New Results on the Disparities between Same-Sex and Different-Sex Couples in the Home Mortgage Market

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Abstract

Despite improving public sentiment towards same-sex couples, research suggests that they still face discrimination in various markets. We empirically estimate disparities between same-sex and different-sex couples in the home mortgage market, an understudied, yet important, market. Improving previous research, we use confidential administrative data on the universe of home mortgage applications in the U.S. from 2018 until 2019. We identify same-sex and different-sex couples according to the gender of the mortgage applicant and co-applicant. Then, controlling for a rich set of lender, borrower, and loan characteristics, some of which are important in mortgage decisions but were not available in previous research like credit scores, we find that same-sex couples are 8.8 percent more likely to be denied a home mortgage than similar opposite-sex couples and conditional on being approved, are quoted an interest rate that is 0.8 percent higher. We explore heterogeneity by regions, by acceptance of same-sex marriage, and pre and post COVID. Interestingly, we also find that same-sex couples default significantly more (53.9%) than similar different-sex couples during COVID period, which suggests unobserved characteristics that cause same-sex couples to default more, and could explain a part of observed disparities in mortgage approval, undermining results in previous research.

Keywords: same-gender couples, same-sex couples, LGBTQ, residential mortgage, discrimination, disparities

JEL Codes: D1, D4, G2, G5

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1 Introduction

1.1 Work Product Summary

CSI Data: Confidential HMDA (Home Mortgage Disclosure Act). The main data source for this research project is the confidential version of the Home Mortgage Disclosure Act (HMDA) data managed by the Federal Reserve Board. The HMDA data are collected by the Federal Financial Institutions Examination Council (FFIEC) and the Consumer Financial Protection Bureau (CFPB). This dataset contains a rich set of information on mortgage applicant demographics, mortgage application outcomes, mortgage loan characteristics and lender characteristics.

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Project Description: Despite improving public sentiment towards same-sex couples, research suggests that they still face discrimination in various markets. We empirically estimate disparities between same-sex and different-sex couples in the home mortgage market, an understudied, yet important, market. Improving previous research, we use confidential administrative data on the universe of home mortgage applications in the US from 2018 until 2019. We identify same-sex and different-sex couples according to the gender of the mortgage applicant and co-applicant. Then, controlling for a rich set of lender, borrower, and loan characteristics, some of which are important in mortgage decisions but were not available in previous research like credit scores, we find that same-sex couples are 8.8 percent more likely to be denied a home mortgage than similar opposite-sex couples and conditional on being approved, are quoted an interest rate that is 0.8 percent higher. We explore heterogeneity by regions, by acceptance of same-sex marriage, and pre and post COVID. Interestingly, we also find that same-sex couples default significantly more (53.9%) than similar different-sex couples, which suggests unobserved characteristics that cause same-sex couples to default more, and could explain a part of observed disparities in mortgage approval, undermining results in previous research.

Usage of CSI Data (Confidential HMDA): The reason for needing the CSI version of HMDA is to know the two dates information (application and decision dates), borrowers' FICO scores, and loan officer identification. The summary statistics and regression analyses are performed at aggregated levels. In sum, no identity of any lender or any borrower will be revealed in the study.

1.2 Introduction

Homeownership is still considered a pivotal part of the American dream. In a recent poll, homeownership was cited as part of the American dream by 74% of Americans; more than any of other life outcomes such as having a successful career or getting a college degree (Ostrowkski, J., 2023). Indeed, homeownership entails numerous social and economic benefits. Yun and Evangelou (2016) provide a review of the evidence; the authors cite educational achievement, civic participation, and improved health among the benefits that have been associated with homeownership in the literature. Two later papers find additional benefits; Sodini et al. (2016) find that home ownership is a beneficial wealth accumulation tool, and that it promotes mobility, increases consumption, and improves consumption smoothing; and Goodman and Mayer (2018) find that the internal rate of return to homeownership is favorable compared to alternative investments. According to the United States Census Bureau (2023), 65.9% of households owned a home in the second quarter of 2023. Of recent buyers, 78% financed their home purchase (Consumer Financial Protection Bureau, 2022). Therefore, any disadvantage in securing financing could be detrimental to the possibility of owning a home.

In this paper we provide new estimates for the disparities in mortgage application outcomes between same-sex and different-sex couples. To estimate disparities, we use the confidential version of the Home Mortgage Disclosure Act (HMDA) data which encompasses data at the application level on the universe of mortgage applications in the United States. The data contains a rich set of information that allows us to control for borrower, lender, and loan characteristics that were not available in previous research. We focus on the period after January 2018 including it, for which the data contains the most comprehensive information on applications, up to December 2019, before the onset of COVID. We restrict the analysis to applications that have both an applicant and co-applicant and categorize an application as either male-female, female-male, male-male, and female-female according to the sex of the applicant and co-applicant. We also use the HMDA and McDash merged dataset to examine loan performance.

In order to estimate disparities in mortgages application outcomes, our main specification regresses one of three mortgage outcomes - mortgage application rejection, mortgage application interest rate, and mortgage application default (i.e. 90-day delinquency) - on the sex composition of the mortgage application (e.g. male-male) as well as a rich set of controls. Specifically, we are able to control for applicant and co-applicant credit scores, as well as lender-county-month, loan-type, and loan officer fixed effect. Thus, we are comparing mortgage outcomes of two applications submitted in the same month, in the same county, to the same lender, have similar observable characteristics, and are judged by a similar loan officer, where the sex composition of one application is male-female, and the sex composition of the other application is one of the other three sex composition categories.

We find that male-male mortgage applications are 8.8% more likely to be rejected, and if approved, are quoted an interest rate that is 0.8% higher relative to similar male-female applications. We find weaker evidence of disparities between female-female applications and male-female applications. We explore several heterogeneous effects and find that disparities between male-female and male-male mortgages applications are higher in states in the Midwest and the South, where acceptance of LGBTQ people is lower than in states in the Northeast and the West. We also estimate the disparities during the COVID period and find that the disparities widen during this period.

Next, we turn to examine loan performances. We find that male-male mortgage applications are 53.9% more likely to be 90-day delinquent within 36 months of origination relative to similar male-female originations. Although the base 90-day delinquency rate for male-female applications is low (3.81%), the significantly higher 90-day delinquency for male-male applications is surprising. This suggests that male-male applications carry a higher risk than similar male-female applications. This could be driven by same-sex couples having different saving behavior, higher susceptibility to employment shocks, especially during COVID, lower paternal support, or other differences. This result means that some of the disparities in mortgage rejection and interest rate between male-female and male-male applications are explained by higher risk of the latter due to some unobserved characteristics. We plan to explore this further in the future. This result also differs significantly from previous research that found no difference in risk between same-sex and opposite-sex applications (e.g. Sun and Gao (2019)) and have therefore inferred that the disparities in mortgage rejection and interest rate are due to discrimination.

The paper continues as follows; in section 2, we discuss the related literature; in section 3, we discuss the data and provide descriptive statistics; in section 4, we discuss the empirical strategy; in section 5, we discuss the main results and the heterogeneity analysis; and we conclude in section 6.

2 Related Literature

Ample research documents discrimination against LGBTQ people. Most of the studies focus on labor market discrimination and employ either experimental (mostly audit studies) or observational methods. The first provide the most convincing evidence of discrimination; they suggest that LGBTQ job candidates were less likely to be invited for an interview or to be offered a job than otherwise identical non-LGBTQ people. The second type of studies, those that use observational methods provide consistent evidence of wage and income differentials between LGBTQ and non-LGBTQ workers. For example, they find that gay/bisexual men earned less than heterosexual men with similar characteristics (see Badgett et al. (2021) and Neumark (2018) for a review of labor market discrimination against LGBTQ people).

Other studies focus on discrimination against LGBTQ people in the housing market. Using experimental methods, Ahmed and Hammarstedt (2009), Levy et al. (2017), and Schwegman (2019) find that LGBTQ applicants are less likely to be successful in securing a rental unit.

Other papers on this topic are more closely related to our paper. Sun and Gao (2019), Dillbary and Edwards (2019), and Hagendorff et al. (2022) estimate disparities in mortgage outcomes between same-sex and different-sex couples using data and methods similar to ours. Sun and Gao (2019) estimate these disparities in the years of 1990 - 2015 using public HMDA data and also in 1990 using data on a small sample (2,316) of mortgage applications from the Boston area, which includes information not available in the public HMDA. Similar to our paper, the authors estimate disparities in mortgage application rejection, interest rate, and performance. Nonetheless, our paper improves upon their results. First, we estimate disparities in a more recent period. This is especially important in the context of this paper as several landmark decisions affecting LGBTQ people have been implemented in recent years including the 2015 Obergefell v. Hodges U.S. Supreme Court decision that federally legalized same-sex marriage and the 2021 Biden administration executive order to include protections against discrimination in housing financing of LGBTQ people under The Fair Housing Act. These, in addition to secular trends in the acceptance of LGBTQ people over time, could affect the disparities estimates. Second, whereas Sun and Gao (2019) use the public HMDA data, we use the confidential HMDA data. This allows us to include a much richer set of controls in our regressions that result in decreased omitted variable bias stemming from Sun and Gao (2019)'s exclusion of certain variables that are correlated with both same-sex status, and mortgage outcomes. Specifically, we are able to include the applicant and co-applicant credit scores, an important measure used by lenders to assess risk, as well as the month of the application (rather than year), and control for the loan officer. The latter are important as same-sex couples could potentially select into specific lenders. Furthermore, whereas Sun and Gao (2019) include demographic information at the census-tract level, we are able to include it at the loan application level. Although the Boston sample allows Sun and Gao (2019) to include some of the variables that are missing from the public HMDA data, the sample is only from a single year - 1990, and also from only one geographical area, thus might lack external validity. Third, we estimate disparities separately for female-male, male-male, and female-female couples compared to male-female couples, rather than for same-sex compared to different-sex couples, as Sun and Gao (2019) do. Lastly, we estimate how disparities change during an economics crises as well.

Dillbary and Edwards (2019), and Hagendorff et al. (2022) also use public HMDA data to estimate disparities between same-sex and different-sex couples and therefore suffer from the same aforementioned issues that Sun and Gao (2019)'s paper does. Our paper is more broadly related to recent papers that estimate disparities in mortgage lending related to other applicant characteristics such as race or gender (Cheng et al., 2011; Hanson et al., 2016; Ambrose et al., 2021; Wei and Zhao, 2022; Bartlett et al., 2022), or in other lending contexts, such as business loans (Chernenko and Scharfstein, 2022).

3 Data

3.1 Data

The main data source for the paper is the confidential version of HMDA data managed by the Federal Reserve Board. The HMDA data are collected by the Federal Financial Institutions Examination Council (FFIEC) and the Consumer Financial Protection Bureau (CFPB). The data contains a rich set of information on applicant demographics, application outcomes, loan characteristics and lender characteristics. Using the data, we limit our analysis to home purchase applications[1] that include a co-applicant (39.9% of total applications), so we can infer the applications' sex composition. Specifically, we categorize applications' sex composition as either male-female, female-male, male-male, and female-female, where the first is the applicant and the second is the co-applicant. We limit our analysis to applications in which the age difference between the applicant and co-applicant is less than 25 years. This is to exclude applications submitted by a father and son, for example, when the father is a co-signor because credit score of his son is not established. We also exclude applications in which the occupancy type is an investment property. By focusing on principal residence and second residence occupancy types, we exclude investors who are generally thought of as low credit quality and are at a high risk of default. Our data confirms that there are disproportionately more male-male relationships among investors. Misclassifying these applications as male same-sex would have resulted in overestimating the disparities in mortgage outcomes between

[1] In the appendix, we provide results for the refinancing market as well.

male same-sex and different-sex applications.

Our main analysis focuses on the period 2018 - 2019, the period before the onset of COVID and after data on credit scores, that are crucial for mortgage applications decisions, became available. Our analysis utilizes the rich set of application information in the data - loan type[2]; applicant and co-applicant credit score[3]; the interest rate quoted if the loan is approved[4]; applicant income[5]; and applicant demographics.

For the loan performance analysis, we use HMDA and ICE McDash Data merged dataset (HMDA-McDash dataset). We keep first-lien, primary owner, 30-year fixed rate, one unit observations. We track each originated loan for 36 months and, as standard in the literature, define a 90-day delinquency of the loan binary variable in case loan payment was not received within a 90-day period.

3.2 Descriptive Statistics

Columns (1)-(4) in Table 1 provide summary statistics for mortgage applications by the sex composition of the applicant - co-applicant and column (5) provides summary statistics for all mortgage applications. Additional summary statistics appear in Table A0.1. As detailed in the table, male-female applications have a lower rejection rate and, conditional on approval, are quoted a lower average interest rate than male-male applications (23.39% versus 28.03% and 4.39% versus 4.49%, respectively). This can be partially explained by male-female applications having mostly better observable characteristics than male-male applications; male-female applications have lower loan-to-value and debt-to-income ratios than male-male applications (85.91% versus 87.63% and 37.64% versus 40.58%, respectively) and male-female applicants have higher applicant and co-applicant credit scores than male-male applications (733.03 versus 717.20 and 734.65 versus 724.46, respectively). In contrast, the applicant income in male-female applications is lower than in male-male applications ($124,875 versus $128,003). In terms of demographics, a larger share of male-female applications have a White main applicant than male-male applications (80% versus 75%), and a smaller share of male-female applications has a young (aged 20 - 29) main applicant compared to male-male applications (15% versus 22%).[6]

[2]Applications are categorized as conventional, Federal Housing Administration insured, Veterans Administration insured, and Farm Service Agency / USDA Rural Housing Service guaranteed.

[3]We drop observations in which the applicant or co-applicant credit scores are smaller than 200 or greater than 1000.

[4]We drop observations in which the interest rate is negative or greater than 20%.

[5]We drop observations in which the applicant income is negative or greater than $500,000.

[6]For discussions on age and mortgage access, see Amornsiripanitch (2024)

4 Empirical Strategy

In order to estimate disparities in mortgage application outcomes by sex compositions, we estimate the following specification using the HMDA data:

$$Y_{i,c,t,lo,le,lt} = \sum_{s=\{FM,MM,FF\}} \beta_s \cdot Sex\_Composition_{i,c,t,lo,le,lt} + \gamma \cdot X_{i,c,t,lo,le,lt} + \mu_{c,t,le} + \tau_{lt} + \theta_{lo} + \epsilon_{i,c,t,lo,le,lt} \tag{1}$$

where $Y_{i,c,t,lo,le,lt}$ is an outcome of interest for application i, submitted in county c, in month-year t, to loan officer lo, working for lender le, for a loan type lt. We consider two outcomes - first, a binary variable that takes the value of 100 if the application is rejected and 0 otherwise; second, the interest rate quoted in case the application was approved. $X_{i,c,t,lo,le,lt}$ is a vector of application characteristics that might affect the application outcome. Specifically, we flexibly control for loan-to-value ratio, debt-to-income ratio, applicant and co-applicant credit scores, main applicant race (White is the omitted racial group), and main applicant age in 5-years bins (Age 20 - 24 is the omitted age group).

We include county×month×lender fixed effects, $\mu_{c,t,le}$, to control for factors that affect the application outcome at specific county at specific month for certain lender, for example local economic shocks; loan type fixed effects, τ_{lt}, to control for time-invariant differences in loan types (see section 3.1 for the definition of loan types) between applications that might be correlated with the sex composition of the application and the application outcome (e.g. it could be the case that male-female applications are more likely to apply for an FHA-insured loan which is more likely to be approved); and loan officer fixed effects, θ_{lo}, to control for time-invariant differences between loan officers' propensity to approve an application.

The treatment variable $Sex\_Composition_{i,c,t,lo,le,lt}$ takes the value of 1 if the application is in sex composition category s where $s \in \{female-male, male-male, female-female\}$ and 0 otherwise. The omitted category is male-female. Thus, the coefficients of interest, β_s, measure the disparity in the outcome between each respective sex composition category s relative to male-female. Standard errors are clustered at the county level.

As we include the rich set of controls and fixed effects detailed above, the disparities are estimated as the difference in the outcome between two applications that are submitted in the same month, in the same county, to the same lender, have similar observable characteristics, and are judged by similar loan officers but the sex composition of one application is male-female whereas the sex composition of the other application is either of the three other sex composition categories.

In order to estimate loan performance, we estimate equation (1) using the merged HMDA-

McDash data without loan officer fixed effects and age [7] on a subsample of mortgage applications that were approved and originated in the pre-COVID period (2018 - 2019) where the outcome variable is a binary variable that takes the value 100 if a mortgage loan is 90-day or more delinquent within 36 months of origination and 0 otherwise.

5 Results

5.1 Main Regression Results

Table 2 details the results of estimating equation (1) with the outcome being a binary variable that takes the value of 100 if the application is rejected and 0 if it is approved. Each column refers to a different specification that includes the fixed effects detailed in the lower panel. In column (1), we control only for county-month; in column (2), we control for county-month and loan type; in column (3), we control for lender-county-month and loan type; lastly, in column (4), we control for lender-county-month, loan type, and loan officer. The last column is our preferred specification. All specifications include the controls listed in the middle panel and the coefficients in the table are interpreted as percentage points. Additional results appear in Table A0.2.

The results for the coefficients of interest appear in the upper panel. The coefficients for male-male are significant at 1% - 5% levels across specifications. The coefficient in our preferred specification (column (4)) is 2.046, meaning, male-male applications are associated with 2.046 percentage point higher rejection rate relative to similar male-female applications. Given that the mean male-female rejection rate is 23.39%, this result suggests that male-male applications are 8.8% more likely to be rejected relative to similar male-female applications.

Next, we compare our preferred specification with the other less saturated specifications. Starting with specification (1), which controls for county-month only and the set of controls listed in the middle panel, and then adding controls for loan type in specification (2), and lender type in specification (3), does not significantly change the coefficient. Whereas, adding controls for loan officer increases the coefficient from 1.385 (column (3)) to 2.046 (column(4)). The coefficients for female-male and female-female are statistically insignificant under the saturated specifications, suggesting there are no disparities in application approval between these borrowers relative to similar male-female borrowers.

Table 3 shows the results of estimating equation (1) with the outcome being the interest

[7] Data on loan officers and on applicant age is not available in the McDash data

rate quoted. We estimate our preferred specification, which include the fixed effects detailed in the lower panel, for the set of approved loan applications. cHMDA Controls variable includes Loan-to-Value, Loan-to-Value Squared, Debt-to-Income, Debt-to-Income Squared, Applicant Credit Score, Applicant Credit Score Squared, Co-applicant Credit Score, Co-applicant Credit Score Squared, Applicant Income, Hispanic, Black, Asian, Other Races, Age 25 - 29, Age 30 - 34, Age 35 - 39, Age 40 - 44, Age 45 - 49, Age 50 - 54, Age 55 - 59, Age 60 - 64, Age 65 - 69, and Age 70+. The coefficients of interest are interpreted as interest rate percentage points. The coefficient for male-male is 0.035 and is statistically significant at 5%, meaning, approved male-male applications are associated with 0.035 percentage point higher interest rates relative to similar approved male-female applications. Given that the mean interest rate for approved male-female applications is 4.39%, this result suggests that approved male-male borrowers are quoted an interest rate that is 0.8% higher relative to similar approved male-female applications. The coefficient for female-male is statistically significant at 1% but is a third of the magnitude of the coefficient for male-male, and the coefficient for female-female is significant at 5% and is 20% smaller in magnitude than the coefficient for male-male. These suggest there are disparities, albeit weak, in interest rate quoted for approved applications between male-female borrowers and female-male/female-female borrowers.

Table 4 details the results of estimating our preferred specification with the outcome being a binary variable that takes the value of 100 if a 90-day delinquency occurred during 36 months following loan origination and 0 otherwise. The coefficient for male-male is statistically significant at 1%. Male-male loan originations are associated with 2.053 percentage point higher default rate relative to similar male-female applications. Given that the mean male-female delinquency rate is 3.81%, this result suggests that male-male applications are 53.9% more likely to be 90-day delinquent relative to similar male-female applications. The coefficient for female-male is statistically insignificant and the coefficient for female-female is statistically significant at 1% level and is about a third of the male-male coefficient.

In contrast to Table 4, Table 5 shows default rate results during normal times instead of recessions. The coefficient estimate for male-male is statistically insignificant and it shows a negative sign. The coefficient estimates for female-male and female-female are both statistically insignificant as well. It tells us that while male-male applications carry higher risk on average during economic crisis such as COVID, they do not default significantly more than observationally similar male-female applications during normal times.

Table 6 details the results of estimating our preferred specification with the outcome being a binary variable that takes the value of 100 if the application is rejected and 0 if it is approved separately for two subsamples - applications that were approved by the Automated Underwriting System (AUS) (70,923) and other applications (4,209). Column (1) details the results of the former, column (2) details the results of the latter, and column (3) details the results of the entire sample. The coefficient estimate for male-male in the subsample of applications approved by the AUS is 2.168 and is significant at 1%. This means that the AUS recommendation for these applications is overturned by loan officers (i.e. the application ended up being denied) more for male-male applications than for similar male-female applications. The coefficient for male-male in the subsample of not AUS-approved applications is higher, 5.493, although it is noisily estimated due to the small share of male-male application of this already smaller subsample of only 4,209 applications. Thus, it is statistically insignificant.

Tables A0.3, A0.4, A0.5, and A0.6 repeat the analysis above for refinancing mortgage applications. The results suggest disparities do not exist in this market.

5.2 Heterogeneity Analysis

Table 7 reports the results of estimating our preferred specification with the outcome being a binary variable for rejection, separately for the four census regions[8]. The coefficient estimates for male-male are statistically significant at 10% for the Midwest and at 5% for the South and are statistically insignificant for the Northeast and West. Male-male applications in the Midwest and in the South are associated with 5.664 and 3.042 percentage point higher rejection rates, respectively, relative to similar male-female applications in the same region. Given that the mean male-female rejection rates in the Midwest and the South are 24.9% and 29.5%, respectively, these results suggests that male-male applications are 22.7% and 10.3% more likely to be rejected in the Midwest and in the South, respectively, relative to similar male-female applications. The coefficient estimates for female-male and female-female are statistically insignificant.

Table 8 shows the results of estimating our preferred specification with the outcome being a binary variable for rejection, separately for three sub-groups of states. We ranked states

[8]Table A0.7 details the states included in each of the census regions.

according to their acceptance of same-sex marriage, as reflected in the 2014 PEW Research Religious Landscape Study, and divided them into tertiles, where the first tertile includes states with the lowest acceptance of same-sex marriage and the third tertile includes states with the highest acceptance of same-sex marriage[9]. The coefficient estimates for male-male are statistically significant at 5% only for the second tertile and are statistically insignificant for the first and third tertile. Male-male applications in the second tertile are associated with 3.123 percentage point higher rejection rate relative to similar male-female applications. Given that the mean male-female rejection rate in the second tertile is 28.2%, this result suggests that male-male applications are 11.1% more likely to be rejected in the second tertile relative to similar male-female applications. The coefficient estimates for female-male and female-female are statistically insignificant.

Table 9 reports the results of estimating our preferred specification with the outcome being a binary variable for rejection, for applications submitted during the COVID period (January 2020 - December 2021). The coefficient for male-male is statistically significant at 1%. Male-male applications submitted during COVID period are associated with a 2.368 percentage point higher rejection rate relative to similar male-female applications. This result is not statistically different than the result for the pre-COVID period (2.046). Given that the mean male-female rejection rate for applications during the COVID period is 27.4%, this result suggests that male-male applications are 8.6% more likely to be rejected during the COVID period, relative to similar male-female applications. The coefficient estimates for female-male and female-female are statistically insignificant.

In Table 10, we show the results of estimating our preferred specification with the outcome being the interest rate quoted, for applications submitted during the COVID period (January 2021 - December 2021). We estimate our preferred specification for the set of approved loan applications. The coefficient estimate for male-male is statistically significant at 1%. Approved male-male applications are associated with 0.04 percentage point higher interest rate relative to similar approved male-female applications. Given that the mean interest rate for approved male-female applications is 3.06%, this result suggests that approved male-male applications are quoted an interest rate that is 1.3% higher relative to similar approved male-female applications. The coefficient estimates for female-male and female-female are also statistically significant at 1%, although the former is a third of the magnitude as the male-male coefficient estimate. These suggest disparities in the interest rate quoted for

[9] Table A0.8 details the states included in each of the tertiles.

approved applications for female-male and female-female applications relative to male-female applications.

6 Labor Market Conditions and Mortgage Defaults

6.1 Mortgage Data

The significantly higher 90-day delinquency rates of male-male applications relative to male-female applications during times of stress, reported in section 5.1, could be driven by several factors. In this section we explore how labor market outcomes interact with mortgage delinquency. Specifically, we examine whether male-male applicants are more likely to experience a negative income shock relative to male-female applicants and conditional on experiencing a negative income shock, whether they are more likely to be delinquent than male-female applicants are. Both could lead to higher delinquency rates. The former could be due to differences in the labor market characteristics of male-male applicants relative to male-female applicants such as employment in different sectors or occupations and hours worked, as well as other explanation, such as discrimination. The latter could be due to male-male applicants saving less than male-female applicants so they do not have resources to tap into given a negative income shock, having lower marriage rates so they do not have a partner to insure against a negative income shock, discrimination so they are less likely to return to their income prior to the negative income shock, differences in risk aversion, or differences in trust in institutions. To examine these, we utilize the HMDA-McDash-CRISM merged dataset, in addition to tracking the loan performance of approved mortgage applications, which has data on the monthly income of the mortgage applicant. It does not include data on the income of the co-applicant; thus, comparing male-male applications to male-female applications entails comparing the income of the male applicant of these applications.

We begin with examining whether different sex composition applicants are more likely to experience a negative income shock relative to male-female applicants. To do so, we estimate the following regression:

$$Y_{i,c,t,lt} = \sum_{s=\{FM,MM,FF\}} \beta_s \cdot Sex\_Composition_{i,c,t,lo,le,lt} + \gamma \cdot X_{i,c,t,lt} + \mu_{c,t} + \tau_{lt} + +\epsilon_{i,c,t,lt} \quad (2)$$

Where $Y_{i,c,t,lt}$ is the outcome of interest for application i, submitted in county c, in quarter-year t, for a loan type lt. The first outcome of interest is a binary variable that takes the value 1 if the applicant experienced a negative income shock, defined as a decline in monthly income of more than 67% from the previous month, at any point following 3 years from the origination. $X_{i,c,t,lt}$ is a vector of application and applicant characteristics. Specifically, we flexibly control for loan-to-value ratio, debt-to-income ratio, applicant credit scores, applicant race. As the data lacks the applicant labor market characteristics, any differences in the frequency of the negative income shocks could be attributed to differences in sectors, occupations, etc. between the different sex compositions applicants.

We include county×quarter fixed effects, $\mu_{c,t}$, and loan type fixed effects, τ_{lt}. The CRISM dataset does not include data on the applications' lender and loan officer so we are unable to estimate the previous saturated model. The treatment variable $Sex\_Composition_{i,c,t,lo,le,lt}$ is defined as detailed in section 4.1. Standard errors are clustered at the county level.

6.2 Results

Next, we examine how negative income shocks affect the likelihood of delinquency or default. We estimate equation 2 with the outcome of interest a binary variable that takes the value 100 if the loan originated was ever 90-day delinquent within 36 months of origination. We estimate the equation separately for applications in which the applicant did experience a negative income shock within 36 months of origination and applications in which the applicant did not experience a negative income shock within 36 months of origination. Tables 12 and 13 detail the results of the former and the latter, respectively.

Taken together, these results suggest that the higher delinquency rate of male-male applications relative to male-female applications is partially driven by a higher likelihood of experiencing negative income shocks rather than a differential effect of a negative income shock on delinquency. It is also driven by a higher likelihood of delinquency absent of negative income shocks.

7 Conclusion

In this paper, we provide new estimates of the disparities in mortgage application outcomes between same-sex and opposite-sex couples. Using confidential data on the universe of mortgage applications in the United States in the years 2018 - 2019, we compare the mortgage outcomes of same-sex and different-sex couples while controlling for a rich set of borrower, lender, and loan characteristics, that were not available to previous researchers. We find that male-male mortgage applications are 8.8% more likely to be rejected than similar male-female mortgage applications and that if approved, are quoted an interest rate that is 0.8% higher. On the other hand, we also find that male-male mortgage applications are 53.9% more likely to default within 36 months of origination during economic crisis. This suggests that there are unobserved characteristics that make male-male mortgage applications riskier, which explains part of the disparities in mortgage application outcomes. We also investigate potential channels for this by linking mortgage market with labor market conditions.

Acknowledging the existence of disparities in mortgage lending is important. Although sentiment towards LGBTQ people has improved in recent decades, research suggest that they still suffer from various forms of discrimination. Documenting disparities observed in the market and identifying mechanism channels are important steps toward eliminating inequalities.

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Tables and Figures

Table 1: Summary Statistics

		(1) Male-Female	(2) Female-Male	(3) Male-Male	(4) Female-Female	(5) All
Rejection Rate (%)	Mean	23.39	24.98	28.03	27.06	23.96
	SD	42.33	43.29	44.92	44.43	42.68
Interest Rate (%)	Mean	4.39	4.43	4.49	4.52	4.40
	SD	0.65	0.65	0.66	0.65	0.65
Loan-to-Value (%)	Mean	85.91	87.60	87.63	88.37	86.41
	SD	14.62	13.32	13.04	13.37	14.28
Debt-to-Income (%)	Mean	37.64	37.66	40.58	41.06	37.80
	SD	11.14	11.18	11.75	11.76	11.20
Applicant Credit Score	Mean	733.03	723.35	717.20	708.90	729.84
	SD	59.53	61.44	59.57	62.83	60.32
Co-applicant Credit Score	Mean	734.65	720.81	724.46	715.99	730.73
	SD	59.88	62.91	59.48	64.78	61.04
Applicant Income ($)	Mean	124,875	121,050	128,003	107,177	123,608
	SD	77,975	73,099	82,436	66,968	76,779
White	Mean	0.80	0.78	0.75	0.73	0.79
	SD	0.39	0.41	0.43	0.44	0.40
Hispanic	Mean	0.11	0.11	0.23	0.19	0.11
	SD	0.31	0.32	0.42	0.39	0.32
Black	Mean	0.05	0.06	0.05	0.11	0.05
	SD	0.21	0.24	0.22	0.31	0.22
Asian	Mean	0.06	0.06	0.10	0.06	0.06
	SD	0.24	0.24	0.30	0.25	0.24
Age 20 - 24	Mean	0.03	0.06	0.07	0.06	0.04
	SD	0.17	0.24	0.26	0.24	0.20
Age 25 - 29	Mean	0.12	0.17	0.15	0.14	0.13
	SD	0.32	0.38	0.36	0.35	0.34
Age 30 - 34	Mean	0.17	0.20	0.16	0.15	0.17
	SD	0.37	0.40	0.37	0.36	0.38
Age 35 - 39	Mean	0.15	0.16	0.14	0.13	0.15
	SD	0.36	0.36	0.35	0.33	0.36
Age 40 - 44	Mean	0.11	0.10	0.11	0.11	0.11
	SD	0.31	0.31	0.32	0.31	0.31
Age 45 - 49	Mean	0.09	0.08	0.10	0.10	0.09
	SD	0.29	0.27	0.30	0.30	0.28
	N	543,708	175,796	18,229	19,100	756,833

Notes: This table provides summary statistics for home purchase mortgage applications by the sex composition of the applicant - co-applicant in columns (1)-(4) (e.g. Male-Female refers to mortgages in which the applicant is a male and the co-applicant is a female) and for all applications in column (5). We include applications submitted between 2018 - 2019. For conciseness, we do not include summary statistics for applications in which the applicant is any race other than White, Hispanic, Black, or Asian and applications in which the applicant is 50 or above. These are detailed in Table A0.1.

Table 2: Rejection Rates - Baseline

	(1)	(2)	(3)	(4)
Female-Male	0.329**	0.166	-0.093	0.054
	(0.14)	(0.14)	(0.22)	(0.31)
Male-Male	1.695***	1.642***	1.385**	2.046**
	(0.46)	(0.46)	(0.67)	(0.93)
Female-Female	0.387	0.350	0.330	0.648
	(0.45)	(0.44)	(0.61)	(0.79)
Loan-to-Value	0.127***	-0.043	-0.062*	-0.005
	(0.03)	(0.03)	(0.04)	(0.04)
Loan-to-Value Squared	-0.001***	0.001***	0.001***	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Debt-to-Income	-1.211***	-1.223***	-1.301***	-1.367***
	(0.03)	(0.03)	(0.05)	(0.06)
Debt-to-Income Squared	0.019***	0.020***	0.020***	0.021***
	(0.00)	(0.00)	(0.00)	(0.00)
Applicant Credit Score	-0.486***	-0.554***	-0.625***	-0.671***
	(0.04)	(0.04)	(0.05)	(0.07)
Applicant Credit Score Squared	0.000***	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
Co-applicant Credit Score	-0.617***	-0.658***	-0.618***	-0.662***
	(0.05)	(0.05)	(0.07)	(0.09)
Co-applicant Credit Score Squared	0.000***	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
Applicant Income	0.004***	0.003***	0.000	0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Hispanic	1.038***	1.148***	1.076***	0.619
	(0.27)	(0.27)	(0.34)	(0.42)
Black	1.732***	1.953***	0.594	-0.381
	(0.35)	(0.35)	(0.55)	(0.68)
Asian	3.096***	2.906***	1.670***	1.143**
	(0.29)	(0.29)	(0.42)	(0.57)
Age 25 - 29	-1.327***	-1.198***	-1.264***	-0.622
	(0.31)	(0.31)	(0.48)	(0.66)
Age 30 - 34	-1.205***	-0.967***	-1.210**	-0.432
	(0.31)	(0.31)	(0.50)	(0.67)
Age 35 - 39	-0.877***	-0.564*	-0.913*	-0.169
	(0.33)	(0.32)	(0.50)	(0.64)
Age 40 - 44	-0.983***	-0.630*	-0.659	-0.220
	(0.34)	(0.34)	(0.52)	(0.68)
Age 45 - 49	-0.142	0.267	0.211	0.374
	(0.36)	(0.36)	(0.60)	(0.76)
County-Month FE	Yes	Yes	Yes	Yes
Loan Type FE	No	Yes	Yes	Yes
Lender-County-Month FE	No	No	Yes	Yes
Loan Officer FE	No	No	No	Yes
R^2	0.193	0.198	0.447	0.591
N	196,220	196,220	104,483	84,673

Notes: This table provides the results of estimating equation (1) with the outcome being a binary variable that takes the value of 100 if the application is rejected and 0 otherwise. Each column refers to a different regression that includes the fixed effects details in the lower panel. We include applications submitted in 2018 - 2019. Rows (1)-(3) provide the estimates for each sex composition with male-female being the omitted category. The other rows provide the estimates for the control variables. White is the omitted race category and age below 24 is the omitted age category. Robust standard errors clustered at the county level are in parentheses. For conciseness, we do not include the regression results for the following controls - other race, and the age bins above 50. These are detailed in Table A0.2.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3: Interest Rates - Baseline

Female-Male	0.013***
	(0.00)
Male-Male	0.035**
	(0.01)
Female-Female	0.028**
	(0.01)
cHMDA Controls	Yes
Lender-County-Month FE	Yes
Loan Type FE	Yes
Loan Officer FE	Yes
R^2	0.838
N	72,651

Notes: This table provides the results of estimating equation (1) on the subset of approved applications with the outcome being the interest rate. The regression is our preferred specification which includes lender×county×month fixed effects, loan type fixed effects, loan officer fixed effects and the cHMDA Controls are listed in Section 5. We include applications submitted in 2018 - 2019. The table provides the estimates for each sex composition with male-female being the omitted category. Robust standard errors clustered at the county level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4: Default Rates - Economic Crisis (COVID)

Female-Male	-0.146
	(0.10)
Male-Male	2.053***
	(0.31)
Female-Female	0.779***
	(0.29)
Interest Rate	1.715***
	(0.13)
HMDA-McDash Controls	Yes
Loan Type FE	Yes
County-Quarter FE	Yes
R^2	0.103
N	311,114

Notes: This table provides the results of estimating equation (1) with the outcome being a binary variable that takes the value of 100 if a 90-day delinquency ever occurred within 36 months of origination and 0 otherwise. The regression includes county×quarter fixed effects, loan type fixed effects, and the HMDA-McDash controls. We include applications submitted in 2018 - 2019. The table provides the estimates for each sex composition with male-female being the omitted category. Robust standard errors clustered at the county level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5: Default Rates - Normal Times (Pre-COVID)

Female-Male	0.112
	(0.12)
Male-Male	-0.405
	(0.26)
Female-Female	-0.081
	(0.36)
Interest Rate	-0.045
	(0.16)
HMDA-McDash Controls	Yes
Loan Type FE	Yes
County-Quarter FE	Yes
R^2	0.152
N	58,613

Notes: This table provides the results of estimating equation (1) with the outcome being a binary variable that takes the value of 100 if a 90-day delinquency ever occurred within 36 months of origination and 0 otherwise. The regression includes county×quarter fixed effects, loan type fixed effects, and the HMDA-McDash controls. We include applications submitted in 2018 - 2019. The table provides the estimates for each sex composition with male-female being the omitted category. Robust standard errors clustered at the county level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6: Rejection Rates - Automated Underwriting System (AUS)

	(1) AUS-Approved	(2) Not AUS-Approved	(3) All
Female-Male	0.179	1.134	0.054
	(0.27)	(1.53)	(0.31)
Male-Male	2.168***	5.493	2.046**
	(0.74)	(3.84)	(0.93)
Female-Female	1.032	6.061	0.648
	(0.73)	(4.95)	(0.79)
cHMDA Controls	Yes	Yes	Yes
Lender-County-Month FE	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes
R^2	0.563	0.764	0.591
N	70,923	4,209	84,673

Notes: This table provides the results of estimating equation (1) with the outcome being a binary variable that takes the value of 100 if the application is rejected and 0 otherwise. Each column refers to a different regression on a subset of applications - those approved by the AUS (column 1), other loan applications (column 2), as well as for the entire sample (column 3). The regressions are our preferred specification which includes lender$\times$county$\times$month fixed effects, loan type fixed effects, loan officer fixed effects, and the cHMDA controls detailed in Section 4. We include applications submitted in 2018 - 2019. The table provides the estimates for each sex composition with male-female being the omitted category. Robust standard errors clustered at the county level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 7: Rejection Rates - Regional Heterogeneity

	(1) Northeast	(2) Midwest	(3) South	(4) West
Female-Male	0.433	-0.287	0.215	-0.211
	(0.53)	(0.45)	(0.43)	(0.71)
Male-Male	1.267	5.664*	3.042**	-0.169
	(2.41)	(2.99)	(1.53)	(1.20)
Female-Female	-0.771	0.042	1.554	0.306
	(1.69)	(1.75)	(1.19)	(1.57)
cHMDA Controls	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes
Lender-County-Month FE	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes
R^2	0.647	0.609	0.591	0.570
N	8,956	13,547	36,178	24,828

Notes: This table provides the results of estimating equation (1) with the outcome being a binary variable that takes the value of 100 if the application is rejected and 0 otherwise. Each column refers to a different regression on the subset of applications submitted in that broad region of the U.S. The regressions are our preferred specification which includes lender$\times$county$\times$month fixed effects, loan type fixed effects, loan officer fixed effects, and the cHMDA controls detailed in Section 4. We include applications submitted in 2018 - 2019. The table provides the estimates for each sex composition with male-female being the omitted category. Robust standard errors clustered at the county level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 8: Rejection Rates - PEW Heterogeneity

	(1) First Tertile	(2) Second Tertile	(3) Third Tertile
Female-Male	0.414	-0.711	0.521
	(0.45)	(0.53)	(0.54)
Male-Male	2.568	3.123**	0.544
	(1.90)	(1.47)	(1.56)
Female-Female	0.982	0.833	0.258
	(1.39)	(1.32)	(1.53)
cHMDA Controls	Yes	Yes	Yes
Lender-County-Month FE	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes
R^2	0.585	0.591	0.610
N	28,911	30,883	23,174

Notes: This table provides the results of estimating equation (1) with the outcome being a binary variable that takes the value of 100 if the application is rejected and 0 otherwise. We ranked states according to their acceptance of same-sex marriage, as reflected in the 2014 PEW Research Religious Landscape Study, and divided them into tertiles, where the first tertile includes states with the lowest acceptance of same-sex marriage and the third tertile includes states with the highest acceptance of same-sex marriage. Each column refers to a different regression on the subset of applications submitted in that tertile. The regressions are our preferred specification which includes lender×county×month fixed effects, loan type fixed effects, loan officer fixed effects, and the cHMDA controls detailed in Section 4. We include applications submitted in 2018 - 2019. The table provides the estimates for each sex composition with male-female being the omitted category. Robust standard errors clustered at the county level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 9: Rejection Rates - COVID Period

Female-Male	-0.128
	(0.18)
Male-Male	2.368***
	(0.69)
Female-Female	0.354
	(0.57)
cHMDA Controls	Yes
Lender-County-Month FE	Yes
Loan Type FE	Yes
Loan Officer FE	Yes
R^2	0.604
N	95,286

Notes: This table provides the results of estimating equation (1) with the outcome being a binary variable that takes the value of 100 if the application is rejected and 0 otherwise. The regressions are our preferred specification which includes lender$\times$county$\times$month fixed effects, loan type fixed effects, loan officer fixed effects, and the cHMDA controls detailed in Section 4. We include applications submitted during the COVID period (2020 - 2021). The table provides the estimates for each sex composition with male-female being the omitted category. Robust standard errors clustered at the county level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 10: Interest Rates - COVID Period

Female-Male	0.012***
	(0.00)
Male-Male	0.040***
	(0.01)
Female-Female	0.040***
	(0.01)
cHMDA Controls	Yes
Lender-County-Month FE	Yes
Loan Type FE	Yes
Loan Officer FE	Yes
R^2	0.769
N	85,176

Notes: This table provides the results of estimating equation (1) on the subset of approved applications with the outcome being the interest rate. The regressions are our preferred specification which includes lender×county×month fixed effects, loan type fixed effects, loan officer fixed effects, and the cHMDA controls detailed in Section 4. We include applications submitted during the COVID period (2020 - 2021). Rows (1)-(3) provide the estimates for each sex composition with male-female being the omitted category. Robust standard errors clustered at the county level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 11: Employment Regression

Number of obs	2,865,219
Absorbing 1 HDFE group	F(13, 50) = 82.50
Statistics robust to heteroskedasticity	Prob > F = 0.0000
	R-squared = 0.0004
	Adj R-squared = 0.0004
	Within R-sq. = 0.0004
Number of clusters (statefip)	51
Root MSE	0.4547

	Coefficient	std. err.	t	P>|t|	[95% conf. interval]	
employed						
1.male_same_sex_part	0.0818416	0.0106698	7.67	0.000	0.0604107	0.1032725
year						
2016	-0.0020449	0.0011066	-1.85	0.071	-0.0042676	0.0001779
2017	-0.0013649	0.0012574	-1.09	0.283	-0.0038904	0.0011606
2018	-0.0016376	0.0011528	-1.42	0.162	-0.0039531	0.000678
2020	-0.0155939	0.0016346	-9.54	0.000	-0.0188771	-0.0123107
2021	-0.0126001	0.0020345	-6.19	0.000	-0.0166865	-0.0085136
2022	-0.0001141	0.0016758	-0.07	0.946	-0.0034802	0.0032519
male_same_sex_part#year						
1#2016	-0.0359244	0.0079432	-4.52	0.000	-0.0518788	-0.0199699
1#2017	-0.0347543	0.0109294	-3.18	0.003	-0.0567067	-0.0128018
1#2018	-0.0343989	0.00986	-3.49	0.001	-0.0542033	-0.0145945
1#2020	-0.0222329	0.0114048	-1.95	0.057	-0.0451402	0.0006743
1#2021	-0.0198274	0.0088042	-2.25	0.029	-0.0375113	-0.0021436
1#2022	-0.0015941	0.0095482	-0.17	0.868	-0.0207722	0.017584
_cons	0.7117601	0.0082954	85.80	0.000	0.6950983	0.728422

A Appendix

Table A0.1: Summary Statistics - Additional

		(1) Male-Female	(2) Female-Male	(3) Male-Male	(4) Female-Female	(5) All
Other Races	Mean	0.00	0.01	0.01	0.01	0.01
	SD	0.09	0.11	0.10	0.10	0.10
Age 50 - 54	Mean	0.07	0.06	0.08	0.08	0.07
	SD	0.26	0.24	0.27	0.28	0.26
Age 55 - 59	Mean	0.07	0.05	0.06	0.07	0.06
	SD	0.25	0.22	0.24	0.25	0.24
Age 60 - 64	Mean	0.05	0.04	0.03	0.04	0.05
	SD	0.23	0.19	0.19	0.21	0.22
Age 65 - 69	Mean	0.04	0.02	0.02	0.03	0.04
	SD	0.21	0.15	0.16	0.18	0.20
Age 70+	Mean	0.05	0.01	0.02	0.03	0.04
	SD	0.23	0.13	0.15	0.19	0.21
	N	543,708	175,796	18,229	19,100	756,833

Notes: This table provides summary statistics for home purchase mortgage applications by the sex composition of the applicant - co-applicant in columns (1)-(4) (e.g. Male-female refers to mortgages in which the applicant is a male and the co-applicant is a female) and for all applications in column (5). We include applications submitted between 2018 - 2019. Full results are detailed in Table 1.

Table A0.2: Mortgage Rejection Results - Additional

	(1)	(2)	(3)	(4)
Other Races	2.736***	3.053***	1.651*	0.617
	(0.70)	(0.70)	(0.96)	(1.17)
Age 50 - 54	0.167	0.617	0.489	0.856
	(0.38)	(0.38)	(0.57)	(0.74)
Age 55 - 59	0.527	0.974***	0.591	1.499**
	(0.37)	(0.36)	(0.57)	(0.72)
Age 60 - 64	-0.537	-0.111	-0.293	0.398
	(0.37)	(0.37)	(0.57)	(0.77)
Age 65 - 69	-0.607	-0.091	-0.402	-0.272
	(0.41)	(0.41)	(0.65)	(0.84)
Age 70+	-0.579	0.095	-1.234**	-1.242
	(0.39)	(0.39)	(0.62)	(0.86)
County-Month FE	Yes	Yes	Yes	Yes
Loan Type FE	No	Yes	Yes	Yes
Lender-County-Month FE	No	No	Yes	Yes
Loan Officer FE	No	No	No	Yes
R^2	0.193	0.198	0.447	0.591
N	196,220	196,220	104,483	84,673

Notes: This table provides the results of estimating equation (1) with the outcome being a binary variable that takes the value of 1 if the application is rejected and 0 otherwise. Each column refers to a different regression that includes the fixed effects details in the lower panel. We include applications submitted in 2018 - 2019. White is the omitted race category and age below 24 is the omitted age category. Robust standard errors clustered at the county level are in parentheses. Full results are detailed in Table 2

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A0.3: Summary Statistics - Mortgage Refinancing Applications

		(1) Male-Female	(2) Female-Male	(3) Male-Male	(4) Female-Female	(5) All
Rejection Rate (%)	Mean	38.33	39.15	41.35	40.76	38.58
	SD	48.61	48.80	49.25	49.14	48.68
Interest Rate (%)	Mean	4.19	4.26	4.30	4.33	4.21
	SD	0.74	0.73	0.79	0.74	0.74
Processing Time (days)	Mean	42.55	41.81	45.80	44.05	42.49
	SD	36.23	35.92	39.01	38.53	36.26
Loan-to-Value (%)	Mean	72.54	71.32	71.44	70.91	72.25
	SD	18.49	17.89	17.80	18.41	18.36
Debt-to-Income (%)	Mean	36.94	37.06	38.51	39.37	37.03
	SD	13.28	13.06	13.58	13.32	13.25
Applicant Credit Score	Mean	725.79	719.39	723.11	711.90	724.23
	SD	64.54	65.58	61.98	66.57	64.81
Coapplicant Credit Score	Mean	727.58	720.12	725.88	715.06	725.89
	SD	67.19	67.82	64.82	69.09	67.39
Applicant Income ($)	Mean	121,306	118,297	136,694	110,425	120,766
	SD	82,521	76,411	94,740	72,754	81,425
	N	397,609	102,784	8,864	8,793	518,050

Notes: This table provides summary statistics for mortgage refinancing applications by the sex composition of the applicant - co-applicant (e.g. male-female refers to mortgages in which the applicant was a male and the co-applicant was a female) and for all applications. We include applications submitted in 2018 - 2019.

Table A0.4: Mortgage Rejection Results - Mortgage Refinancing Applications

	(1)	(2)	(3)	(4)
Female-Male	2.023***	1.578***	0.508	-0.597
	(0.32)	(0.32)	(0.44)	(0.69)
Male-Male	1.515	1.332	1.548	1.895
	(0.96)	(0.97)	(1.42)	(2.80)
Female-Female	1.099	0.819	0.679	0.403
	(1.01)	(1.01)	(1.82)	(2.58)
Loan to Value	-0.277***	-0.467***	-0.511***	-0.491***
	(0.04)	(0.04)	(0.07)	(0.12)
Loan to Value Squared	0.002***	0.004***	0.005***	0.005***
	(0.00)	(0.00)	(0.00)	(0.00)
Debt to Income	-1.300***	-1.335***	-1.419***	-1.395***
	(0.05)	(0.05)	(0.07)	(0.12)
Debt to Income Squared	0.024***	0.024***	0.024***	0.024***
	(0.00)	(0.00)	(0.00)	(0.00)
Applicant Credit Score	-0.610***	-0.667***	-0.586***	-0.770***
	(0.05)	(0.05)	(0.08)	(0.14)
Applicant Credit Score Squared	0.000***	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
Coapplicant Credit Score	-0.805***	-0.830***	-0.848***	-0.926***
	(0.05)	(0.05)	(0.09)	(0.13)
Coapplicant Credit Score Squared	0.001***	0.001***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
Applicant Income	0.018***	0.013***	-0.003	0.003
	(0.00)	(0.00)	(0.00)	(0.00)
County-Month FE	Yes	Yes	Yes	Yes
Loan Type FE	No	Yes	Yes	Yes
Lender-County-Month FE	No	No	Yes	Yes
Loan Officer FE	No	No	No	Yes
R^2	0.331	0.336	0.561	0.730
N	87,798	87,798	37,266	22,213

Notes: This table provides the results of estimating equation (1) for mortgage refinancing applications with the outcome being a binary variable that takes the value of 1 if the application is rejected and 0 otherwise. Each column refers to a different regression that includes the fixed effects details in the lower panel. Rows (1)-(3) provide the estimates for each sex composition with male-Female being the omitted category. The other rows provide the estimates for the controls. We include applications submitted in 2018 - 2019. Robust standard errors clustered at the county level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A0.5: Mortgage Interest Rate Results - Mortgage Refinancing Applications

Female-Male	0.006
	(0.01)
Male-Male	0.062
	(0.06)
Female-Female	0.023
	(0.04)
HMDA Controls	Yes
Lender-County-Month FE	Yes
Loan Type FE	Yes
Loan Officer FE	Yes
R^2	0.868
N	16,094

Notes: This table provides the results of estimating equation (1) on the subset of approved mortgage refinancing applications with the outcome being the interest rate. The regressions are our preferred specification which includes lender×county×month fixed effects, loan type fixed effects, loan officer fixed effects, and the HMDA controls detailed in Section 4. The table provides the estimates for each sex composition with male-female being the omitted category. We include applications submitted in 2018 - 2019. Robust standard errors clustered at the county level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A0.6: Loan Performance Analysis - Mortgage Refinancing Applications

Female-Male	-0.235
	(0.22)
Male-Male	1.102
	(0.93)
Female-Female	0.981
	(0.80)
HMDA-McDash Controls	Yes
County-Quarter FE	Yes
Loan Type FE	Yes
R^2	0.130
N	42,881

Notes: This table provides the results of estimating equation (1) for mortgage refinancing applications with the outcome being a binary variable that takes the value of 1 if a 90-day delinquency occurred in the 2 years following the application approval and 0 otherwise. The regression includes county×quarter fixed effects, loan type fixed effects, and the HMDA-McDash controls detailed in section 4. We include applications submitted in 2018 - 2019. The table provides the estimates for each sex composition with male-female being the omitted category. Robust standard errors clustered at the county level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A0.7: List of States by Their Region

Northeast	**Midwest**	**South**	**West**
Connecticut	Indiana	Delaware	Arizona
Maine	Illinois	District of Columbia	Colorado
Massachusetts	Michigan	Florida	Idaho
New Hampshire	Ohio	Georgia	New Mexico
Rhode Island	Wisconsin	Maryland	Montana
Vermont	Iowa	North Carolina	Utah
New Jersey	Nebraska	South Carolina	Nevada
New York	Kansas	Virginia	Wyoming
Pennsylvania	North Dakota	West Virginia	Alaska
	Minnesota	Alabama	California
	South Dakota	Kentucky	Hawaii
	Missouri	Mississippi	Oregon
		Tennessee	Washington
		Arkansas	
		Louisiana	
		Oklahoma	
		Texas	

Notes: This table provides a list of states according to their census region.

Table A0.8: List of States by Their Acceptance of Same-sex Marriage

First Tertile	**Second Tertile**	**Third Tertile**
Alabama	South Dakota	Wisconsin
Mississippi	Wyoming	Alaska
Arkansas	Ohio	Delaware
Tennessee	Virginia	Minnesota
Kentucky	Iowa	New Jersey
West Virginia	Kansas	Maryland
South Carolina	Nebraska	Washington
Louisiana	Utah	California
Oklahoma	Florida	Colorado
Georgia	Michigan	New York
Indiana	Montana	District of Columbia
North Carolina	Nevada	Maine
Texas	Pennsylvania	Rhode Island
Missouri	Hawaii	New Hampshire
New Mexico	Arizona	Connecticut
North Dakota	Illinois	Massachusetts
Idaho	Oregon	Vermont

Notes: We ranked states according to their acceptance of same-sex marriage, as reflected in the 2014 PEW Research Religious Landscape Study, and divided them into tertiles, where the first tertile includes states with the lowest acceptance of same-sex marriage and the third tertile includes states with the highest acceptance of same-sex marriage. This table provides the list of states in each of the tertiles.

Table A0.9: Variable Definitions

cHMDA Controls	Loan-to-Value, Loan-to-Value Squared, Debt-to-Income, Debt-to-Income Squared, Applicant Credit Score, Applicant Credit Score Squared, Co-applicant Credit Score, Co-applicant Credit Score Squared, Applicant Income, Hispanic, Black, Asian, Other Races, Age 25 - 29, Age 30 - 34, Age 35 - 39, Age 40 - 44, Age 45 - 49, Age 50 - 54, Age 55 - 59, Age 60 - 64, Age 65 - 69, and Age 70+
cHMDA-McDash Controls	Income, Hispanic, Black, Asian, Other Races, Loan-to-Value, Loan-to-Value Squared, Debt-to-Income, Debt-to-Income Squared, Applicant Credit Score, Applicant Credit Score Squared
cHMDA-McDash-CRISM Controls-1	Ln(Income), Hispanic, Black, Asian, Other Races
cHMDA-McDash-CRISM Controls-2	Ln(Income), Hispanic, Black, Asian, Other Races, Loan-to-Value, Loan-to-Value Squared, Debt-to-Income, Debt-to-Income Squared, Applicant Credit Score, Applicant Credit Score Squared
Default	Indicator equal to 100 if the borrower ever becomes 90 or more days delinquent within 3 years after loan origination
Negative Income Shock	Indicator equal to 1 if the applicant income of this month drops more than 67% compared to income of the previous month. 0 otherwise

Notes: This table provides variable definitions