)	-0.172*** (0.0214)	-0.023	-0.0210*** (0.00141)	-0.0222*** (0.00168)
Other race	-0.624*** (0.0621)	-0.624*** (0.0621)	-0.624*** (0.0621)	-0.083	-0.0581*** (0.00531)	-0.0506*** (0.00299)
Purpose: Improvement	-0.793*** (0.114)	-0.798*** (0.113)	-0.798*** (0.113)	-0.111	-0.0825*** (0.0151)	-0.0789*** (0.0133)
Purpose: Refinancing	-0.479*** (0.101)	-0.482*** (0.1000)	-0.482*** (0.0999)	-0.061	-0.0337*** (0.00486)	-0.0305*** (0.00459)
Type: FHA	0.272*** (0.0787)	0.270*** (0.0782)	0.270*** (0.0781)	0.034	-0.00755 (0.00485)	-0.0136*** (0.00418)
Type: VA	0.308*** (0.112)	0.303*** (0.112)	0.302*** (0.112)	0.038	0.00947** (0.00439)	0.00339 (0.00405)
Type: FSA/RHS	0.326*** (0.110)	0.322*** (0.109)	0.322*** (0.109)	0.040	-0.00723 (0.0108)	-0.0140 (0.0109)
Census Tract Demographic Controls	Y	Y	Y		Y	Y
County Fixed Effect	Y	Y	Y		N	N

Year Fixed Effect	Y	Y	Y	Y	N
Lender*County Fixed Effect	N	N	N	Y	N
Lender*County*Year Fixed Effect	N	N	N	N	Y
Constant	-3.344***	-3.074***	-3.054***	0.320***	0.329***
	(0.562)	(0.526)	(0.524)	(0.0392)	(0.0256)
N	28988939	28988939	28988939	28988939	28988939
Adj. R^2				0.200	0.251

Model 1: logit with basic control variables only.
Model 2: model 1 plus lg_countypct.
Model 3: model 2 plus samsex and lg_county pct interaction effect.
Model 4: model 2 plus samsex and lg_county pct interaction effect and with lender * county fixed effects.
Model 5: linear probability model with model 2 plus lender*state*year fixed effects.
Note: standard errors in parentheses is robust and clustered at lender level
* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$

Table 5: Result Using Boston Fed Data

	Logit (1) Approve	Logit (2) Approve	Logit (3) Approve	Logit (4) Approve	Logit (5) Approve	Average Marginal Effect Logit (5)
Same-Sex	-1.159*** (0.404)	-1.030*** (0.394)	-1.190*** (0.415)	-1.296*** (0.487)	-1.285** (0.544)	-0.084
LG_Tractpct		-0.0245 (0.0159)	-0.0254 (0.0170)	-0.0295* (0.0167)	-0.0330** (0.0151)	-0.002
Minority	-0.506** (0.204)	-0.500** (0.205)	-0.525** (0.253)	-0.381 (0.284)	-0.377 (0.279)	-0.025
Co-applicant	0.576* (0.302)	0.552* (0.304)	0.589* (0.344)	0.639* (0.371)	0.634* (0.363)	0.042
HETI	0.000194 (0.0126)	0.000536 (0.0126)	-0.00268 (0.0153)	-0.0251 (0.108)	0.122 (0.186)	0.002
TDTI	-0.0603*** (0.0167)	-0.0604*** (0.0167)	-0.0750*** (0.0203)	0.0370 (0.0758)	0.0899 (0.144)	-0.006
Net worth	-0.0721 (0.0458)	-0.0761* (0.0462)	-0.0638 (0.0560)	-0.0546 (0.0647)	-0.00239 (0.0721)	0.000
Predicted Unemp	-0.0740** (0.0374)	-0.0726* (0.0387)	-0.0583 (0.0464)	-0.0538 (0.0468)	-0.0450 (0.0493)	-0.003
Self-employed	-0.475** (0.203)	-0.491** (0.206)	-0.831*** (0.225)	-0.889*** (0.236)	-1.014*** (0.254)	-0.066
LTV	-0.541 (0.380)	-0.521 (0.370)	-0.618 (0.434)	4.783** (2.116)	-14.21** (6.487)	-0.221
Denied PMI	-5.267*** (0.660)	-5.262*** (0.654)	-5.684*** (0.821)	-5.815*** (0.873)	-5.918*** (0.878)	-0.388
Multi-Family	-0.427* (0.222)	-0.398* (0.217)	-0.450* (0.268)	-0.344 (0.282)	-0.310 (0.279)	-0.020
Fixed Rate	-0.158 (0.213)	-0.173 (0.217)	-0.229 (0.288)	-0.322 (0.298)	-0.414 (0.315)	-0.027
Special Program	0.599** (0.271)	0.589** (0.258)	0.878*** (0.334)	0.873** (0.362)	0.978** (0.415)	0.064
Loan Term	-0.00857 (0.0200)	-0.00907 (0.0201)	0.000221 (0.0240)	-0.0000882 (0.0239)	0.0111 (0.0271)	0.001
Gift	-0.0292 (0.226)	-0.0292 (0.225)	-0.0784 (0.259)	-0.217 (0.270)	-0.175 (0.264)	-0.011
Cosigner	0.745* (0.397)	0.698* (0.394)	0.710 (0.477)	0.656 (0.477)	0.449 (0.451)	0.029
Age	-0.272 (0.181)	-0.275 (0.180)	-0.194 (0.193)	-0.259 (0.212)	-0.225 (0.227)	-0.015
Male	-0.338* (0.187)	-0.347* (0.188)	-0.313 (0.205)	-0.250 (0.199)	-0.187 (0.202)	-0.012

Married	-0.0429	-0.0384	0.0585	0.0379	-0.00339	0.000
	(0.229)	(0.231)	(0.269)	(0.276)	(0.279)	
Owner Occupied	1.073***	1.054***	1.152***	0.985**	0.869**	0.057
	(0.297)	(0.297)	(0.382)	(0.460)	(0.429)	
Log Income	-0.194	-0.252	-0.340	-0.439*	-0.481*	-0.032
	(0.222)	(0.223)	(0.251)	(0.254)	(0.270)	
Minority tract	-0.370	-0.342	-0.282	-0.459	-0.389	-0.025
	(0.279)	(0.272)	(0.289)	(0.286)	(0.291)	
Public Records	-1.338***	-1.335***	-1.498***	-3.117	0.617	-0.076
	(0.218)	(0.218)	(0.261)	(2.776)	(3.560)	
Mortgage payments	-0.441***	-0.439***	-0.421***	1.407*	2.637	-0.029
	(0.139)	(0.138)	(0.154)	(0.819)	(1.932)	
Consumer payments	-0.351***	-0.354***	-0.416***	0.112	-0.583	-0.028
	(0.0320)	(0.0313)	(0.0367)	(0.334)	(0.652)	
High LTV	-2.694***	-2.724***	-3.121***	-2.735***	-2.859***	-0.187
	(0.389)	(0.407)	(0.740)	(0.723)	(0.812)	
Extreme LTV	2.658	2.706	3.383*	4.382***	4.018*	0.263
	(1.940)	(1.917)	(1.999)	(1.589)	(2.303)	
Short Work Experience	0.103	0.131	-0.0211	0.160	0.210	0.014
	(0.282)	(0.287)	(0.333)	(0.346)	(0.327)	
High School	-0.00529	0.00688	0.233	0.279	0.273	0.018
	(0.205)	(0.203)	(0.217)	(0.216)	(0.218)	
Dependents	-0.0632	-0.0642	-0.0960	-0.0883	-0.0930	-0.006
	(0.0796)	(0.0802)	(0.0910)	(0.0837)	(0.0794)	
County Fixed Effect	Y	Y	Y	Y	Y	
Lender Fixed Effect	N	N	Y	Y	Y	
Key Underwriting Variable Interactions	N	N	N	Y	Y	
Key Underwriting Variable And Lender Portfolio Interactions	N	N	N	N	Y	
Constant	6.689***	6.859***	24.16***	18.69***	22.62***	
	(1.221)	(1.260)	(1.859)	(2.332)	(3.015)	
N	2316	2316	2316	2316	2316	

Model 1: logit with basic control variables and county fixed effects.
Model 2: logit is model 1 plus lg_countypct.
Model 3: logit with lender and county fixed effect.
Model 4: logit with lender and county fixed effect, key lending variable interactions.
Model 5: logit with lender and county fixed effect, key lending variable interactions, and key underwriting variable and lender portfolio interactions.
Standard errors in parentheses is robust and clustered at lender level
* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$

Table 6: Robustness Check with HMDA National Data (1990-2015)

	Logit (1) Approve	Logit (2) Approve	Logit (3) Approve	Linear Probability (4) Approve	Linear Probability (5) Approve
Same-Sex	-0.159*** (0.0498)	-0.146*** (0.0507)	-0.410*** (0.0838)	-0.0341*** (0.00843)	-0.0253*** (0.00652)
LG_Countypct		-0.0607*** (0.00960)	-0.0611*** (0.00961)	-0.00212*** (0.000513)	N/A
Same * LG_County			0.0498*** (0.0137)	0.00301** (0.00140)	0.000819 (0.000898)
Lendershare_County	0.00978 (0.00960)	0.00986 (0.00936)	0.00985 (0.00936)	0.00167** (0.000849)	N/A
LTI	-0.0661*** (0.0167)	-0.0659*** (0.0167)	-0.0659*** (0.0167)	-0.0191*** (0.00103)	-0.0216*** (0.00120)
Log Income	0.459*** (0.0518)	0.459*** (0.0515)	0.459*** (0.0515)	0.0286*** (0.00298)	0.0219*** (0.00314)
Male	0.469*** (0.0236)	0.468*** (0.0235)	0.468*** (0.0235)	0.0362*** (0.00205)	0.0321*** (0.00189)
Occupied	0.0233 (0.0483)	0.0226 (0.0483)	0.0225 (0.0483)	0.0276*** (0.00307)	0.0301*** (0.00311)
Hispanic	-0.387*** (0.0214)	-0.386*** (0.0215)	-0.386*** (0.0215)	-0.0497*** (0.00438)	-0.0494*** (0.00447)
Black	-0.818*** (0.0216)	-0.815*** (0.0220)	-0.815*** (0.0220)	-0.0931*** (0.00320)	-0.0905*** (0.00307)
Asian	-0.166*** (0.0211)	-0.166*** (0.0211)	-0.166*** (0.0211)	-0.0202*** (0.00141)	-0.0215*** (0.00169)
Other race	-0.630*** (0.0629)	-0.629*** (0.0629)	-0.629*** (0.0629)	-0.0580*** (0.00533)	-0.0504*** (0.00305)
Purpose: Improvement	-0.797*** (0.115)	-0.802*** (0.114)	-0.802*** (0.114)	-0.0816*** (0.0148)	-0.0780*** (0.0131)
Purpose: Refinancing	-0.490*** (0.102)	-0.493*** (0.101)	-0.492*** (0.101)	-0.0339*** (0.00484)	-0.0308*** (0.00459)
Type: FHA	0.248*** (0.0789)	0.246*** (0.0784)	0.246*** (0.0784)	-0.00895* (0.00482)	-0.0148*** (0.00418)
Type: VA	0.302*** (0.113)	0.297*** (0.112)	0.297*** (0.112)	0.00938** (0.00439)	0.00336 (0.00406)
Type: FSA/RHS	0.313*** (0.111)	0.309*** (0.110)	0.308*** (0.110)	-0.00774 (0.0110)	-0.0143 (0.0110)
Census Tract Demographic Controls	Y	Y	Y	Y	Y
County Fixed Effect	Y	Y	Y	N	N
Year Fixed Effect	Y	Y	Y	Y	N

Lender*County Fixed Effect	N	N	N	Y	N
Lender*County*Year Fixed Effect	N	N	N	N	Y
Constant	-3.344***	-3.074***	-3.054***	0.320***	0.329***
	(0.562)	(0.526)	(0.524)	(0.0392)	(0.0256)
N	28988939	28988939	28988939	28988939	28988939
Adj. R^2				0.200	0.251

In this table, to rule out dad-son or brothers like same-sex pairs, we restrict same sex==1 only if race~=co applicant race. And then we re-run the regressions similar to table 4.

Standard errors in parentheses is robust and clustered at lender level

* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$

Table 7: Robustness Check With Boston Fed Data: A

	(1) Approve	(2) Approve	(3) Approve	(4) Approve	(5) Approve
Same-sex	-1.525***	-1.409***	-1.682***	-1.872***	-1.714**
	(0.466)	(0.465)	(0.502)	(0.601)	(0.687)
LG_Tractpct		-0.0177	-0.0254*	-0.0279*	-0.0244
		(0.0151)	(0.0152)	(0.0155)	(0.0160)
Minority	-0.540**	-0.536**	-0.529*	-0.358	-0.291
	(0.222)	(0.224)	(0.281)	(0.298)	(0.306)
Co-applicant	0.819**	0.800**	0.903**	0.966**	1.039**
	(0.361)	(0.365)	(0.427)	(0.456)	(0.423)
HETI	-0.0107	-0.00997	-0.0127	-0.0405	-0.0877
	(0.0148)	(0.0148)	(0.0193)	(0.125)	(0.180)
TDTI	-0.0494***	-0.0499***	-0.0674***	0.0120	0.195
	(0.0175)	(0.0177)	(0.0220)	(0.0763)	(0.146)
Net worth	-0.0562	-0.0598	-0.0371	-0.0446	0.00514
	(0.0551)	(0.0556)	(0.0636)	(0.0811)	(0.0833)
Predicted Unemp	-0.0806*	-0.0805*	-0.0640	-0.0483	-0.0344
	(0.0434)	(0.0432)	(0.0518)	(0.0528)	(0.0489)
Self-employed	-0.465**	-0.479**	-0.879***	-0.969***	-1.032***
	(0.228)	(0.229)	(0.264)	(0.275)	(0.300)
LTV	-0.697	-0.690	-0.946	3.655	-10.47
	(0.845)	(0.835)	(0.878)	(2.803)	(9.059)
Denied PMI	-5.158***	-5.139***	-5.396***	-5.449***	-5.874***
	(0.741)	(0.732)	(0.912)	(0.971)	(0.964)
Fixed Rate	-0.123	-0.134	-0.259	-0.347	-0.499
	(0.232)	(0.234)	(0.296)	(0.292)	(0.308)
Special	0.649**	0.629**	0.757*	0.753*	0.836**
	(0.276)	(0.264)	(0.395)	(0.407)	(0.415)
Loan term	-0.0141	-0.0144	-0.0194	-0.0208	-0.0155
	(0.0235)	(0.0237)	(0.0289)	(0.0316)	(0.0307)
Gift	0.0200	0.0174	0.00254	-0.110	-0.0425
	(0.220)	(0.219)	(0.233)	(0.238)	(0.256)
Age	-0.335	-0.334	-0.212	-0.308	-0.244
	(0.208)	(0.211)	(0.243)	(0.270)	(0.290)
Male	-0.644***	-0.640***	-0.600**	-0.600**	-0.542**
	(0.226)	(0.224)	(0.262)	(0.260)	(0.241)
Married	-0.123	-0.126	-0.0717	-0.138	-0.116
	(0.264)	(0.263)	(0.305)	(0.326)	(0.348)
Owner Occupied	1.375***	1.348***	1.430***	1.265**	1.162**
	(0.355)	(0.360)	(0.469)	(0.508)	(0.459)
Log Income	-0.429*	-0.478**	-0.660**	-0.724**	-0.829**

	(0.239)	(0.244)	(0.267)	(0.294)	(0.337)
Minority tract	-0.565*	-0.548*	-0.362	-0.612	-0.622
	(0.306)	(0.307)	(0.330)	(0.402)	(0.476)
Public Records	-1.332***	-1.334***	-1.574***	-1.802	5.448
	(0.250)	(0.252)	(0.285)	(2.965)	(4.645)
Mortgage payments	-0.375**	-0.374**	-0.411**	1.465	7.375***
	(0.163)	(0.164)	(0.185)	(0.953)	(2.440)
Consumer payments	-0.356***	-0.357***	-0.432***	-0.152	-2.069**
	(0.0410)	(0.0407)	(0.0517)	(0.388)	(0.857)
High LTV	-2.485***	-2.496***	-2.752***	-2.251***	-2.071***
	(0.517)	(0.515)	(0.930)	(0.775)	(0.642)
Extreme LTV	2.238	2.263	2.913	3.428*	4.087*
	(1.872)	(1.811)	(2.466)	(1.792)	(2.356)
Short Work Experience	0.0309	0.0305	-0.187	-0.0210	0.0237
	(0.389)	(0.390)	(0.456)	(0.465)	(0.436)
High School	0.117	0.125	0.449**	0.433**	0.512**
	(0.200)	(0.202)	(0.203)	(0.199)	(0.207)
Dependents	-0.00222	-0.00180	-0.0392	-0.0344	-0.0388
	(0.105)	(0.105)	(0.119)	(0.106)	(0.101)
County Fixed Effect	Y	Y	Y	Y	Y
Lender Fixed Effect	N	N	Y	Y	Y
Key Underwriting Variable Interactions	N	N	N	Y	Y
Key Underwriting Variable And Lender Portfolio Interactions	N	N	N	N	Y
Constant	6.948***	7.106***	24.79***	22.48***	23.65***
	(1.493)	(1.540)	(2.102)	(2.826)	(3.252)
N	1935	1935	1935	1935	1935

To address the concern that same-sex borrowers have more presence in multi-family units, and are more likely to have a cosigner, we now restrict our sample to those applicants for single-family units and without cosigner. Standard errors in parentheses, and they are robust and clustered at lender level
* P < 0.1, ** P < 0.05, *** P < 0.01

Table 8: Robustness Check With Boston Fed Data: B

	(1) Approve	(2) Approve	(3) Approve	(4) Approve	(5) Approve
Same-sex	-2.196***	-1.963***	-2.152*	-2.546**	-2.810**
	(0.708)	(0.755)	(1.099)	(1.045)	(1.165)
LG_Tractpct		-0.0296*	-0.0281	-0.0323	-0.0494*
		(0.0175)	(0.0226)	(0.0221)	(0.0258)
Minority	-0.286	-0.274	-0.436	-0.284	-0.0333
	(0.269)	(0.263)	(0.334)	(0.386)	(0.474)
Co-applicant	0.466	0.443	0.710*	0.583	0.803
	(0.388)	(0.387)	(0.427)	(0.497)	(0.489)
HETI	-0.0121	-0.0118	-0.0144	-0.160	-0.655**
	(0.0156)	(0.0155)	(0.0181)	(0.146)	(0.283)
TDTI	-0.0510**	-0.0513**	-0.0866***	-0.0162	0.848***
	(0.0228)	(0.0228)	(0.0308)	(0.0996)	(0.241)
Net worth	0.0908	0.0918	0.205	0.332	0.512*
	(0.152)	(0.147)	(0.254)	(0.262)	(0.294)
Predicted Unemp	-0.0773	-0.0721	-0.0188	-0.0235	0.0419
	(0.0601)	(0.0609)	(0.0728)	(0.0818)	(0.0981)
Self-employed	-0.411	-0.430	-1.012**	-1.339***	-1.658***
	(0.295)	(0.301)	(0.413)	(0.373)	(0.465)
LTV	0.0465	0.0604	-1.244	2.695	-52.04**
	(0.399)	(0.389)	(1.143)	(5.077)	(22.54)
Denied PMI	-17.57***	-17.56***	-34.74***	-36.01***	-40.24***
	(0.606)	(0.601)	(1.541)	(2.236)	(7.512)
Multi family	-0.549	-0.515	-0.443	-0.249	-0.490
	(0.345)	(0.342)	(0.458)	(0.512)	(0.524)
Fixed Rate	0.300	0.291	0.169	0.0625	-0.117
	(0.238)	(0.242)	(0.361)	(0.393)	(0.443)
Special	0.312	0.302	1.108**	1.117**	1.096
	(0.399)	(0.389)	(0.484)	(0.566)	(0.719)
Loan term	-0.0122	-0.0136	0.0255	0.0119	0.00987
	(0.0245)	(0.0249)	(0.0422)	(0.0403)	(0.0448)
Gift	-0.323	-0.330	-0.159	-0.300	-0.374
	(0.342)	(0.336)	(0.410)	(0.470)	(0.566)
Cosigner	1.218**	1.143**	2.021**	1.929**	2.051*
	(0.521)	(0.522)	(0.942)	(0.820)	(1.067)
Age	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
Male	-0.757***	-0.817***	-1.133***	-1.032***	-1.150***
	(0.281)	(0.284)	(0.348)	(0.358)	(0.426)
Married	0.0295	0.0445	0.235	0.287	-0.0426
	(0.347)	(0.350)	(0.489)	(0.530)	(0.563)

Owner Occupied	0.333	0.282	0.522	0.385	0.104
	(0.439)	(0.432)	(0.634)	(0.726)	(0.583)
Log Income	-0.568*	-0.679**	-0.884**	-0.983**	-1.362**
	(0.291)	(0.288)	(0.419)	(0.467)	(0.580)
Minority tract	-0.984***	-0.983***	-1.251***	-1.564***	-1.975***
	(0.333)	(0.326)	(0.393)	(0.483)	(0.546)
Public Records	-1.092***	-1.091***	-1.198***	-2.149	26.35**
	(0.294)	(0.294)	(0.434)	(4.040)	(12.82)
Mortgage payments	-0.371**	-0.369**	-0.408*	1.678	7.574*
	(0.178)	(0.177)	(0.240)	(1.347)	(4.227)
Consumer payments	-0.349***	-0.349***	-0.468***	0.292	-0.172
	(0.0442)	(0.0442)	(0.0606)	(0.540)	(1.711)
High LTV	-2.502***	-2.596***	-1.863*	-1.940*	-1.904
	(0.585)	(0.583)	(1.083)	(1.088)	(1.461)
Extreme LTV	0.916	1.074	-13.12***	-12.59***	-10.95
	(1.729)	(1.686)	(1.630)	(2.686)	(.)
Short Work Experience	0.395	0.358	0.333	0.513	0.551
	(0.540)	(0.551)	(0.626)	(0.794)	(1.026)
High School	-0.221	-0.201	0.241	0.299	0.255
	(0.311)	(0.311)	(0.417)	(0.449)	(0.434)
Dependents	-0.0495	-0.0551	-0.0902	-0.0796	-0.133
	(0.0932)	(0.0950)	(0.119)	(0.121)	(0.144)
County Fixed Effect	Y	Y	Y	Y	Y
Lender Fixed Effect	N	N	Y	Y	Y
Key Underwriting Variable Interactions	N	N	N	Y	Y
Key Underwriting Variable And Lender Portfolio Interactions	N	N	N	N	Y
Constant	8.205***	8.541***	25.94***	23.40	28.39***
	(1.690)	(1.745)	(2.895)	(2539.9)	(5.422)
N	1072	1072	1072	1072	1072

To address the concern that same-sex borrowers are younger, and the possible dad-son pairs, here we restrict sample to be over 50 years and with no dependent. And re-run regressions similar to table 5.
Standard errors in parentheses, and they are robust and clustered at lender level
* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$

Table 9: Plug In Same-Sex Attributes to Non-Same-sex Regression.

Boston Fed Data	
Characteristics And Experience	Rates
Actual Denial Rate For Same-Sex Borrowers In Sample (N=69)	20.29%
Predicted Denial Rate For Same-Sex Borrowers With Their Characteristics But Non-Same-sex Experience	11.72%
Odds Ratio	1.7312

Our treatment here is similar to Munnell et al., (1996). We first run a full logit regression (Logit (5) in table 5, but excluding Same-sex as control variable) on non-same-sex observations. Then for the same-sex applicants, we plug in their attributes to the model, and compare the average predicted denial probability with the actual denial rate observed in data. Compared to otherwise similar non-same-sex applicants, same-sex applicant are 73.12% more likely to be rejected!

Table 10: High Rate Spread Disclosure

	(1) Premium_Report	(2) Premium_Report	(3) Premium_Report
Same-sex	0.00702***	0.00708***	0.0112***
	(0.00205)	(0.00205)	(0.00411)
LG_Countypct		-0.000398	-0.000343
		(0.000314)	(0.000307)
Same * LG_County			-0.000801
			(0.000557)
Lendershare_County	0.000922*	0.000916*	0.000917*
	(0.000483)	(0.000483)	(0.000483)
Male	-0.00437***	-0.00439***	-0.00437***
	(0.000956)	(0.000959)	(0.000960)
LTV	-0.0000642**	-0.0000656**	-0.0000654**
	(0.0000326)	(0.0000328)	(0.0000328)
Log Income	-0.00922***	-0.00920***	-0.00920***
	(0.000970)	(0.000967)	(0.000967)
Borrower Score	-0.000112***	-0.000112***	-0.000112***
	(0.0000134)	(0.0000134)	(0.0000135)
Co-borrower Score	-0.0000782***	-0.0000782***	-0.0000783***
	(0.0000114)	(0.0000114)	(0.0000114)
First Time	-0.00468**	-0.00462**	-0.00463**
	(0.00205)	(0.00204)	(0.00204)
Num_Unit	-0.00303***	-0.00299***	-0.00298***
	(0.00109)	(0.00109)	(0.00109)
Mortgage insurance_Pct	0.00132***	0.00132***	0.00132***
	(0.000250)	(0.000250)	(0.000250)
Hispanic	0.0132***	0.0133***	0.0133***
	(0.00188)	(0.00189)	(0.00189)
Black	0.0400***	0.0402***	0.0402***
	(0.00412)	(0.00413)	(0.00413)
Asian	-0.00344***	-0.00335***	-0.00335***
	(0.00110)	(0.00109)	(0.00109)
Other race	0.00422	0.00424	0.00424
	(0.00303)	(0.00303)	(0.00303)
Loan Purpose	-0.00830***	-0.00831***	-0.00831***
	(0.00233)	(0.00233)	(0.00233)
Loan Occupancy	0.0350***	0.0350***	0.0350***
	(0.00497)	(0.00497)	(0.00497)
Census Tract Demographic Controls	Y	Y	Y
Loan Month Fixed Effect	Y	Y	Y
Lender*County Fixed Effect	Y	Y	Y

Constant	0.526***	0.524***	0.523***
	(0.0520)	(0.0514)	(0.0514)
N	425239	425239	425239
Adj. R^2	0.078	0.078	0.078

Standard errors in parentheses are robust and clustered at lender level

* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$

Table 11: Tobit Regression on Rate Spread

	Model 1 (Pre-2010) Rate Spread	Model 2 (Pre-2010) Rate Spread	Model 3 (Pre-2010) Rate Spread	Model 4 (Post-2010) Rate Spread	Model 5 (Post-2010) Rate Spread	Model 6 (Post-2010) Rate Spread
Same-sex	0.176***	0.177***	0.202***	0.0388***	0.0397***	0.111***
	(0.0113)	(0.0113)	(0.0158)	(0.00944)	(0.00947)	(0.0142)
LG_Countypct		-0.00367	-0.00320		-0.00394	-0.00276
		(0.00425)	(0.00426)		(0.00334)	(0.00334)
Same*LG_County			-0.00505*			-0.0159***
			(0.00273)			(0.00278)
Lendershare_County	0.0430***	0.0429***	0.0429***	-0.00195**	-0.00204**	-0.00199**
	(0.00161)	(0.00161)	(0.00161)	(0.000974)	(0.000975)	(0.000975)
Male	-0.155***	-0.155***	-0.155***	-0.0295**	-0.0297**	-0.0295**
	(0.0208)	(0.0208)	(0.0208)	(0.0148)	(0.0148)	(0.0148)
LTV	-0.00180***	-0.00182***	-0.00182***	0.00326***	0.00324***	0.00325***
	(0.000279)	(0.000280)	(0.000280)	(0.000197)	(0.000197)	(0.000197)
Log Income	-0.296***	-0.295***	-0.295***	-0.167***	-0.167***	-0.167***
	(0.00515)	(0.00516)	(0.00517)	(0.00365)	(0.00366)	(0.00366)
Borrower score	-0.00164***	-0.00164***	-0.00164***	-0.00294***	-0.00294***	-0.00293***
	(0.0000322)	(0.0000323)	(0.0000323)	(0.0000229)	(0.0000229)	(0.0000229)
Co-borrower Score	-0.000830***	-0.000831***	-0.000831***	-0.00274***	-0.00274***	-0.00274***
	(0.0000321)	(0.0000322)	(0.0000322)	(0.0000228)	(0.0000229)	(0.0000229)
First Time	-0.165***	-0.164***	-0.164***	0.160***	0.160***	0.160***
	(0.0154)	(0.0154)	(0.0154)	(0.00983)	(0.00990)	(0.00991)
Num_Units	-0.0446**	-0.0441**	-0.0440**	-0.0530***	-0.0527***	-0.0525***
	(0.0176)	(0.0176)	(0.0176)	(0.0132)	(0.0133)	(0.0133)
Mortgage Insurance_Pct.	0.0246***	0.0246***	0.0246***	0.0148***	0.0148***	0.0148***
	(0.000531)	(0.000532)	(0.000532)	(0.000369)	(0.000369)	(0.000369)
Hispanic	0.201***	0.202***	0.202***	0.107***	0.107***	0.107***
	(0.0118)	(0.0119)	(0.0119)	(0.00926)	(0.00930)	(0.00929)
Black	0.509***	0.511***	0.511***	0.240***	0.242***	0.242***
	(0.0133)	(0.0134)	(0.0134)	(0.01000)	(0.0100)	(0.0100)
Asian	-0.164***	-0.163***	-0.163***	-0.00934	-0.00833	-0.00805
	(0.0107)	(0.0107)	(0.0107)	(0.0103)	(0.0103)	(0.0103)
Other race	0.152***	0.152***	0.152***	0.0676***	0.0675***	0.0679***
	(0.0137)	(0.0137)	(0.0137)	(0.00937)	(0.00938)	(0.00937)
Loan purpose	-0.320***	-0.320***	-0.320***	0.0743***	0.0741***	0.0740***
	(0.0192)	(0.0192)	(0.0192)	(0.0135)	(0.0136)	(0.0136)
Loan Occupancy	0.649***	0.649***	0.649***	0.615***	0.615***	0.614***
	(0.0146)	(0.0146)	(0.0146)	(0.0150)	(0.0150)	(0.0150)
Census Tract Demographic	Y	Y	Y	Y	Y	Y

Controls						
Loan Month Fixed Effect	Y	Y	Y	Y	Y	Y
Lender*County Fixed Effect	Y	Y	Y	Y	Y	Y
Constant	5.354***	5.318***	5.273***	4.513***	4.496***	4.520***
	(0.0239)	(0.0240)	(0.0240)	(0.0170)	(0.0170)	(0.0170)
Sigma						
Constant	1.143***	1.143***	1.143***	0.710***	0.710***	0.710***
	(0.0108)	(0.0109)	(0.0109)	(0.00707)	(0.00710)	(0.00709)
N	181460	181460	181460	237197	237197	237197
Adj. R^2						

Standard errors in parentheses are robust and clustered at lender level
* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$

Table 12: Linear Regression on Contractual Rate

	Ols 1 (Full Sample) Contractual Rate	Ols 2 (Full Sample) Contractual Rate	Ols 3 (Full Sample) Contractual Rate	Ols 4 (Pre 2010) Contractual Rate	Ols 5 (Post 2010) Contractual Rate
Same-sex	0.0195***	0.0193***	0.0285***	0.0182**	0.0302***
	(0.00298)	(0.00297)	(0.00526)	(0.00872)	(0.00613)
LG_Countypct		0.00130*	0.00142*	0.00282**	0.00171**
		(0.000775)	(0.000766)	(0.00134)	(0.000799)
Same * LG_County			-0.00182**	0.000860	-0.00271**
			(0.000875)	(0.00134)	(0.00107)
Lendershare_County	-0.000940	-0.000921	-0.000919	-0.00202	0.00104
	(0.000851)	(0.000852)	(0.000852)	(0.00154)	(0.00110)
Male	-0.00433***	-0.00425***	-0.00419***	-0.00118	-0.00686***
	(0.00162)	(0.00162)	(0.00162)	(0.00208)	(0.00216)
LTV	0.00165***	0.00165***	0.00165***	0.000847***	0.00242***
	(0.000104)	(0.000103)	(0.000103)	(0.000124)	(0.000100)
Log Income	-0.0597***	-0.0598***	-0.0598***	-0.0642***	-0.0556***
	(0.00166)	(0.00166)	(0.00166)	(0.00328)	(0.00218)
Borrower score	-0.00115***	-0.00115***	-0.00115***	-0.000889***	-0.00146***
	(0.0000450)	(0.0000450)	(0.0000450)	(0.0000565)	(0.0000258)
Co-borrower Score	-0.000846***	-0.000846***	-0.000846***	-0.000596***	-0.00120***
	(0.0000452)	(0.0000452)	(0.0000452)	(0.0000433)	(0.0000255)
First Time	-0.00377	-0.00396	-0.00396	-0.00757	-0.00346
	(0.00346)	(0.00346)	(0.00346)	(0.00476)	(0.00393)
Num_Units	0.0657***	0.0656***	0.0656***	0.0427***	0.0822***
	(0.00453)	(0.00454)	(0.00454)	(0.00727)	(0.00331)
Mortgage Insurance_Pct	0.00114***	0.00114***	0.00114***	0.00377***	-0.000701***
	(0.000348)	(0.000348)	(0.000348)	(0.000446)	(0.000130)
Hispanic	0.0110***	0.0107***	0.0107***	-0.00759	0.0226***
	(0.00337)	(0.00337)	(0.00337)	(0.00474)	(0.00416)
Black	0.0199***	0.0194***	0.0194***	0.0139**	0.0261***
	(0.00386)	(0.00387)	(0.00387)	(0.00646)	(0.00476)
Asian	-0.00502*	-0.00531**	-0.00531**	-0.00595	-0.00639*
	(0.00270)	(0.00266)	(0.00266)	(0.00390)	(0.00341)
Other race	0.00384	0.00376	0.00375	0.00645	0.000738
	(0.00731)	(0.00730)	(0.00730)	(0.0116)	(0.00877)
Loan purpose	0.0318***	0.0319***	0.0319***	0.0121	0.0500***
	(0.00668)	(0.00668)	(0.00668)	(0.00811)	(0.00853)
Occupancy	0.305***	0.305***	0.305***	0.324***	0.284***
	(0.00705)	(0.00704)	(0.00704)	(0.0117)	(0.00481)
Census Tract Demographic Controls	Y	Y	Y	Y	Y
Loan Month Fixed Effect	Y	Y	Y	Y	Y

Lender*County Fixed Effect	Y	Y	Y	Y	Y
Constant	8.288***	8.297***	8.295***	8.587***	7.637***
	(0.0662)	(0.0652)	(0.0651)	(0.125)	(0.0768)
N	425239	425239	425239	181460	237197
Adj. R^2	0.909	0.909	0.909	0.748	0.744

Standard errors in parentheses are robust and clustered at lender level
* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$

Table 13: Logit Model on Mortgage Default

	Logit (1) Default	Logit (2) Default	Logit (3) Default	Logit (4) Default
Same-Sex	-0.000850 (0.0548)	-0.000253 (0.0550)	0.0735 (0.149)	0.0612 (0.146)
LG_Countypct		-0.0157 (0.0377)	-0.0150 (0.0382)	-0.0102 (0.0366)
Same*LG_County			-0.0137 (0.0291)	-0.0132 (0.0281)
Contractual Rate	0.388*** (0.0294)	0.388*** (0.0294)	0.388*** (0.0294)	0.369*** (0.0296)
Lendershare_County				-0.0235*** (0.00483)
Male	-0.0112 (0.0287)	-0.0113 (0.0287)	-0.0110 (0.0287)	-0.0132 (0.0290)
LTV	0.0368*** (0.00145)	0.0368*** (0.00146)	0.0368*** (0.00146)	0.0366*** (0.00148)
Log Income	-0.214*** (0.0242)	-0.214*** (0.0243)	-0.214*** (0.0243)	-0.213*** (0.0249)
Borrower score	-0.00940*** (0.000296)	-0.00940*** (0.000296)	-0.00940*** (0.000295)	-0.00943*** (0.000298)
Co-borrower Score	-0.00716*** (0.000259)	-0.00716*** (0.000259)	-0.00716*** (0.000259)	-0.00728*** (0.000260)
First Time	-0.259*** (0.0463)	-0.259*** (0.0462)	-0.259*** (0.0460)	-0.262*** (0.0461)
Num_Units	0.128*** (0.0307)	0.128*** (0.0307)	0.128*** (0.0307)	0.132*** (0.0311)
Mortgage Insurance_Pct	0.00218* (0.00132)	0.00217 (0.00132)	0.00216 (0.00132)	0.00243* (0.00135)
Hispanic	0.177*** (0.0427)	0.176*** (0.0427)	0.176*** (0.0427)	0.179*** (0.0434)
Black	0.208*** (0.0482)	0.208*** (0.0482)	0.208*** (0.0482)	0.209*** (0.0484)
Asian	0.00729 (0.0590)	0.00746 (0.0590)	0.00757 (0.0589)	0.0132 (0.0592)
Other race	0.181 (0.111)	0.181 (0.111)	0.180 (0.111)	0.189* (0.112)
Loan purpose	0.538*** (0.0254)	0.538*** (0.0254)	0.538*** (0.0254)	0.524*** (0.0260)
Occupancy	-0.0153 (0.0373)	-0.0154 (0.0372)	-0.0157 (0.0375)	-0.0233 (0.0380)
Census Tract Demographic Controls	Y	Y	Y	Y

Loan Month Fixed Effect	Y	Y	Y	Y
County Fixed Effect	Y	Y	Y	Y
Lender Fixed Effect	N	N	N	Y
Constant	5.965***	6.017***	6.006***	7.113***
	(0.836)	(0.868)	(0.875)	(1.062)
N	214934	214934	214934	214934

Standard errors in parentheses are robust and clustered at MSA level
* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$

Table 14: Cox Proportional Hazard Model on Duration before Default

	Hazard (1) Duration	Hazard (2) Duration	Hazard (3) Duration	Hazard (4) Duration
Same-sex	-0.0581	-0.0580	-0.132	-0.131
	(0.0417)	(0.0417)	(0.105)	(0.105)
LG_Countypct		-0.0276	-0.0282	-0.0205
		(0.0332)	(0.0332)	(0.0354)
Same * LG_County			0.0139	0.0145
			(0.0186)	(0.0185)
Lendershare_County				-0.00417
				(0.00433)
Contractual Rate	0.160***	0.160***	0.160***	0.147***
	(0.0232)	(0.0232)	(0.0232)	(0.0251)
Male	-0.00176	-0.00175	-0.00181	0.00382
	(0.0246)	(0.0246)	(0.0246)	(0.0257)
LTV	0.00499***	0.00498***	0.00497***	0.00483***
	(0.00112)	(0.00112)	(0.00112)	(0.00121)
Log Income	0.0649***	0.0650***	0.0652***	0.0652***
	(0.0179)	(0.0179)	(0.0179)	(0.0188)
Borrower score	-0.00161***	-0.00161***	-0.00161***	-0.00171***
	(0.000234)	(0.000235)	(0.000235)	(0.000256)
Co-borrower Score	-0.00118***	-0.00118***	-0.00118***	-0.00128***
	(0.000259)	(0.000257)	(0.000256)	(0.000265)
First Time	-0.101***	-0.101***	-0.101***	-0.105***
	(0.0326)	(0.0325)	(0.0325)	(0.0345)
Num_Units	-0.0254	-0.0258	-0.0263	-0.0347
	(0.0273)	(0.0271)	(0.0272)	(0.0283)
Mortgage Insurance_Pct	0.000249	0.000258	0.000278	0.000337
	(0.00104)	(0.00104)	(0.00104)	(0.00112)
Hispanic	0.0607*	0.0603*	0.0603*	0.0567
	(0.0334)	(0.0332)	(0.0332)	(0.0352)
Black	-0.0259	-0.0252	-0.0254	-0.0310
	(0.0378)	(0.0376)	(0.0376)	(0.0382)
Asian	0.0156	0.0140	0.0134	0.0248
	(0.0626)	(0.0631)	(0.0628)	(0.0633)
Other race	-0.0348	-0.0319	-0.0317	-0.0345
	(0.123)	(0.122)	(0.122)	(0.116)
Loan purpose	0.0610***	0.0612***	0.0614***	0.0542***
	(0.0198)	(0.0198)	(0.0198)	(0.0201)
Occupancy	-0.127***	-0.127***	-0.127***	-0.117***
	(0.0256)	(0.0257)	(0.0258)	(0.0284)
Census Tract Demographic Controls	Y	Y	Y	Y

Loan Month Fixed Effect	Y	Y	Y	Y
County Fixed Effect	Y	Y	Y	Y
Lender Fixed Effect	N	N	N	Y
N	17137	17137	17137	17137

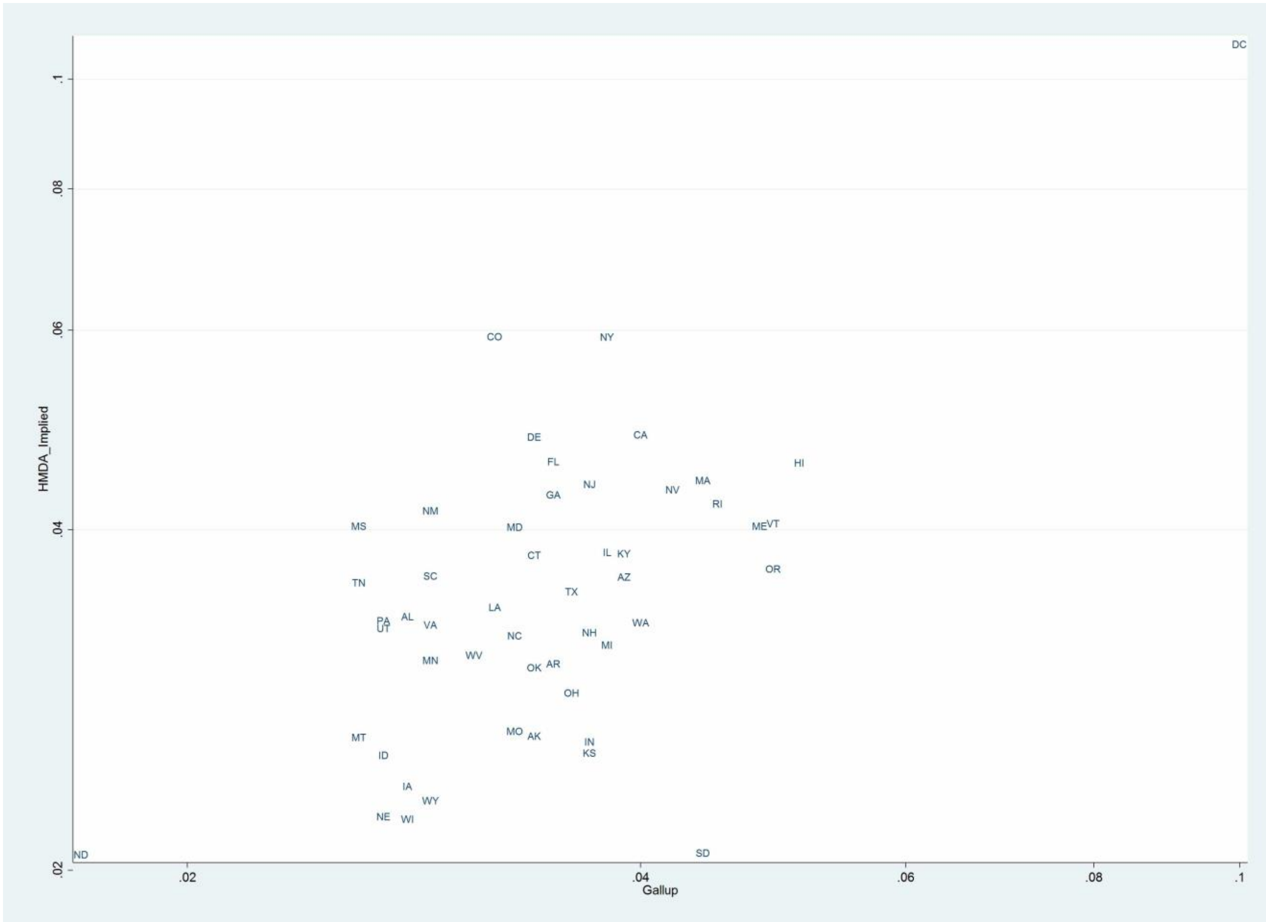
Standard errors in parentheses are robust and clustered at MSA level
* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$

Table 15: OLS Model On the Same-Sex Percentage across Lenders

	(1) Same_Pct	(2) Same_Pct
Lendersize_100pct	-0.00287	-0.00511
	(0.00362)	(0.00352)
Male_Pct	-0.116***	-0.117***
	(0.0208)	(0.0209)
Hispan_Pct	0.0184**	0.0180**
	(0.00842)	(0.00884)
Black_Pct	0.0539***	0.0429***
	(0.0131)	(0.0132)
Asian_Pct	0.0269***	0.0194*
	(0.0102)	(0.0105)
Otherrace_Pct	0.0844	0.0856
	(0.0595)	(0.0595)
Occup_Pct	-0.116***	-0.122***
	(0.0216)	(0.0219)
Lti_Avg	0.562**	0.553**
	(0.244)	(0.248)
Lincome_Avg	-1.919***	-2.230***
	(0.537)	(0.541)
State Fixed Effect	N	Y
Constant	31.59***	33.56***
	(4.953)	(4.939)
N	112206	112206
Adj. R^2	0.021	0.031

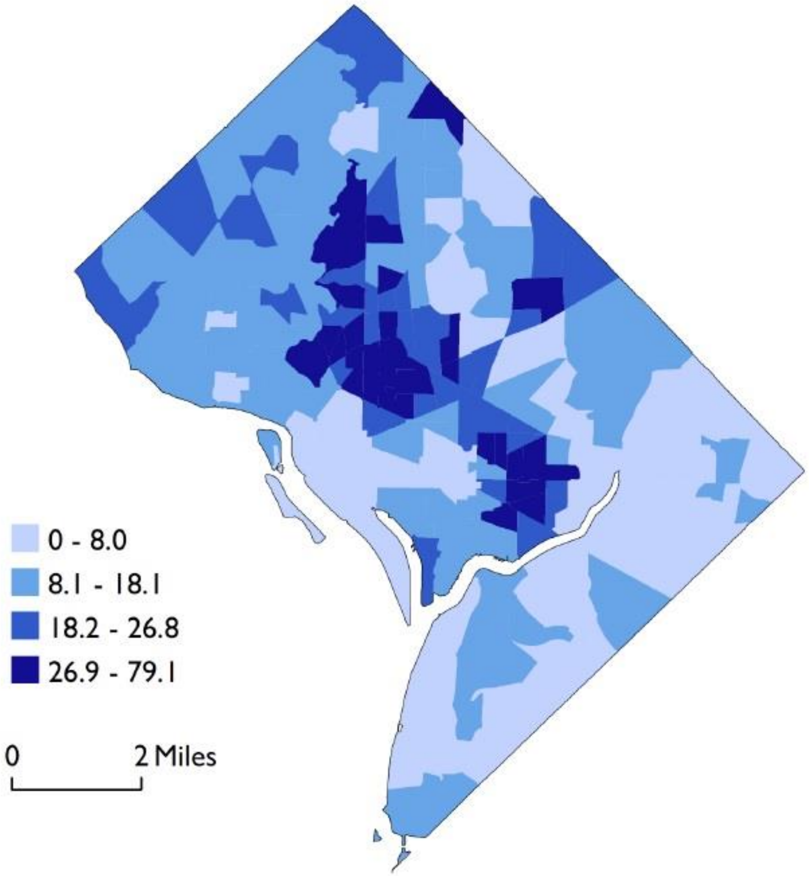
Standard errors in parentheses are robust and clustered at lender level
* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$

Figure 1a: Percentage of State Level Same-sex Borrowers and Gallup 2012 LGBT Estimate



Gallup estimate can be found at http://www.gallup.com/poll/160517/lgbt-percentage-highest-lowest-north-dakota.aspx

Figure 1b: The Williams Institute 2010 DC Same-sex Couples Estimate (Based on Census Data)



The Williams Institute http://williamsinstitute.law.ucla.edu/

Figure 1c: The Heat Map of DC Same-sex Borrowers (Based on HMDA Implied)

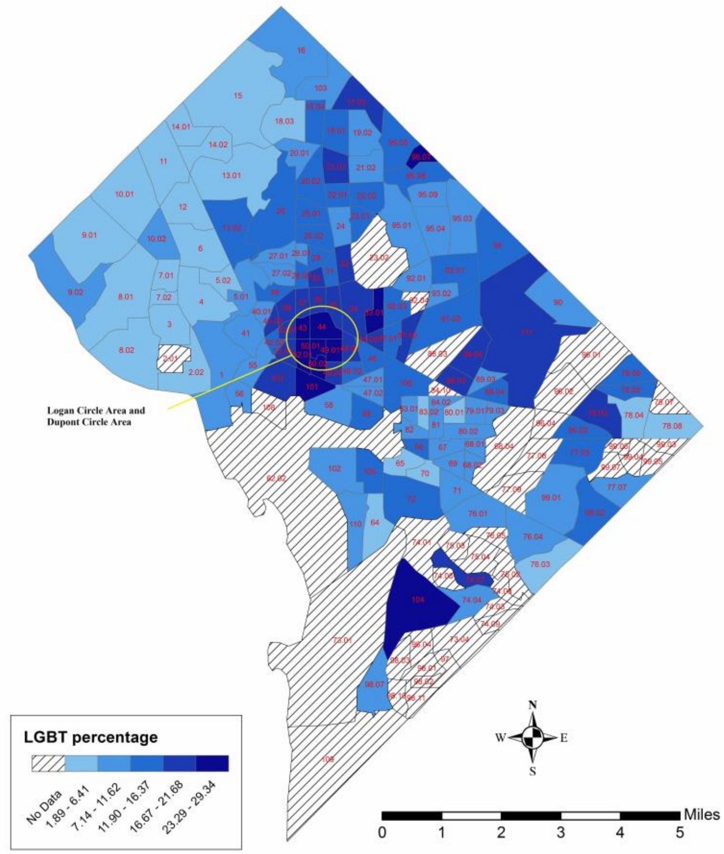


Figure 2: Graph of the "same-sex" Coefficient and Associated 5% Confidence Interval using HMDA 100% National Data from 1990 to 2015

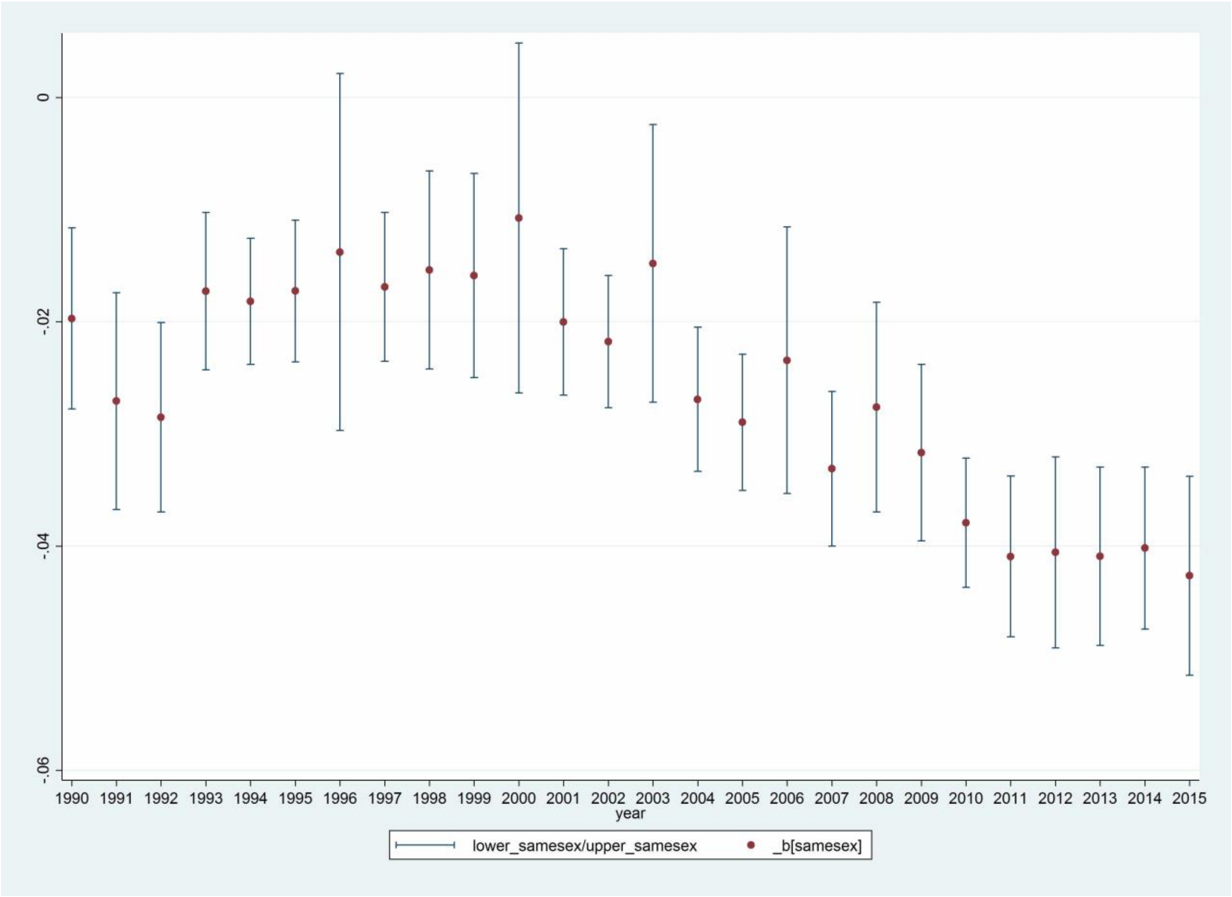


Figure 3: Graph of the "same-sex" Coefficient from Lender Level Loan Approval and Cost Regressions