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 toward the LGBTQ+ population, research suggests that disparities persist across various outcomes. In this study, we use confidential administrative data covering the universe of U.S. home mortgage applications from 2018 to 2021 to estimate disparities between same-sex and different-sex couples in the mortgage market. Controlling for a rich set of lender, borrower, and loan characteristics, we find that male same-sex couples are 27.6% more likely to be denied a mortgage than otherwise similar different-sex couples and, conditional on approval, are quoted interest rates that are, on average, 0.73% higher. While these disparities are substantially smaller than those reported in earlier studies based on publicly available data—suggesting potential omitted variable bias in prior estimates—they remain significant and have meaningful consequences for same-sex couples. We also find that during the COVID crisis, male same-sex couples defaulted significantly more than similar different-sex couples (by 53.9%), which may partly account for the observed disparities in mortgage approval.

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

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1 Introduction

Homeownership remains a central aspect of the American dream. In a recent poll, 74% of Americans identified homeownership as part of this dream — surpassing other life goals like a successful career or a college degree (Ostrowkski, J., 2023). Indeed, homeownership offers numerous social and economic benefits. In a review of the literature, Yun and Evangelou (2016) cite educational achievement, civic participation, and improved health among the benefits that have been associated with homeownership. Subsequent studies reveal additional benefits: Sodini et al. (2016) find that homeownership is a beneficial wealth accumulation tool, and that it promotes mobility, increases consumption, and improves consumption smoothing, while 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). Thus, any barriers to securing financing could significantly hinder homeownership prospects.

While societal attitudes toward LGBTQ+ individuals have improved in recent decades, concerns remain about whether equal treatment has been achieved in financial markets. Legal and institutional milestones—such as the 2015 Obergefell v. Hodges ruling legalizing same-sex marriage nationwide and the 2021 executive order extending Fair Housing Act protections to sexual minorities—have marked important progress. Yet, research suggests that same-sex couples still face disadvantages in mortgage lending (Sun and Gao, 2019; Hagendorff et al., 2022; Dillbary and Edwards, 2019). Understanding the extent and nature of these disparities is particularly timely, as access to credit remains a key determinant of wealth accumulation, housing stability, and long-term financial security.

In this paper, we contribute to this discussion by presenting new estimates of the disparities in mortgage application outcomes between same-sex and different-sex couples. Our analysis uses the confidential Home Mortgage Disclosure Act (HMDA) data, which provide application-level data on the universe of U.S. mortgage applications. The dataset contain a rich set of information that allows us to control for borrower, lender, and loan characteristics that were not available in previous research. Our analysis focuses on two periods: pre-COVID period (2018-2019), and COVID period (2020-2021). 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. Additionally, we merge HDMA with Black Knight McDash data

to examine loan performance.

To estimate disparities in mortgage application outcomes, our main specification regresses one of three mortgage outcomes—application rejection, interest rate, and default (i.e. 90-day or longer delinquency within 36 months of origination)—on the sex composition of the application (e.g. male-male) along with a rich set of controls. Specifically, we control for applicant and co-applicant credit scores, as well as lender-county-month, loan type, and loan officer fixed effects. Thus, we are theoretically comparing mortgage outcomes of two applications submitted in/to the same county-lender-month, have similar observable characteristics, and are evaluated by a similar loan officer, but differ in their sex composition: one application is male-female (our baseline) and the other is one of the three other sex composition categories.

In the pre-COVID period, we find that male-male applications were 27.6% more likely to be rejected and, if approved, were quoted an interest rate 0.73% higher than similar male-female applications. Evidence of disparities between male-female applications and female-female or male-female applications is weaker. Examining regional variation, we find that the disparities between male-female and male-male applications were larger in Midwest and Southern states, where LGBTQ+ acceptance is generally lower than in Northeastern and Western states, suggesting that taste-based discrimination may partially account for the observed differences. During the COVID period, we observe a slight widening of the disparities.

Overall, the disparities we estimate are considerably lower than those reported in previous studies that employed similar methodologies but used publicly available data, which lacks the rich set of information that our confidential data has, such as credit scores (Sun and Gao, 2019; Hagendorff et al., 2022; Dillbary and Edwards, 2019). These studies analyze earlier time periods, when less favorable public sentiment toward LGBTQ+ individuals may have contributed to larger observed disparities. Nonetheless, when we replicate their estimations using only publicly available data for our study period, we find significantly larger disparities than those estimated using our more comprehensive confidential dataset. This suggests that previous studies may have overstated disparities due to omitted variable bias.

Next, we examine loan performance. We do not find a statistically significant difference in 90-day delinquency within 36 months of origination between male-male and male-female applications in the pre-COVID period. In contrast, for the COVID period, we find that male-male applications were 53.9% more likely to be delinquent relative to similar male-female applications. 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 during the COVID period is surprising. This suggests that male-male applications carry a higher

risk than similar male-female applications during periods of economic uncertainty-a novel finding. This heightened risk may be attributed to male same-sex couples' differing saving behaviors, increased vulnerability to employment shocks, especially during COVID, due to differential labor market characteristics or discrimination, lower familial support, or other factors. This result suggests that some of the disparities in mortgage rejection rates and interest rates between male-female and male-male applications may stem from the greater risk associated with the latter during periods of economic uncertainty that is not reflected in observed characteristics. This finding contrasts with Sun and Gao (2019), who find no significant difference in default risk between same-sex and different-sex applications, and thus conclude that disparities in mortgage rejection and interest rates are primarily due to discrimination.

We then draw on recent studies to discuss potential factors that may explain the higher delinquency rates observed among male same-sex couples during the COVID period. We also analyze data from the Survey of Household Economics and Decision Making to compare the financial well-being of self-identified gay and straight individuals—used here as a summary measure that captures the potential factors discussed—across COVID and non-COVID years. Our results indicate that the financial well-being of gay individuals declined relative to that of their straight counterparts during the COVID period, which may have contributed to the elevated delinquency rates among male same-sex applicants.

Finally, we leverage data on automated underwriting system (AUS) recommendations to compare algorithmic assessments with human lending decisions. By contrasting AUS-generated recommendations with loan officers' final decisions, we provide suggestive evidence of potential human bias in the mortgage approval process that disproportionately affects male same-sex applicants. We first document that loan officers were more likely to overturn AUS decisions to the applicant's detriment in the case of male–male applications than for male–female applications. We then show, using a regression framework, that while the AUS exhibited no significant difference in rejection rates between male–male and similar male–female applications, male–male applications were significantly more likely to be rejected by loan officers—suggesting either the use by loan officers of additional observed information not taken into consideration by the AUS, such as clarification of credit history concerns, or the presence of human bias, potentially in the form of statistical or taste-based discrimination, in the final lending decision process.

Our paper makes several contributions. First, we provide estimates of disparities in mortgage outcomes across two recent periods—immediately prior to COVID and during the

COVID period—thereby updating estimates from the literature for earlier periods and contributing to the literature on disparities during times of economic uncertainty, which were not measured previously. Second, we disaggregate our analysis by the sex composition of mortgage applicants (i.e., male-male, male-female, female-male, and female-female), rather than limiting the comparison to same-sex versus different-sex couples, offering a more nuanced view of differential outcomes. Third, using confidential data, we show that previous studies relying on publicly available data have significantly overestimated these disparities, partially due to the exclusion of important predictors of mortgage outcome that differ between same-sex and different-sex couples. We believe that the discrepancies between the disparities estimated from publicly available data and those estimated from confidential data should be taken into considerations in broader contexts than that of this paper, such as the estimation of various racial disparities. Fourth, to the best of our knowledge, we are the first to show that even the smaller disparities observed in our analysis may be partially explained by a higher default risk associated with male same-sex applications during periods of economic uncertainty, particularly during the COVID period. We also discuss evidence of the underlying factors that may have contributed to this elevated default risk. Finally, we are the first to supplement the analysis of disparities in mortgage outcomes by sexual orientation with a comparison of the decisions generated by the AUS with those ultimately made by the loan officers, providing novel evidence of potential human bias in the mortgage decision-making process.

2 Related Literature

Extensive research documents discrimination against LGBTQ+ individuals, primarily focusing on labor market discrimination through experimental (mostly audit studies) or observational methods. Experimental studies provide compelling evidence that LGBTQ+ job candidates are less likely to be invited for interviews or offered jobs compared to otherwise identical non-LGBTQ+ candidates. Observational studies consistently show wage and income differentials between LGBTQ+ and non-LGBTQ+ workers; for instance, gay and bisexual men earn 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 disparities from 1990 to 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. However, our study improves upon their work in several ways. First, we estimate disparities for a more recent period. This is especially important in the context of this paper given several landmark policy changes affecting LGBTQ+ individuals in recent years, including the 2015 Obergefell v. Hodges U.S. Supreme Court ruling that legalized same-sex marriage and the 2021 Biden administration executive order extending protections against discrimination in housing financing for LGBTQ+ individuals under the Fair Housing Act. These changes, along with secular trends in LGBTQ+ acceptance, could affect disparity estimates.

Second, whereas Sun and Gao (2019) use the public HMDA data, we use the confidential HMDA data, allowing us to include a richer set of controls in our regressions. This reduces the 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 can include 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 is important as same-sex couples may systematically select into or be assigned to specific loan officers. Furthermore, whereas Sun and Gao (2019) use demographic information at the census-tract level, we include it at the loan application level. Although the Boston sample allowed Sun and Gao (2019) to include some of the variables that are missing from the public HMDA data, it is limited to a single year (1990), and 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 comparing same-sex to different-sex couples. Lastly, we are able to examine how disparities and loan performance change during a period of economic uncertainty.

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 thus face the same limitations identified in Sun and Gao (2019). More broadly, our paper is related to recent studies 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; Frame et al., 2025) and in other lending contexts, such as business loans (Chernenko and Scharfstein, 2022). Lastly, our paper also relates to the literature on the effect of algorithmic underwriting on lending outcomes (Gates et al., 2002; Choi et al., 2022; Bartlett et al., 2022; Jansen et al., 2025).

3 Data

3.1 Data

The main data source of 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.

We limit our analysis to home purchase applications that include a co-applicant (39.9% of total applications), so we can infer the applications' sex composition, similarly to the literature (Sun and Gao, 2019; Eilam and Shahid, 2025). 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 submitted applications in which the age difference between the applicant and co-applicant is less than 25 years.[1] This is to exclude applications potentially submitted by a father and son, for example, when the father is a co-signer because the 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 male same-sex and different-sex applications. Given the large number of observations in the confidential HMDA data, we randomly sample 20% of the data to use in our analysis.

Our analysis focuses on two periods: pre-COVID period (2018–2019), when data on credit scores — crucial for mortgage application decisions — first became available, and COVID

[1]We exclude applications that were not submitted (e.g. applications that were withdrawn, applications that were incomplete, etc.).

period (2020–2021). It utilizes the rich set of applicant and application information in the data including: whether the application was approved or rejected; the interest rate quoted if the loan was approved;[2] loan type;[3] applicant and co-applicant credit score;[4] applicant income;[5] applicant demographics; and other information detailed in Section 4.

For the loan performance analysis, we use HMDA and Black Knight McDash merged dataset (HMDA-McDash dataset). We keep first-lien, primary owner, 30-year fixed rate, one unit loans. We track each originated loan for 36 months, and, as standard in the literature, define default as a 90-day or longer delinquency. We examine loan performance across two periods: the first includes applications originated in 2015–2016, which we track through 2019 and were therefore unaffected by COVID; the second includes applications originated in 2018–2019, which we track through 2022 and were therefore exposed to the effects of COVID.

Lastly, to study the potential reasons for the higher default rate of same-sex applications during the COVID period, we use the Survey of Household Economics and Decision Making (SHED) (Board of Governors of the Federal Reserve, 2024). The survey, conducted by the Board of Governors of the Federal Reserve Board, measures the financial well being of U.S. households. We analyze data from 2019, the first year in which respondents were asked about their sexual orientation, to 2023, the latest data year.[6] Each year included between 11,400 and 12,173 respondents. We keep respondents aged 25-64 who responded that they are either "gay or lesbian" or "straight, that is not gay" which leaves between 6,440 and 7,357 respondents each year. Of these, between 249 and 277 responded that they are "gay or lesbian" each year ($\approx$ 3.7% - 4.2%).[7]

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

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

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

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

[6]The sexual orientation question is: "Do you consider yourself to be..." and the possible answers are - gay or lesbian; straight, that is not gay; bisexual; and something else. Around 7% of respondents have a missing value.

[7]Out of the 1,320 who responded that they are "gay or lesbian" across years, 955 are male and 365 are female.

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. 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 (7.25% versus 11.78% and 4.4% versus 4.5%, 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 (85.85% versus 87.6% and 37.57% versus 40.57%, respectively) and male-female applicants have higher applicant and co-applicant credit scores than male-male applications (733.86 versus 717.53 and 735.81 versus 725.03, respectively). In contrast, the applicant income for male-female applications is lower than in male-male applications ($124,198 versus $127,960). In terms of demographics, a larger share of male-female applications have a White main applicant than male-male applications (81.7% versus 75.4%), and a smaller share of male-female applications have a young (aged 20 - 29) main applicant compared to male-male applications (15.5% versus 22.8%).[8] Additional summary statistics appear in Table A0.1.

4 Empirical Strategy

In order to estimate disparities in mortgage application outcomes by sex composition, we estimate the following specification separately for the pre-COVID and COVID periods:

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

where $Y_{i,c,t,lo,le,lt}$ is an outcome of interest for application i of loan type lt, submitted in county c, in month-year t, to loan officer lo, working for lender le. 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 borrower and application characteristics that might affect the application outcome. These are detailed in Table A0.5. Specifically, we flexibly control for loan-to-value ratio and its square, debt-to-income ratio and its square, loan amount, applicant and

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

co-applicant credit scores and their squares, applicant income, applicant race (White is the omitted race category), and applicant age in 5-years bins (age 20 - 24 is the omitted age category). We refer to these controls as confidential HMDA (cHMDA) controls as most are only available in the confidential version of the HMDA data. We also replicate the results from Sun and Gao (2019), including only the controls available in the public version of the HMDA data (pHMDA controls) - applicant income, applicant race, and loan amount.

We include county×month×lender fixed effects, $\mu_{c,t,le}$, to control for factors that affect the application outcome at a specific county, in a specific month, for a specific lender, for example local economic shocks; loan type fixed effects, τ_{lt}, to control for time-invariant differences in loan types between applications that might be correlated with the sex composition of the application and the application outcome (e.g. if male-female applicants are more likely to apply for an FHA-insured loan which is more likely to be approved);[9] and loan officer fixed effects, θ_{lo}, to control for time-invariant differences between loan officers' propensity to approve an application.

The treatment variable $Sex\_Comp_{i,c,t,lo,le,lt}$ takes the value of 1 if the application falls into a given sex composition category s—female-male, male-male, or 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 sex composition category s and the male-female reference category. 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/to the same month-county-lender, have similar observable characteristics, and are judged by similar loan officers but the sex composition of one application is male-female and the sex composition of the other is one of the three other sex composition categories.

To examine loan performance, we estimate equation (1) using the merged HMDA-McDash data on the set of mortgage applications that were approved and originated, with a binary outcome variable that takes the value 100 if a loan is 90-day or more delinquent within 36 months of origination, and 0 otherwise. Due to the absence of information on lender, loan officer, and borrower age in these data, we include county×quarter and loan type fixed effects, and use a slightly different set of controls that still include applicant credit scores (detailed in Appendix Table A0.5 under cHMDA-McDash Controls).

[9]See Section 3.1 for the definition of loan types.

5 Results

5.1 Main Regression Results

Table 2 presents the results of estimating equation (1) for the pre-COVID (baseline) period, using a binary outcome variable that equals 100 if the application is rejected and 0 if it is approved. Each column refers to a different specification that includes the controls and fixed effects detailed in the middle and lower panels, respectively. Specifications (1) and (2) include loan type and lender-county-year fixed effects. Specification (3) includes loan type and lender-county-month fixed effects instead. Specification (4) further includes age fixed effects, and specification (5) adds loan officer fixed effects. The last is our preferred specification. The coefficients in the table are interpreted as percentage point differences in the rejection rate.

The results for the coefficients of interest appear in the upper panel. The coefficients for male-male applications are statistically significant at the 1% to 5% levels across all specifications. In our preferred specification (column (5)), the coefficient is 2.002, indicating that male-male applications are associated with a 2 percentage point higher rejection rate relative to similar male-female applications. Given that the mean rejection rate for male-female applications is 7.25%, this result suggests that male-male applications were 27.6% more likely to be rejected relative to similar male-female applications.

Next, we compare our preferred specification with less saturated alternatives. Specifically, we compare specification (1) - which includes loan type and lender-county-year fixed effects, and the public HMDA controls, and is similar to the specification used by Sun and Gao (2019) - with specification (2), which replaces the public HMDA controls with the confidential HMDA controls. Controlling for these additional borrower characteristics, such as applicant and co-applicant credit scores, reduces the coefficient of interest by more than half, from 3.299 to 1.319.[10] This result is expected, as male-male borrowers tend to have worst observable characteristics on average, as discussed in Section 3.2 (e.g. they have lower average credit scores). Thus, omitting these characteristics, as done in prior studies that rely on publicly available HMDA data, leads to an overestimation of the disparities.

Replacing the lender-county-year fixed effects with lender-county-month fixed effects in specification (3), and adding age fixed effects in specification (4), does not meaningfully

[10]The additional controls used in specification (2) result in a drop in the number of utilized observations. Therefore, we also estimate specification (1) that includes the public HMDA controls using the same set of 173,034 observations used in specification (2). The result is a coefficient of 2.439 (standard error: 0.48), still significantly higher than in specification (2) that includes the confidential HMDA controls.

change the magnitude of the coefficient. However, adding loan officer fixed effects in specification (5) increases the coefficient of interest from 1.325 to 2.002, suggesting a selection of same-sex couples to loan officers that are less likely to reject applications. The coefficients for female-male and female-female applications are statistically insignificant under the saturated specifications, suggesting no significant disparities in application rejection between these borrowers relative to similar male-female borrowers.

Table 3 details the results of estimating equation (1) for the pre-COVID period, using the set of approved applications, with the outcome being the quoted interest rate. In column (2), we estimate our preferred specification, which includes the fixed effects detailed in the lower panel and the cHMDA controls. The coefficients in the table are interpreted as percentage point differences in the interest rate.

The coefficient for male-male is 0.032 and is statistically significant at 5%, meaning that approved male-male applications are associated with 0.032 percentage point higher interest rate relative to similar approved male-female applications. Given that the mean interest rate for approved male-female applications is 4.40%, this result suggests that approved male-male borrowers are quoted an interest rate that is 0.73% higher relative to similar approved male-female applications. The coefficient for female-male is statistically significant at 1% but is about a third of the magnitude of the coefficient for male-male, and the coefficient for female-female is significant at 10% and is 16% smaller in magnitude than the coefficient for male-male. These suggest that there are disparities, albeit weak, in interest rate quoted for approved applications between male-female borrowers and female-male/female-female borrowers.

In column (1), we replicate the specification used in prior studies that rely on publicly available HMDA data. The coefficient for male-male applications is 0.069—more than twice as large as in our preferred specification—suggesting that earlier research likely overstated disparities in quoted interest rates, as they did with disparities in rejection rates.

We replicate the above analyses for applications submitted during the COVID period (2020-2021). The results are presented in Appendix table A0.2 with column (1) detailing the results for the rejection rate and column (2) detailing the result for the interest rate. The results for male-male applications are similar to those in the pre-COVID period, albeit slightly larger in magnitude (2.57 versus 2.00 for rejection rate, and 0.035 versus 0.032 for interest rate).

Lastly, we turn to our third outcome of interest, loan performance. Table 4 details the results of estimating our preferred specification with a binary outcome variable that takes the value of 100 if a 90-day or longer delinquency occurred during the 36 months following loan origination and 0 otherwise. The coefficients in the table are interpreted as percentage point differences in the default rate. The specification in column (1) includes applications submitted between 2015 and 2016, which we track through 2018 - 2019 (pre-COVID). The specification in column (2) includes applications submitted between 2018 and 2019, which we track through 2021 - 2022, covering both the peak of the COVID pandemic and its aftermath. The results in column (1) reveal that male-male and male-female loans did not perform differentially in the pre-COVID period. However, the results in column (2) reveal differential loan performance during the COVID period. 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 during this period was 3.81%, this result suggests that male-male applications were 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.

5.2 Regional Heterogeneity

Table 5 reports the results of estimating our preferred specification in the pre-COVID period with a binary outcome variable for rejection, separately for the four census regions.[11] 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 were associated with 5.406 and 3.026 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 were 5.81% and 7.75%, respectively, these results suggest that male-male applications were 95.4% and 39.0% 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.

[11] Table A0.3 details the states included in each of the census regions.

The significantly higher rejection rates for male-male applications in the Midwest and South regions, where public sentiment toward LGBTQ+ individuals tends to be less favorable, suggests that taste-based discrimination may contribute to the observed disparities (Public Religion Research Institute, 2024). However, these disparities may also be partially attributable to higher default rates among male-male applications in these regions. In Table 6 we estimate our preferred specification with a binary outcome variable for default, separately for the four census regions. The results indicate that male-male applications were 2.81 and 1.60 percentage points more likely to default than similar male-female applications in the Midwest and South, respectively. However, male-male applications in the Northeast and West were also more likely to default than similar male-female applications (by 2.87 and 1.33 percentage points, respectively), although they were not more likely to be rejected than similar male-female applications (see Table 5).

5.3 Automated Underwriting System Results

Mortgages eligible for sale to government-sponsored enterprises (Fannie Mae and Freddie Mac) require the use of AUS. An AUS receives applicant and application information and, using algorithms to asses risk, evaluates the applicant's creditworthiness, generating a decision to approve, reject, or manually review the loan application. The final decision on whether to approve or reject the loan application is then handled by the loan officer. Of the 84,457 mortgage applications used to estimate our preferred specification in the pre-COVID period of 2018-2019 (column (5) in Table 2), 74,622 (88.4%) went through the AUS.

By relying on ostensibly objective, algorithmic assessments of creditworthiness, the use of AUS has the potential to reduce human bias in lending decisions. Because AUS must comply with fair lending regulations, they are prohibited from considering sexual orientation - or any proxies for it, such as geographic location - in their evaluations, as they are prohibited from considering race, and other characteristics (Bhutta et al., 2021).[12] Examining whether loan officers' final decisions align with AUS recommendations provides insights into potential human bias in the lending decision.

Before turning to the regression analyses, we present descriptive statistics for all applications processed through an AUS. Specifically, we cross-classify applications based on the AUS recommendation and the loan officer's final decision. The results are presented in Table

[12] Although the Equal Credit Opportunity Act and the Fair Housing Act do not provide explicit protections to sexual minorities, both have been interpreted by the Consumer Financial Protection Bureau and the Department of Housing and Urban Development to include protections for sexual minorities under the category of sex discrimination (Consumer Finance Monitor, 2021; ABA Banking Journal, 2021).

7, with cell entries indicating the number of applications in each category. The upper panel presents results for male-female applications, and the lower panel presents results for male-male applications. In Appendix Table A0.4, we present results for female-male applications and female-female applications.

For male-female applications, loan officers overturned the AUS's approval recommendation in 13,926 of 362,131 cases (3.8%), resulting in rejection. Among the 42,580 applications that the AUS recommended for rejection, loan officers overturned 31,706 (74.4%) and approved the applications instead. For male–male applications, loan officers overturned 795 of 11,876 AUS-recommended approvals (6.7%) - a rate 76% higher than that for male–female applications - resulting in rejection.[13] Of the 1,616 applications the AUS recommended for rejection, 992 (61.4%) were overturned and approved. In both directions - overturning AUS approvals and rejections - male–male applications fared worse than male–female applications.

These disparities in overturn rates may stem from differences in borrower or application characteristics between male–female and male–male applicants that are observed by the loan officer and considered relevant to loan risk, but are either not observed by the AUS or not incorporated into its decision - such as an assessment of future income potential, or a clarification of credit history. However, the disparities could also result from human biases, specifically taste-based or statistical discrimination. In this context, the former refers to decisions driven by personal prejudice; for example, a loan officer overturning an AUS approval for a male–male application based on a bias against same-sex couples, irrespective of actual loan risk. The latter, by comparison, occurs when decisions are based on group-level characteristics; for example, a loan officer rejecting a male–male application approved by the AUS due to the group's higher average default rate (assuming it is observed by the loan officer), even if the individual applicant does not present elevated risk.

To compare the decisions made by the AUS and loan officers for otherwise similar applications that observably differ only in their sex composition, we re-estimate our preferred specification on the subsample of 74,622 applications processed through an AUS. We estimate two regressions: one using a binary outcome variable indicating final rejection by the loan officer, and another using a binary outcome variable indicating rejection by the AUS. The results for the final rejection outcome, reported in column (1) of Table 8, show that the coefficient on male–male applications is statistically significant at the 5% level and nearly identical in magnitude to the estimate from the full sample. In contrast, when using AUS

[13]The overturn rates for AUS-recommended approvals were 4.3% for female–male applications and 5.9% for female–female applications, as detailed in Appendix A0.4

rejection as the outcome (column (2)), the male–male coefficient is no longer statistically significant and is close to zero. That is, the AUS does not generate disparities in rejection between male–male and comparable male–female applications - whereas such disparities emerge only at the stage of loan officer discretion, which may suggest human bias in the final lending decision process stemming from one of the factors detailed in the previous paragraph.[14]

6 Why Do Male Same-sex Couples Default More?

In this section, we discuss factors that may have contributed to the higher 90-day delinquency rates observed for male-male applications relative to male-female applications during the COVID period, a period of economic uncertainty, as reported in section 5.1.

First, the occupational and sectoral distribution of gay men differs from that of their heterosexual counterparts, with many gay men employed in industries more severely affected by the pandemic (Antecol et al., 2008; Ellis et al., 2012). For example, LGBTQ+ individuals are disproportionately represented in the service sector, which experienced significant disruptions during the COVID period (Utz and Cai, 2022). These employment patterns may have resulted in more severe employment losses during that period. Martino et al. (2021) for example, found that 27.3% of LGBTQ+ individuals employed prior to the pandemic reported job loss by mid-2020, compared to a national average of 13.3%. In addition, gay men may differ from heterosexual men in other labor market characteristics, such as hours worked.

Second, discrimination against gay men in the labor market, that can lead to worst employment outcomes and thus reduced ability to repay loans, is well-documented (Drydakis, 2022, 2015, 2009) and evidence suggests it intensifies during economic downturns, when the cost of discriminatory behavior to employers is lower (Biddle and Hamermesh, 2013; Chattopadhyay and Bianchi, 2021).

Third, although the health insurance coverage rates for gay men have been comparable to those of heterosexual men in recent years, substantial disparities in access to care persist—disparities that may have contributed to differential health outcomes during the COVID-19 pandemic. For instance, gay men were significantly more likely to report being unable to afford care, even when insured (Bolibol et al., 2023; Nguyen et al., 2024).

Fourth, male same-sex couples are significantly less likely to be married than opposite-sex couples. Marriage often provides a form of financial protection, serving as a buffer against

[14]With our saturated specifications, we are not powered to estimate regressions in which the outcome is whether an AUS decision was overturned.

income loss by allowing for risk pooling and shared resources. According to the U.S. Census Bureau (2021), only 14.8% of opposite-sex couples were unmarried in 2021, compared to 42.3% of male same-sex couples.

Fifth, as discussed in Section 5.1, male same-sex couples have been shown to face higher interest rates on comparable mortgage loans than different-sex couples, which may exacerbate financial strain.

Lastly, gay men may be less likely to receive financial support from family due to estrangement.

Conversely, several factors may have helped male same-sex couples to weather the economic downturn better than their heterosexual counterparts. These include a higher average savings rate (Negrusa and Oreffice, 2010), fewer children (U.S. Census Bureau, 2020), and higher incomes on average, as detailed in Table 1.

In this paper, we examine how the factors discussed above collectively influence the financial well-being of LGBT individuals. Expanding on the analysis of Carpenter et al. (2024), we present evidence from SHED. Using the data, we estimate the following specification:

$$Y_{it} = \beta_1 LGBT_i + \beta_2 COVID_t + \beta_3 LGBT_i \cdot COVID_t + \theta X_{it} + \tau_t + \epsilon_{it} \tag{2}$$

where Y_{it} is an outcome of interest for respondent i in year t. $LGBT_i$ equals 1 if the respondent is gay or lesbian and 0 otherwise and $COVID_t$ equals 1 if the year is 2020 or 2021 and 0 otherwise.[15] X_{it} is a vector of respondent characteristics - age, education, race, whether they have a partner, and region.[16] Lastly, τ_t is the survey year fixed effects. The regressions are population weighted and robust standard errors are reported.

We estimate the regressions separately for males and females. For males, the coefficient of interest, β_3, identifies the differential effect on the outcome of interest of COVID years, relative to non-COVID years, on gay males relative to straight males. For females, it identifies the differential effect on the outcome of interest of COVID years, relate to non-COVID years, on lesbian females relative to straight females.

We construct several outcomes of interest; the main one is derived from the broad question "Overall, which one of the following best describes how well you are managing financially these days?". Possible answers are "finding it difficult to get by", "just getting by", "doing okay", and "living comfortably". We construct a variable that equals 1 if the respondent an-

[15]The surveys were conducted in the fall. By the fall of 2020, COVID was prevalent, and by the fall of 2022, COVID cases have declined considerably.

[16]Age, education, race, and region have 4, 4, 5, and 9 possible values, respectively.

swered either "doing okay" or "living comfortably", and 0 otherwise. The second is derived from the question "Have you set aside emergency or rainy day funds that would cover your expenses for 3 months in case of sickness, job loss, economic downturn, or other emergencies?". The variable takes the value 1 if the respondent responded "yes", and 0 otherwise. The third is derived from the question "Compared to 12 months ago, would you say that you (and your family living with you) are better off, the same, or worse off financially?". Possible answers are "much worse off", "somewhat worse off", "about the same", "somewhat better off", and "much better off". We construct a variable that equals 1 if the respondent answered either "much worse off" or "somewhat worse off", and 0 otherwise. The last is derived from the question "If you were to apply for a credit card today, how confident are you that your application would be approved?". Possible answers are "don't know", "very confident", "somewhat confident", and "not confident". We construct a variable that equals 1 if the respondent answered "not confident", and 0 otherwise.

Table 9 details the estimation results. Each column corresponds to a different regression where the outcome of interest is the variable detailed in the top row. Results for males are detailed in the top panel, while results for females are detailed in the bottom panel. We also report the pre-COVID mean for each variable for the reference group (straight respondents).

For males, the coefficients of the interaction term $gay \cdot COVID$ all point to worsening financial well-being for gay individuals compared to straight individuals, during the COVID period compared to the non-COVID period. In two out of the four outcomes, the coefficients are statistically significant (managing well financially at 5% and worse off at 10%), while for the other two outcomes, the coefficients are in the direction of worsening financial well-being but are nosily estimated, as the gay sample is small. With respect to the broad question on whether the respondent is managing well financially, the coefficient suggests gay individuals were 6.6 percentage points (8.8% from a pre-COVID mean for straight individuals of 0.75) less likely to be managing well financially during the COVID period relative to the pre-COVID period, compared to straight individuals. With respect to the question on whether the respondent is worse off compared to 12 months prior, the coefficient suggests gay individuals were 5.5 percentage points (24% from a pre-COVID mean for straight individuals of 0.229) more likely to be worse off during the COVID period relative to the pre-COVID period, compared to straight individuals.

For females, the small yearly samples of lesbians in SHED makes it difficult to detect an effect. The interaction terms $lesbian \cdot COVID$ are mostly small in magnitude and none are statistically significant. This suggests that during the COVID period, compared to the non-COVID period, lesbian individuals did not experience worsening financial well-being

compared to straight individuals. Nonetheless, as detailed in section 5.1, we do find that female-female applications were more likely to be 90-day delinquent than male-female applications during the COVID period. But, the magnitude of the difference is about a third of that of male-male applications.

7 Conclusion

In this paper, we provide new estimates of disparities in mortgage application outcomes between same-sex and opposite-sex couples. Using confidential data covering the universe of mortgage applications in the United States from 2018 to 2021, we compare the mortgage outcomes of same-sex and different-sex couples, 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 were 27.6% more likely to be rejected than otherwise similar male-female applications, with this disparity remaining consistent both prior to and during the COVID period. Among approved applications, male-male applicants were quoted interest rates that were, on average, 0.73% higher. Although these disparities are smaller than those reported in earlier studies based on more limited public data, they remain substantial and carry significant implications for same-sex couples.

We also find that during the COVID period, male-male applications were 53.9% more likely to default within 36 months of origination, whereas prior to the pandemic, they did not exhibit a higher risk of default compared to male-female applications. This suggests the presence of risk factors among male-male applicants unobserved to us that may partly explain the disparities in rejection and interest rates. These risk factors may stem from broader labor market discrimination, which could adversely affect male same-sex couples' ability to repay loans, or from other factors that we discuss.

We also provide suggestive evidence that direct discrimination in the mortgage decision-making process may contribute to the observed disparities. First, we find that disparities in mortgage outcomes were significantly larger in regions with lower levels of LGBTQ+ acceptance. Second, we show that loan officers were more likely to overturn AUS-recommended approvals for male–male applications and less likely to overturn AUS-recommended rejections, relative to male–female applications. And that the AUS produced no significant difference in rejection rates between male–male and similar male–female applicants, in contrast to the disparities estimated at the final loan officer stage. This could stem from loan officers acting on additional information not captured by the AUS, or due to taste-based discrimination.

Lastly, we discuss several potential explanations for the elevated delinquency rates among

male-male applicants and present evidence from the Federal Reserve Board's SHED survey that the financial well-being of gay men deteriorated more during the COVID period than that of heterosexual men relative to the pre-COVID period, potentially hurting their ability to repay loans.

Acknowledging the existence of disparities in mortgage lending is important. While public sentiment toward LGBTQ+ individuals has improved in recent decades, significant gaps in mortgage outcomes remain. Documenting these disparities accurately—and identifying whether they reflect underlying risk differences or result from discrimination—is an important step toward achieving equal access to credit for same-sex couples.

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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	7.247	8.215	11.776	10.779	7.667
	SD	25.927	27.459	32.234	31.012	26.607
Interest Rate (%)	Mean	4.397	4.431	4.498	4.528	4.410
	SD	0.650	0.652	0.669	0.652	0.651
Loan-to-Value (%)	Mean	85.849	87.519	87.598	88.332	86.340
	SD	14.650	13.349	13.063	13.348	14.312
Debt-to-Income (%)	Mean	37.570	37.583	40.571	40.988	37.729
	SD	11.008	10.990	11.622	11.608	11.056
Applicant Credit Score	Mean	733.860	724.492	717.528	709.656	730.739
	SD	58.530	60.235	59.089	62.040	59.288
Co-applicant Credit Score	Mean	735.809	722.552	725.031	717.393	732.047
	SD	58.482	61.093	58.622	63.184	59.533
Applicant Income ($)	Mean	124,198	120,804	127,960	107,222	123,073
	SD	77,051	72,431	81,899	66,400	75,933
White	Mean	0.817	0.790	0.754	0.739	0.807
	SD	0.387	0.407	0.431	0.439	0.395
Hispanic	Mean	0.109	0.117	0.234	0.195	0.116
	SD	0.312	0.321	0.424	0.396	0.320
Black	Mean	0.048	0.063	0.052	0.107	0.053
	SD	0.215	0.243	0.221	0.309	0.225
Asian	Mean	0.060	0.064	0.105	0.068	0.062
	SD	0.237	0.245	0.306	0.252	0.241
Age 20 - 24	Mean	0.033	0.064	0.075	0.062	0.042
	SD	0.179	0.244	0.264	0.242	0.201
Age 25 - 29	Mean	0.122	0.181	0.153	0.149	0.137
	SD	0.327	0.385	0.360	0.356	0.344
Age 30 - 34	Mean	0.172	0.201	0.167	0.160	0.178
	SD	0.377	0.401	0.373	0.367	0.383
Age 35 - 39	Mean	0.153	0.159	0.147	0.133	0.154
	SD	0.360	0.366	0.354	0.339	0.361
Age 40 - 44	Mean	0.115	0.109	0.119	0.113	0.113
	SD	0.319	0.312	0.324	0.317	0.317
Age 45 - 49	Mean	0.094	0.082	0.102	0.103	0.092
	SD	0.292	0.275	0.302	0.304	0.289
	N	449,082	143,681	14,869	15,614	623,246

Notes: The table presents summary statistics for home purchase mortgage applications, categorized by the sex composition of the applicant-co-applicant in columns (1)-(4), and for all applications in column (5). We include applications submitted in 2018-2019. For brevity, summary statistics for other race and age categories are not included here but are provided in A0.1.

Table 2: Rejection Results - Baseline

	(1)	(2)	(3)	(4)	(5)
Female-Male	0.496***	-0.040	-0.207	-0.155	0.003
	(0.09)	(0.14)	(0.21)	(0.21)	(0.31)
Male-Male	3.299***	1.319***	1.368**	1.325**	2.002**
	(0.26)	(0.45)	(0.66)	(0.66)	(0.91)
Female-Female	2.041***	0.303	0.259	0.203	0.500
	(0.29)	(0.44)	(0.60)	(0.60)	(0.79)
pHMDA Controls	Yes	Yes	Yes	Yes	Yes
cHMDA Controls	No	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes
Lender-County-Year FE	Yes	Yes	No	No	No
Lender-County-Month FE	No	No	Yes	Yes	Yes
Age FE	No	No	No	Yes	Yes
Loan Officer FE	No	No	No	No	Yes
R^2	0.216	0.311	0.445	0.446	0.590
N	516,190	173,034	104,243	104,243	84,457

Notes: The table presents the results of estimating equation (1), using a binary outcome 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 controls and fixed effects detailed in the middle and lower panels. We include applications submitted in 2018-2019. Rows (1)-(3) report estimates by sex composition, with male-female applications as the reference group. Robust standard errors, clustered at the county level, are provided in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3: Interest Rate Results - Baseline

	(1)	(2)
Female-Male	0.035***	0.012***
	(0.00)	(0.00)
Male-Male	0.069***	0.032**
	(0.01)	(0.01)
Female-Female	0.067***	0.027*
	(0.00)	(0.01)
pHMDA Controls	Yes	Yes
cHMDA Controls	No	Yes
Loan Type FE	Yes	Yes
Lender-County-Year FE	Yes	Yes
Lender-County-Month FE	No	Yes
Age FE	No	Yes
Loan Officer FE	No	Yes
R^2	0.525	0.839
N	460,048	72,651

Notes: The table presents the results of estimating equation (1), using the interest rate as the outcome variable. Each column refers to a different regression that includes the controls and fixed effects detailed in the middle and lower panels. We include applications submitted in 2018-2019. Rows (1)-(3) report estimates by sex composition, with male-female applications as the reference group. Robust standard errors, clustered at the county level, are provided in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4: Default Results

	(1) Pre-COVID Period	(2) COVID Period
Female-Male	0.112	-0.146
	(0.12)	(0.10)
Male-Male	-0.405	2.053***
	(0.26)	(0.31)
Female-Female	-0.081	0.779***
	(0.36)	(0.29)
Interest Rate	-0.045	1.715***
	(0.16)	(0.13)
cHMDA-McDash Controls	Yes	Yes
Loan Type FE	Yes	Yes
County-Quarter FE	Yes	Yes
Reference Group Mean	1.00	4.32
R^2	0.152	0.103
N	58,613	311,114

Notes: The table presents the results of estimating equation (1), using a binary outcome variable that takes the value of 100 if a 90-day delinquency occurs within 36 months of origination, and 0 otherwise. Each column refers to a different regression that includes the controls and fixed effects detailed in the middle and lower panels. Column (1) presents estimates for applications submitted in 2015-2016, tracked through 2018-2019 (pre-COVID period). Column (2) presents estimates for applications submitted in 2018-2019, tracked through 2021-2022 (COVID period). Rows (1)-(3) report estimates by sex composition, with male-female applications as the reference group. Robust standard errors, clustered at the county level, are provided in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5: Rejection Results - Regional Heterogeneity

	(1) Northeast	(2) Midwest	(3) South	(4) West
Female-Male	0.357	-0.136	0.161	-0.320
	(0.52)	(0.44)	(0.43)	(0.67)
Male-Male	1.329	5.406*	3.026**	-0.180
	(2.39)	(2.92)	(1.52)	(1.19)
Female-Female	-0.476	-0.101	1.281	0.107
	(1.69)	(1.64)	(1.21)	(1.55)
cHMDA Controls	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes
Lender-County-Month FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes
R^2	0.638	0.614	0.587	0.574
N	8,918	13,494	36,099	24,787

Notes: The table presents the results of estimating equation (1), using a binary outcome variable that takes the value of 100 if the application is rejected, and 0 otherwise. Each column refers to a different regression for the subset of applications submitted in that census region of the US. We use our preferred specification. We include applications submitted in 2018-2019. Rows (1)-(3) report estimates by sex composition, with male-female applications as the reference group. Robust standard errors, clustered at the county level, are provided in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6: Default Results - Regional Heterogeneity

	(1) Northeast	(2) Midwest	(3) South	(4) West
Female-Male	-0.719***	0.179	-0.102	-0.096
	(0.22)	(0.19)	(0.18)	(0.19)
Male-Male	2.866***	2.812***	1.603***	1.331**
	(0.82)	(0.62)	(0.46)	(0.59)
Female-Female	0.684	1.780**	0.565	0.198
	(0.72)	(0.71)	(0.52)	(0.50)
Interest Rate	1.677***	1.759***	2.000***	1.387***
	(0.36)	(0.24)	(0.24)	(0.29)
HMDA-McDash Controls	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes
County-Quarter FE	Yes	Yes	Yes	Yes
Reference Group Mean	5.26	3.38	4.79	4.01
R^2	0.101	0.117	0.109	0.084
N	52,030	72,753	113,919	72,412

Notes: The table presents the results of estimating equation (1), using a binary outcome variable that takes the value of 100 if a 90-day delinquency occurs within 36 months of origination, and 0 otherwise. Each column refers to a different regression for the subset of applications submitted in that census region of the US. We include applications submitted in 2018-2019, tracked through 2021-2022. Rows (1)-(3) report estimates by sex composition, with male-female applications as the reference group. Robust standard errors, clustered at the county level, are provided in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 7: Number of Applications by AUS and Final Decisions

Male - Female Applications			
		Final Decision	
		Approve	Reject
AUS Decision	Accept	348,205	13,926
	Reject	31,706	10,874
Male - Male Applications			
		Final Decision	
		Approve	Reject
AUS Decision	Accept	11,081	795
	Reject	992	624

Notes: The table reports the number of home-purchase mortgage applications submitted in 2018-2019, cross-classified by AUS recommendation and loan officer final decision. Cell entries are application counts. The upper panel covers male–female applications; the lower panel covers male–male applications.

Table 8: Rejection Results - AUS

	(1) Rejection Rate	(2) AUS Rejection Rate
Female-Male	0.120	0.076
	(0.30)	(0.33)
Male-Male	2.007**	-0.143
	(0.82)	(0.93)
Female-Female	0.760	-0.614
	(0.83)	(0.75)
cHMDA Controls	Yes	Yes
Loan Type FE	Yes	Yes
Lender-County-Month FE	Yes	Yes
Age FE	Yes	Yes
Loan Officer FE	Yes	Yes
Reference Group Mean	6.12	10.52
R^2	0.579	0.620
N	74,622	74,622

Notes: The table presents the results of estimating equation (1), using a binary outcome variable that takes the value of 100 if the application is rejected, and 0 otherwise (column (1)), or a binary outcome variable that takes the value of 100 if the application is AUS rejected and, 0 otherwise (column (2)). We use our preferred specification. We include applications submitted in 2018-2019. Rows (1)-(3) report estimates by sex composition, with male-female applications as the reference group. Robust standard errors, clustered at the county level, are provided in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 9: SHED Survey Results

	Managing Well Financially	Rainy Day Fund	Worse Off	Credit Debt
Males				
Gay	0.014	0.001	-0.013	0.081***
	(0.021)	(0.023)	(0.020)	(0.028)
Covid	0.033***	0.088***	-0.018*	-0.055***
	(.011)	(0.013)	(0.011)	(0.013)
Gay*Covid	-0.066**	-0.049	0.055*	0.046
	(0.033)	(0.037)	(0.033)	(0.040)
Observations	17,654	17,654	17,654	14,304
R-squared	0.120	0.146	0.079	0.042
Pre-COVID Mean	0.750	0.573	0.229	0.241
Females				
Lesbian	0.008	-0.022	-0.011	0.066
	(0.034)	(0.038)	(0.032)	(0.048)
Covid	0.046***	0.075***	-0.017*	-0.036***
	(.011)	(0.012)	(0.010)	(0.013)
Lesbian*Covid	-0.016	-0.005	0.028	-0.047
	(0.050)	(0.056)	(0.047)	(0.063)
Observations	16,131	16,131	16,131	13,041
R-squared	0.137	0.163	0.091	0.038
Pre-COVID Mean	0.697	0.491	0.254	0.275

Notes: This table presents the results of estimating equation (2). Each column refers to a different regression in which the outcome is a binary variable that takes the value of 1 if the respondent's answer matches the definition provided in Section 6. The regressions are estimated separately for males, shown in the top panel, and females, shown in the bottom panel. The regressions are population-weighted, and robust standard errors are reported.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

A Appendix

Table A0.1: Additional Summary Statistics

		(1) Male-Female	(2) Female-Male	(3) Male-Male	(4) Female-Female	(5) All
Other Races	Mean	0.009	0.012	0.010	0.012	0.010
	SD	0.094	0.107	0.102	0.109	0.098
Age 50 - 54	Mean	0.078	0.065	0.082	0.084	0.075
	SD	0.268	0.247	0.274	0.277	0.264
Age 55 - 59	Mean	0.069	0.053	0.063	0.070	0.065
	SD	0.254	0.224	0.243	0.256	0.247
Age 60 - 64	Mean	0.058	0.039	0.037	0.048	0.053
	SD	0.234	0.195	0.190	0.213	0.224
Age 65 - 69	Mean	0.049	0.025	0.025	0.037	0.042
	SD	0.215	0.156	0.157	0.188	0.202
Age 70+	Mean	0.056	0.018	0.025	0.039	0.046
	SD	0.230	0.132	0.157	0.193	0.210
	N	449,082	143,681	14,869	15,614	623,246

Notes: This table presents summary statistics for home purchase mortgage applications, categorized by the sex composition of the applicant-co-applicant in columns (1)-(4), and for all applications in column (5). We include applications submitted in 2018-2019. Full summary statistics are detailed in Table 1.

Table A0.2: Regression Results - COVID Period

	(1) Rejection Rate	(2) Interest Rate
Female-Male	-0.090	0.010***
	(0.18)	(0.00)
Male-Male	2.569***	0.035***
	(0.67)	(0.01)
Female-Female	0.475	0.034***
	(0.57)	(0.01)
cHMDA Controls	Yes	Yes
Loan Type FE	Yes	Yes
Lender-County-Month FE	Yes	Yes
Age FE	Yes	Yes
Loan Officer FE	Yes	Yes
Reference Group Mean	9.68	3.06
R^2	0.603	0.770
N	95,024	85,176

Notes: The table provides the results of estimating equation (1), using a binary outcome variable that takes the value of 100 if the application is rejected, and 0 otherwise (column (1)), or the interest rate (column (2)). The estimation in column (2) uses the subset of approved applications. We use our preferred specification, which includes the controls and fixed effects detailed in the middle and lower panels. We include applications submitted during the COVID period (2020-2021). Rows (1)-(3) report estimates by sex composition, with male-female applications as the reference group. Robust standard errors, clustered at the county level, are provided in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A0.3: List of States by Census 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	

Table A0.4: Number of Applications by AUS and Final Decisions

Female - Male Applications			
		Final Decision	
		Approve	Reject
AUS Decision	Accept	112,654	5,084
	Reject	9,568	3,868
Female - Female Applications			
		Final Decision	
		Approve	Reject
AUS Decision	Accept	12,401	785
	Reject	701	562

Notes: The table reports the number of home-purchase mortgage applications submitted in 2018-2019, cross-classified by AUS recommendation and loan officer final decision. Cell entries are application counts. The upper panel covers female–male applications; the lower panel covers female–female applications.

Table A0.5: 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, Loan Amount
pHMDA Controls	Applicant Income, Hispanic, Black, Asian, Other Races, Loan Amount
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
Default	Indicator equal to 100 if the borrower ever becomes 90 or more days delinquent within 3 years after loan origination
Age FE	Age 24-, 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+