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Mortgage Discrimination and District Manipulation: Deterrents to Minority Mobility

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Honors Thesis

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Abstract

This paper explores the relationship between gerrymandering and home loan discrimination. Gerrymandering, the process of manipulating district plans for political gain, and discrimination in mortgage lending are both illegal; and yet, they still occur in today's society. By using individual loan application data from the HMDA's website, a series of regressions will be run using applicant characteristics to measure loan discrimination at the state level. Once a state level model has been constructed, a measure of gerrymandering called the Efficiency Gap will be added into the regression in order to explore the relationship between home loan discrimination and gerrymandering. Regression results suggest the presence of gerrymandering in a state is associated with more loan discrimination. A relationship of this nature is cause for further, in-depth research. This relationship could suggest that lenders and lawmakers are working collectively to keep minorities in one voting district. In doing so, the power of these individuals' vote is effectively diminished. Seeing as every citizen is supposed to have equal access and opportunity to vote, this presents a new avenue for law makers to explore to further curtail both of these unethical actions.

Acknowledgements

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Introduction

The location of a person's residence has a large impact on future life experiences and opportunities because it provides access to things like quality education and safe neighborhoods. When people talk about the American dream, it often involves moving up in life to a stable financial position and ultimately, buying a home for oneself and one's family. According to a Forbes article by Camilo Maldonado, "32% of applicants with less than perfect credit were denied mortgages in 2017" (2018). Of these applicants, high-income minority families are being denied mortgage loans as often as low-income white families (Gotham, 2012). While other factors such as debt, credit score, and financial history can determine who is granted a mortgage loan, the aforementioned statistic suggests the presence of racial discrimination in lending. There is a vast literature exploring the existence of racial discrimination in mortgage lending. Rick Cohen explains that many people deny the existence of racism in lending by pointing out that the majority of low-income families are Black, and this is why Black families are denied more often. However, Cohen explains that the rather liberal distribution of subprime mortgage loans to those who had first been denied is a clear indicator of racism in lending (2008). In another piece, Vanessa Perry discusses the discrimination in the lending process and the disadvantages that follow (2019). This discrimination in mortgage loan lending is forcing the hand of many minority families by giving them no option but to live where housing prices are more affordable, in lower-income neighborhoods.

Residents of low-income communities face many hardships such as lower-performing public schools, environmental hazards (e.g., unclean water), increased violence, and many other difficulties (Sacks, 2018). Another, more threatening disadvantage that people in poorer neighborhoods encounter is a lack of access to reliable healthcare (Reynolds, 1976). On top of all of this, persons in low-income neighborhoods are more likely to be socially isolated, meaning that they have fewer people in their close circle that they can have meaningful discussions with (Tigges, Browne, & Green, 2008). Residents of poor neighborhoods are more likely to fall victim to voter suppression as well. In the past couple of years, there have been numerous cases of voter suppression, which has, “a disenfranchising affect on racial and ethnic minorities, who are less likely than whites to possess a valid ID,” (Barreto, Nuño, Sanchez, & Walker, 2019). In addition, there is evidence to suggest that it is not just voter ID laws, but partisan control of the electoral college as well that diminishes the voting power of minorities (Hicks, McKee, Sellers, & Smith, 2015).

Through a process that has been identified as gerrymandering, state legislatures draw districts so that the electoral college will be in favor of one political party or voting demographic (O’Loughlin, 2010). Essentially, when the district lines are drawn, those in charge will try to see to it that people of a particular characteristic are “packed” into a few districts so as to lessen the voting power of the designated group had they been spread out over several districts. Alternatively, sometimes voting blocs can be “cracked” across many districts so that they are the minority vote in several districts as opposed to being the majority vote in a few districts (Warrington, 2018). Both methods of gerrymandering tamper with deserving citizens’ right to vote by diminishing the power of their vote. Both methods attempt to manipulate the outcome of an election, in essence, diminishing the power of voters in the targeted demographics. Fixing elections by taking powers from the voters is both unethical and unconstitutional. Redistricting occurs every ten years after the decennial census, meaning that these plans can potentially affect ten years' worth of elections. And yet, because redrawing districts is such a meticulous and somewhat subjective task, gerrymandering can go undetected.

If the people in power can consolidate all of a particular demographic of voters in a given state into one district, the power these underprivileged members of society once had is effectively taken from them. It naturally follows that one might suggest these Black citizens move out of their gerrymandered district in order for their voice to be heard. Here is where this paper aims to add to the literature by drawing the connection between racial discrimination in mortgage loan lending and living in a gerrymandered district. Once placed in these gerrymandered districts, voting-aged Black men and women are stripped of their power to vote politicians into office who will advocate for their concerns, thus perpetuating the system of discrimination because they cannot get access to loans for more expensive homes in other districts. Throughout this paper, the prior research done on gerrymandering and loan discrimination will be explored then a new contribution to the literature will be added by providing a model that measures the effect of gerrymandering on racial discrimination in mortgage lending.

Literature Review

Discrimination in Mortgage Loan Lending

Several published studies have looked into discrimination, specifically racial discrimination, in the mortgage loan lending process. Discrimination use to be a fairly easy practice to detect, and some banks had explicit policies that directed their loan officers to do so. For example, in the 1970s it was found that many financial institutions had told their mortgage lenders to discount a wife's income by 50 percent or more, especially if she was of child-bearing age or had young children (Ladd, 1998). Then through the passage of the Fair Housing Act of 1968 and the 1974 Equal Credit Opportunity Act, racial and gender discrimination in loan lending was made illegal. However, evidence suggests that racial and gender discrimination did not end there.

In 1992, well after the passage of these two laws barring the practice of racial discrimination in mortgage lending, the Boston Fed did a study on 131 financial institutions in the Boston Metropolitan Statistical Area. Authors Alicia H. Munnell, Lynn E. Browne, James McEneaney, and Geoffrey M. B. Tootell found that racial discrimination was to blame for the disproportionate denial rates of minority applicants when compared to their white counterparts (1992). This study drew a lot of negative attention and claims of incorrect findings, so a follow up study was done a couple years later to check the validity of those findings by Dennis Glennon and Mitchell Stengel. They agreed with the Boston Fed's conclusion that racial discrimination was rampant amongst financial institutions in Boston (1994).

A study by Margery Austin Turner and Felicity Skidmore reviewed and critiqued several published pieces on racial discrimination in mortgage lending. Their findings were that racial discrimination happens on an individual level due to a loan lender's own prejudices and on a structural level. The structural level discrimination was discovered when FHA-insured loans were compared to conventional loans. FHA-insured loans are government-backed and often are more flexible but with higher rates or fees for the borrower. Conventional loans on the other hand are insured by private lenders and are often less flexible in their approval process but with the benefit of lower payments, fees, and rates. All else equal, minority applicants are pushed toward FHA-insured loans more than White applicants, which would explain why the discrimination present in the conventional loan market is much higher than that of the FHA-insured loan market. Without the direct presence of the government in the conventional loan lending process, private institutions are more apt to partake in racially discriminatory lending practices at large. An important distinction made in this review of published findings was that racial discrimination in mortgage lending is often disputed with the evidence that minority applicants on average are of lower creditworthiness than White applicants so it would naturally follow that their denial rates are higher (1999). However, several published works, like that of Stephen L. Ross and John Yinger, have found that equally credit worthy minority applicants are being denied a loan or given less favorable amounts or rates than their White counterparts. Additionally, their book mentions how discrimination can happen at any stage of the loan lending process, including preapproval, loan approval, and setting the terms of the mortgage loan (2002).

Yet again, a qualitative study by Douglas S. Massey, Jacob S. Rugh, Justin P. Steil, and Len Albright looked into statements from loan officers in fair lending lawsuits and found that 76 percent of the statements suggested the presence of structural discrimination in the lending process, while only 11 percent were indicative of individual discrimination based on the loan officer's personal biases (2016). These published findings and so many others have time and time again shown that despite the passage of the Housing Act of 1968 and the 1974 Equal Credit Opportunity Act, racial discrimination in mortgage lending is still prevalent throughout the country.

Gerrymandering

Gerrymandering was made unconstitutional with the passage of the Voting Rights Act of 1965. Stated in this new legislation is the illegality of any, “voting practices and procedures (including redistricting plans) that discriminate on the basis of race, color or membership in a language minority group” (U.S. Department of Justice, 2020). The first major court case regarding gerrymandering was presented to the Supreme Court of the United States in 1993. A group of North Carolina residents challenged the North Carolina 1992 redistricting plan, claiming it had been racially gerrymandered. What was special about this case is that North Carolina elected officials were attempting to give greater representation to Black voters in the state. However, they had drawn in a second majority Black district that was so disproportionate to the point where some areas of the district were, “no wider than the interstate road along which it stretched” (*Shaw v. Reno*, 1993).The case was first brought to the U.S. District Court for the Western District of North Caroline in 1992 under the name *Pope v. Blue* but was dismissed on lack of evidence of racial gerrymandering (*Pope v. Blue*, 1992). When the case was tried again, the plaintiffs in *Shaw v. Reno* modified the question before the court to ask whether or not racial gerrymandering, especially in cases of benefiting minority voters, raised a valid constitutional issue. The Supreme Court ruled that although the intentions of the district plan were noble, the plan was unconstitutional because it was still manipulated for political gain. An article written by The Washington Post found the ten most gerrymandered districts in 2012. Maryland, a historically blue state, and North Carolina, a historically red state, were tied for the most gerrymandered states (Ingraham). An important point to make here is that gerrymandering is bipartisan; this is an issue on both sides of the aisle. However, when it comes to race, it is not so equal; gerrymandering primarily affects Black Americans and the power of their vote (Issacharoff & Goldstein, 1996).

In two different studies, Stephanopoulos, and McGhee (2018 & 2014) explore the differences in the Efficiency Gap and the declination metric. The Efficiency Gap measures how many lost votes a given state has. Defining lost votes comes in two parts: districts with the presence of “packing” and districts with the presence of “cracking.” In districts with the presence of “packing” one demographic into a given area, all the votes for a candidate over the maximum percentage it takes to win would be considered lost because they were unnecessary to secure the seat for the winning candidate. On the flipside, districts with the presence of “cracking,” or spreading out a certain voting demographic amongst multiple districts, would define lost votes as the number of votes for a losing candidate. In a different study done by McGhee, he argues that it is important to use a measure as detailed with respect to measuring individual votes as the Efficiency Gap when detecting gerrymandering (2017). As can be seen in Equation (1), to ensure the

$$\mathrm{EG} = \frac{|Number\ of\ Party\ B's\ Wasted\ Votes\ - Number\ of\ Party\ A's\ Wasted\ Votes|}{Total\ Votes\ in\ the\ State} \qquad (1)$$

Efficiency Gap is a nonpartisan measure, the absolute value of the numerator was taken. Throughout the rest of this paper, the Efficiency Gap will be utilized as a metric for detecting gerrymandering in a given state.

There is much debate over a good way to quantify gerrymandering. Of the current research on quantifying gerrymandering, the majority of them are mathematical models that can show the existence of gerrymandering via computer algorithms. Padilla, Ratliff, and Veomett (2018) did a study on quantifying gerrymandering at the state level. They use a metric of asymmetry amongst seats won and the vote distribution called declination. This metric was defined by Gregory Warren in another study that was also aiming to quantify gerrymandering (2018). Put simply, the declination metric is calculated by plotting the vote distribution of a state and the seats won by each party in order to find an angular difference in the two measures. Padilla, Ratliff, and Veomett (2018) used an algorithm to plot thousands of different potential outcomes for a state to see if the declination varied significantly from zero. Essentially, a zero measure of declination states that vote shares and seat shares are evenly distributed. A declination coefficient greater or less than zero suggests the presence of gerrymandering. However, because of the limited number of available seats in every state and the natural distribution of people throughout a given state, it's extremely unlikely that the vote share will exactly equal the awarded seat distribution in states that don't actually have any presence of gerrymandering. So, by running the algorithm, it aims to compare whether the declination coefficient is an extreme variation of the baseline cases that are possible for a given state. With all of this said, there is debate over whether or not the declination model is a better measure of gerrymandering than the Efficiency Gap.

Model

The regression model used to test the effects of gerrymandering and race on mortgage loan approval is shown in Equation (2). The dummy variable for approval is

$$\begin{gathered} A = \beta_0 + \beta_1 EG + \beta_2 BB + \beta_3 BW + \beta_4 BO + \beta_5 WB + \beta_6 WO + \beta_7 OB + \beta_8 OW + \\ \beta_9 OO + \beta_{10} \ln(L) + \beta_{11} \ln(I) + \beta_{12} P + \beta_{13} F + \beta_{14} HH + \beta_{15} HN + \beta_{16} NH + \varepsilon \end{gathered} \tag{2}$$

denoted as "A" and the Efficiency Gap is denoted as "EG". The second through ninth variables denote the applicant/co-applicant race interaction variables. The first letter represents the applicant's race and the second later signifies the co-applicant's race. The letter "B" stands for Black applicants or co-applicants, "W" stands for White applicants or co-applicants, and "O" stands for Other applicants or co-applicants. The variable "ln(L)" stands for the natural log of the loan amount being applied for and "ln(I)" represents the natural log of the applicant's income. A dummy variable for whether someone was preapproved is denoted by the letter "P" and the dummy variable for an applicant's gender is denoted with an "F" equal to one for female applicants and zero for male applicants. The last three variables are the applicant/co-applicant ethnicity interaction variables with the first letter representing the applicant's ethnicity and the second letter representing the co-applicant's ethnicity. A Hispanic applicant or co-applicant is represented by an "H" and a Non-Hispanic applicant or co-applicant is represented with an "N." The White applicant applying with a White co-applicant variable, the Non-Hispanic applicant applying with a Non-Hispanic co-applicant variable, and the male variable will be omitted to avoid collinearity. The FHA-insured loan and conventional loan variables were also omitted from this model because separate regressions were run for each type of loan as opposed to putting them in the model.

The unit of observation is a single applicant. All variables, aside from the Efficiency Gap, are measured using individual applications for mortgage loan data from across the country. The Metropolitan Statistical Division of each applicant/co-applicant pair is recorded, the Efficiency Gap is measured at the state level so the model only specifies geographic application details at the state level. Of all the information provided in the loan dataset; income, loan amount, gender, applicant and co-applicant race and ethnicity, and preapproval are included in the model. It is expected that the income variable will have a positive coefficient, because an increase in income would suggest that one is more apt to repay their loan, thus warranting a higher chance of being approved. The loan amount variable is expected to have a negative coefficient, seeing as an increase in the size of the loan implies larger monthly mortgage payments and a greater likelihood of not being able to make one of those payments, a reason to hesitate on approving an applicant. The natural log was taken of the loan amount and income variables so as to identify the effects of percentage changes in these variables and reduce the effects of high-end outliers. As for the gender variables, it is expected that females will have a negative coefficient because gender discrimination is prevalent in the loan approval process (Fang & Munneke, 2016). The preapproval variable coefficient estimate is expected to be positive because the preapproval process is indicating whether or not someone is financially sound enough to repay a loan, thus increasing one's chances of being approved.

As for the ethnicity, race, and Efficiency Gap variables, all are expected to have negative coefficients. As discussed above, there is previously published evidence to suggest racial and ethnic discrimination exists in the mortgage loan lending process. Thus, it would be expected that a White applicant applying with a White co-applicant (the omitted racial category) would have the highest chance of getting approved, and every other applicant/co-applicant race pairing would have a lower likelihood of being approved due to racial discrimination. The same can be said for the Non-Hispanic applicant applying with a Non-Hispanic co-applicant (the omitted ethnic category), where that pairing would have the highest likelihood of being approved while the other applicant/co-applicant ethnic pairings would have a lower likelihood of being approved due to ethnic discrimination.

The regression model is estimated using Ordinary Least Squares (OLS). The Efficiency Gap measure is measured as a percentage. All other variables are dummy variables. One thing to note before continuing is that any coefficient results obtained from this model indicate the relationship between that variable and the likelihood of being approved for a loan, but are not necessarily causal effects.

The largest assumption made for this analysis is that if one was denied a mortgage loan, they were going to be living in the same neighborhood or voting district as before and that if approved for a mortgage loan they could be moving to a new neighborhood or voting district. Since old residence and desired residence of an applicant and co-applicant pair were not available via this dataset, this assumption allows for the connection to be made between being denied a mortgage loan and how that exacerbates the effects of gerrymandering because one is not only barred from buying a new home, but they are also barred from being moved to a new voting district.

Data Analysis

When compiling my data, I utilized MIT's Election Lab for the gerrymandering data and the Consumer Financial Protection Bureau's (CFPB) website for public mortgage loan data disclosed under the Home Mortgage Disclosure Act (HMDA). All variables and their sources are shown in Table 1 in Appendix A. The data for calculating the efficiency gap are from the House of Representatives elections because the large number of representatives better captures the disparity between vote share and seat share. The CFPB data are from thousands of financial institutions across the country that report their mortgage loan application information by releasing detailed information on each loan application. Application data from 2007 was used for the regressions. Election results from 2004 were used in the regression for 2007 loan applicants in order to account for the delayed effect between when politicians are elected and when the effects of the policies they enacted trickle down to the civilian level. A study done by Richard T. Smith, Michele Scheumack, and Ian Eddington discussed the problem of there being a time lag between when an issue is brough to the public's attention and when legislation that has been passed finally addresses that issue (n.d.). Seeing as House of Representative elections are every other year, 2004 data was chosen over 2006 data because a year (2006 to 2007) is still not always enough time for politicians, especially newly elected ones, to pass legislation that can have an effect on discriminatory practices in day to day life.

Because the CFPB dataset is so detailed, it needs to be cleaned up before regressions are run. First, the natural log was taken of the loan amount and income variables. Next, the applicant/co-applicant race and ethnicity interaction variables were created. Each paring is a dummy variable, with a 1 denoting if the applicant/co-applicant pair is that racial or ethnic pairing, and a 0 if they are not. Only owner occupied, single-family homes are used for the regressions because the question at hand is concerned with how individuals or families purchasing a home are affected by the relationship between gerrymandering and racial discrimination in mortgage loan lending. The applications in the data set that applied for mortgage loan refinancing or loans for home improvement are also left out of the regression because this paper is strictly focused on mortgage loans for home purchases. Lastly, mortgage loan applications for Veterans Administration guaranteed loans and Farm Service Agency or Rural Housing Services loans are omitted because applicants have to meet certain criteria to apply for these loans, and they go through a different process than for conventional or FHA-insured loans. The final regression sample includes 269,491 applications.

I also consider whether FHA-insured loans and conventional loans may have different levels of discrimination. Therefore, regressions are estimated for all loans, and then split into separate regressions for FHA-insured loan applications and conventional loan applications. There were 13,792 FHA-insured loan applications and 255,699 conventional loan applications. The last two sets of regressions run were looking at the differences between those who were preapproved and those who were not. Of the 19,894 preapproved applications, 18,522 were for conventional loans and 1, 372 were for FHA-insured loans. Of the 246,982 non-preapproved applications, 234,713 were for conventional loans and 12,269 were for FHA-insured loans. All four regressions had a large enough sample to get meaningful regression results.

Looking at the summary statistics in Table 1, it appears that no one applicant/co-applicant racial or ethnic pairing makes up an overwhelming percentage of the applications. White applicants applying with a White-co-applicant, White applicants applying with a Non-White or -Black co-applicant, and Non-Hispanic applicants applying with a Non-Hispanic co-applicant made up the largest percentage of applications. Male applicants made up the majority of applications. A little bit more than half of the applications in the dataset were approved for loans. A separate table of summary statistics filtered by FHA-insured loan applicants and conventional loan applicants is shown in Appendix A Table 2.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	25th Percentile	Median	75th Percentile	Max
Approved	269,491	0.616	0.486	0	0	1	1	1
Efficiency Gap	269,491	0.122	0.099	0.003	0.051	0.101	0.172	0.426
Black Applicant, Black Co-Applicant	269,491	0.021	0.142	0	0	0	0	1
Black Applicant White Co-Applicant	269,491	0.002	0.048	0	0	0	0	1
Black Applicant Other Co-Applicant	269,491	0.096	0.295	0	0	0	0	1
White Applicant Black Co-Applicant	269,491	0.002	0.040	0	0	0	0	1
White Applicant White Co-Applicant	269,491	0.310	0.462	0	0	0	1	1
White Applicant Other Co-Applicant	269,491	0.438	0.496	0	0	0	1	1
Other Applicant Black Co-Applicant	269,491	0.000	0.019	0	0	0	0	1
Other Applicant White Co-Applicant	269,491	0.005	0.071	0	0	0	0	1
Other Applicant with Other Co-Applicant	269,491	0.126	0.332	0	0	0	0	1
Loan Amount	269,491	4.91	0.953	2.565	2.304	4.970	5.561	9.908
Income	269,491	4.331	0.735	2.773	3.850	4.290	4.771	9.210
Preapproved	269,491	0.076	0.265	0	0	0	0	1
Female	269,491	0.330	0.470	0	0	0	1	1
Male	269,491	0.670	0.470	0	0	1	1	1
Hispanic Applicant Hispanic Co-Applicant	269,491	0.042	0.202	0	0	0	0	1
Hispanic Applicant Non-Hispanic Co-Applicant	269,491	0.006	0.079	0	0	0	0	1
Non-Hispanic Applicant Hispanic Co-Applicant	269,491	0.006	0.079	0	0	0	0	1
Non-Hispanic Applicant Non-Hispanic Co-Applicant	269,491	0.312	0.463	0	0	0	1	1

Empirical Analysis

Confirming Published Findings

In order to begin any discussions on the effect of gerrymandering on mortgage loan discrimination, it must first be shown that the data gathered was consistent with prior literature. The income variable in Table 2 Column 1 suggests that a 10 percent increase in one's income will result in a 1.04 percentage point increase in the likelihood of being approved. Related to this, the coefficient on the loan amount variable signifies a 0.61 percentage point decrease in one's likelihood of being approved for every 10 percent increase in the amount of the loan. Additionally, those who seek and are granted preapproval are 17.8 percentage points more likely to be approved. All three of these variables fit basic facts about taking out a mortgage loan according to the FDIC (2018).

As discussed above, previous findings have determined that there is gender and racial discrimination in the mortgage lending process. This regression found that women are 2.6 percentage points less likely to be approved than men. Additionally, all non-white applicants as well as Hispanic applicants were less likely to be approved than their white counterpart. Notably, Black applicants were least likely to be approved at 24 percentage points less likely to be approved than a White applicant. Those who chose not to disclose their race are the second least likely to be approved at almost half the rate of Black applicants. These results are consistent with the previous studies mentioned above.

Conventional vs. FHA-Insured Loans

As discussed above, FHA-insured loans are much easier to be approved for than conventional loans. Subsequently, it would be expected that discrimination is higher in the more competitive conventional loan market than the FHA-insured loan market. To confirm that the results matched this statement, two separate regressions were run: one for just conventional loan applicants in Table 2 Column 2 and one for FHA-insured loan applicants in Column 3. The results for the conventional loan regression are close to the original regression in Table 2 Column 1, with all coefficients only increasing or

Table 2: Previous Findings and Conventional vs. FHA-Insured Loans

VARIABLES	1 2007	2 Conventional	3 FHA-Insured
Conventional Loan	0.059***		
	[0.004]		
Loan Amount	-0.061***	-0.060***	-0.059***
	[0.001]	[0.001]	[0.010]
Income	0.104***	0.102***	0.174***
	[0.001]	[0.001]	[0.010]
Preapproved	0.178***	0.179***	0.160***
	[0.003]	[0.003]	[0.013]
Female Applicant	-0.026***	-0.028***	0.008
	[0.002]	[0.002]	[0.009]
Hispanic Applicant	-0.110***	-0.115***	-0.014
	[0.003]	[0.003]	[0.011]
American Indian Applicant	-0.072***	-0.087***	0.103***
	[0.010]	[0.011]	[0.034]
Asian Applicant	-0.028***	-0.029***	-0.024
	[0.004]	[0.004]	[0.036]
Black Applicant	-0.240***	-0.250***	-0.130***
	[0.003]	[0.003]	[0.011]
Pacific Islander Applicant	-0.108***	-0.119***	0.120**
	[0.011]	[0.012]	[0.052]
Race Not Disclosed Applicant	-0.150***	-0.149***	-0.170***
	[0.004]	[0.004]	[0.020]
Constant	0.464***	0.535***	0.132***
	[0.007]	[0.006]	[0.043]
Observations	269,491	255,699	13,792
R-squared	0.073	0.073	0.050

Notes: Robust standard errors are noted in the parentheses below each coefficient estimate. The asterisks next to the coefficient estimates are indicative of the statistical level of significance: * denotes significance at the 0.10 level; ** denotes significance at the 0.05 level; *** denotes significance at the 0.01 level.

decreasing by a percentage point or two. Black applicants are still the least likely to be approved at 25 percentage points when compared to White applicants.

The FHA-insured loan regression yields slightly different results. First, the results show that women were 0.8 percentage points more likely to be approved than men for an FHA-insured loan, but not at a statistically significant level. This suggests that women are not discriminated against when applying for an FHA-insured loan. Also noteworthy is that every 10 percent increase in an applicant's income is now related to a 1.74

percentage point increase in the likelihood of being approved for an FHA-insured loan, whereas with the original and conventional regressions there was only a 1.04 and 1.02 percentage point increase in the likelihood of being approved, respectively. Looking at the race and ethnicity variables; American Indian, Black, and Pacific Islander applicants in addition to applicants who chose not to disclose their race are the only statistically significant race-related coefficients. American Indian and Pacific Islander applicants actually became 10.3 and 12 percentage points more likely to be approved for an FHA-insured loan than a White applicant, respectively. Those who did not disclose their race became even less likely to be approved for an FHA-insured loan dropping down to 17 percentage points. Finally, Black applicants are now only 13 percentage points less likely to be approved. Both the conventional and FHA-insured loan regressions suggest that there is evidence of racial discrimination in both markets, but that the conventional loan market is much more discriminatory.

Applicant/Co-Applicant Races

When applying for a loan, applying with a co-applicant can increase one's chances of being approved. Because a co-applicant often represents a second income stream, loan officers find applications with a co-applicant more creditworthy (Kagan, 2020). Table 3 Columns 1 and 2 show a regression for conventional and FHA-insured applicants and co-applicant pairs. The race categories were consolidated from the previous regressions in Table 2 into the Black, White, and Other categories. This was due to the fact that Black applicants had the most statistically significant results and White applicants are the comparison point to which all other race categories are being compared. All other races, including those who chose not to disclose their race, were merged into the "Other" category. Black applicants applying with a Black co-applicant are 26.5 percentage points less likely to be approved for a conventional loan and 14.1 percentage points less likely to be approved for an FHA-insured loan, still fitting the previous findings discussed above. Furthermore, Black applicants applying with a Non-Black and Non-White co-applicant are 33 and 12.7 percentage points less likely to be approved for a conventional and FHA-insured mortgage loan, respectively. Both variables in the FHA-insured and conventional loan regressions were statistically significant at the 0.01 level.

Table 3: Simplified Co-Applicant Pairings

VARIABLES	1 Conventional B,W,Other	2 FHA-Insured B,W,Other
Loan Amount	-0.060***	-0.058***
	[0.001]	[0.011]
Income	0.094***	0.177***
	[0.002]	[0.010]
Preapproved	0.177***	0.159***
	[0.003]	[0.013]
Female Applicant	-0.010***	0.008
	[0.002]	[0.009]
H Applicant H Co-Applicant	-0.106***	-0.013
	[0.005]	[0.017]
H Applicant Non-H Co-Applicant	-0.042***	-0.036
	[0.011]	[0.049]
Non-H Applicant H Co-Applicant	-0.047***	0.009
	[0.011]	[0.048]
B Applicant B Co-Applicant	-0.265***	-0.141***
	[0.007]	[0.019]
W Applicant B Co-Applicant	-0.130***	-0.045
	[0.024]	[0.078]
B Applicant O Co-Applicant	-0.330***	-0.127***
	[0.004]	[0.014]
W Applicant O Co-Applicant	-0.127***	0.006
	[0.002]	[0.011]
O Applicant B Co-Applicant	-0.268***	-0.194
	[0.052]	[0.149]
O Applicant O Co-Applicant	-0.165***	-0.087***
	[0.003]	[0.018]
Constant	0.618***	0.110**
	[0.007]	[0.046]

Observations	255,699	13,792
R-squared	0.075	0.046

Notes: The applicant/co-applicant abbreviations are as follows: Black (B), White (W), Other (O). Robust standard errors are noted in the parentheses below each coefficient estimate. The asterisks next to the coefficient estimates are indicative of the statistical level of significance: * denotes significance at the 0.10 level; ** denotes significance at the 0.05 level; *** denotes significance at the 0.01 level.

Gerrymandering Effects

Table 4: Gerrymandering Effects

	1	2	3	4
VARIABLES	**Conventional B,W,Other**	**FHA-Insured B,W,Other**	**Conventional B,W,Other w/ Interaction**	**FHA-Insured B,W,Other w/ Interaction**
2004 EG	-0.120***	-0.491***	-0.094***	-0.322***
	[0.011]	[0.054]	[0.017]	[0.102]
Loan Amount	-0.061***	-0.058***	-0.061***	-0.057***
	[0.001]	[0.011]	[0.001]	[0.011]
Income	0.090***	0.170***	0.090***	0.170***
	[0.002]	[0.010]	[0.002]	[0.010]
Preapproved	0.196***	0.170***	0.196***	0.171***
	[0.003]	[0.013]	[0.003]	[0.013]
Female Applicant	-0.011***	0.005	-0.011***	0.005
	[0.002]	[0.009]	[0.002]	[0.009]
H Applicant H Co-Applicant	-0.112***	-0.023	-0.135***	0.032
	[0.005]	[0.017]	[0.009]	[0.039]
H Applicant Non-H Co-Applicant	-0.046***	-0.040	-0.040**	-0.073
	[0.011]	[0.049]	[0.017]	[0.076]
Non-H Applicant H Co-Applicant	-0.051***	0.008	-0.031*	-0.044
	[0.011]	[0.048]	[0.017]	[0.073]
B Applicant B Co-Applicant	-0.268***	-0.148***	-0.234***	-0.130***
	[0.007]	[0.019]	[0.011]	[0.030]
W Applicant B Co-Applicant	-0.129***	-0.059	-0.087**	-0.072
	[0.024]	[0.079]	[0.035]	[0.154]
B Applicant O Co-Applicant	-0.332***	-0.132***	-0.308***	-0.114***
	[0.004]	[0.014]	[0.006]	[0.022]
W Applicant O Co-Applicant	-0.130***	0.001	-0.132***	0.019
	[0.002]	[0.011]	[0.003]	[0.017]
O Applicant B Co-Applicant	-0.274***	-0.207	-0.232***	-0.466*
	[0.052]	[0.150]	[0.072]	[0.265]
O Applicant O Co-Applicant	-0.169***	-0.092***	-0.154***	-0.038
	[0.003]	[0.018]	[0.005]	[0.025]
(H Applicant H Co-Applicant) x EG			0.298***	-0.634
			[0.093]	[0.403]
(H Applicant Non-H Co-Applicant) x EG			-0.072	0.397
			[0.157]	[0.650]
(Non-H Applicant H Co-Applicant) x EG			-0.247	0.557
			[0.159]	[0.582]
(B Applicant B Co-Applicant) x EG			-0.375***	-0.191
			[0.089]	[0.265]
(B Applicant O Co-Applicant) x EG			-0.248***	-0.189
			[0.045]	[0.169]

(W Applicant B Co-Applicant) x EG			-0.511	0.252
			[0.329]	[1.891]
(W Applicant O Co-Applicant) x EG			0.028	-0.194
			[0.024]	[0.133]
(O Applicant B Co-Applicant) x EG			-0.581	3.449
			[0.615]	[4.436]
(O Applicant O Co-Applicant) x EG			-0.188***	-0.624***
			[0.042]	[0.196]
Constant	0.653***	0.191***	0.651***	0.175***
	[0.007]	[0.046]	[0.007]	[0.047]
Observations	253,235	13,641	253,235	13,641
R-squared	0.077	0.054	0.078	0.055

Notes: The applicant/co-applicant abbreviations are as follows: Black (B), White (W), Other (O). The interaction terms are denoted with "x EG" next to the variable. The Efficiency Gap is represented by "EG." Robust standard errors are noted in the parentheses below each coefficient estimate. The asterisks next to the coefficient estimates are indicative of the statistical level of significance: * denotes significance at the 0.10 level; ** denotes significance at the 0.05 level; *** denotes significance at the 0.01 level.

Adding the Efficiency Gap measure to the regressions, the results in Table 4 Columns 1 and 2 show that gerrymandering has a negative relationship with being approved for a mortgage loan. Specifically, for conventional loan applicants, for every 1 percentage point increase in the Efficiency Gap of a state, an applicant is 0.12 percentage points less likely to be approved for a mortgage loan. The FHA-insured loan regression shows a 1 percentage point increase in the Efficiency Gap of a state means an applicant is 0.491 percentage points less likely to be approved. Both coefficients are statistically significant at the 0.01 level. Because we are most interested in the effects gerrymandering has on racial discrimination in mortgage lending, another set of regressions were created using the Efficiency Gap/applicant/co-applicant interaction variables.

The question being asked in this paper is not about how racial discrimination and gerrymandering independently affect one's chances of being approved, but rather how the relationship between the two affect mortgage loan approval, so applicant/co-applicant and gerrymandering interaction terms are added to the regression. Table 4 Columns 3 and 4 show the regressions with the new interaction variables included. Interacted variable coefficients cannot be interpreted on their own; one must multiply the coefficient estimate on the interaction term by some value of the Efficiency Gap (e.g. 25th, 50th, 75th percentile, etc.) and then add it to the non-interacted applicant/co-applicant coefficient estimate. This will now show the effect of being an applicant of a *n* race applying with a co-applicant of *n* race on loan approval specifically when the Efficiency Gap is *x*. To give context, an Efficiency Gap measure of 0.5 would suggest that the winning party won 50% more seats than they would have if both parties had wasted an equal number of votes. If both parties waste an equal number of votes, it is assumed that voting districts are evenly drawn. The 50th percentile for the efficiency gap measure in all 50 states in 2004 was 0.1011, meaning that the winning party won 10.11% more seats. Black applicants applying with a Black co-applicant in a state with a median Efficiency Gap of 0.1011 are 27.2 percentage points and 14.9 percentage points less likely to be approved for a conventional and FHA-insured mortgage loan, respectively. This is not necessarily indicative of the presence of gerrymandering because in a state like Alaska, the winning party being given 10.11% more seats than the losing party does not have a meaningful interpretation seeing as there is only one House of Representatives seat given to Alaska, making it unclear whether gerrymandering is present at all because the winning party did not actually gain an additional seat. Thus, for these coefficient interpretations to hold value, it is important to identify a state with each chosen Efficiency Gap measure.

Taking a look at Nebraska, a state with an Efficiency Gap measure of 0.128, the vote distribution was approximately 30% Democrat and 70% Republican. Of the 3 House of Representatives seats Nebraska had to fill that year, all 3 were awarded to Republican representatives. However, following the vote distribution, 1 Democrat and 2 Republican representatives should have been elected which is clear evidence of gerrymandering. Using Table 4 Column 3, in a state with Nebraska's Efficiency Gap, a Black applicant applying for a conventional loan with a Black co-applicant is now 28.2 percentage points less likely to be approved than a White applicant with a White co-applicant. Looking at the same criteria for FHA-insured loan applicants, Black applicants with a Black co-applicant are 15.4 percentage points less likely to be approved than a White applicant with a White co-applicant. Even more striking in Table 4 Column 3, Black applicants applying with a non-White and non-Black co-applicant are 33.97 percentage points less likely to be approved for a conventional loan than a White applicant with a White co-applicant in Nebraska.

State Fixed Effects

Table 5: State Fixed Effects

	1	**2**
VARIABLES	**Conventional B,W,Other**	**FHA-Insured B,W,Other**
Loan Amount	-0.058***	-0.102***
	[0.001]	[0.012]
Income	0.095***	0.160***
	[0.002]	[0.010]
Preapproved	0.187***	0.161***
	[0.003]	[0.014]
Female Applicant	-0.014***	0.005
	[0.002]	[0.009]
H Applicant H Co-Applicant	-0.155***	0.063
	[0.009]	[0.041]
H Applicant Non-H Co-Applicant	-0.028*	-0.022
	[0.017]	[0.077]
Non-H Applicant H Co-Applicant	-0.023	-0.026
	[0.017]	[0.069]
B Applicant B Co-Applicant	-0.238***	-0.095***
	[0.011]	[0.031]
W Applicant B Co-Applicant	-0.099***	-0.032
	[0.035]	[0.154]
B Applicant O Co-Applicant	-0.301***	-0.085***
	[0.006]	[0.023]
W Applicant O Co-Applicant	-0.124***	0.009
	[0.003]	[0.016]

O Applicant B Co-Applicant	-0.231***	-0.330*
	[0.074]	[0.193]
O Applicant O Co-Applicant	-0.145***	-0.075***
	[0.005]	[0.025]
(H Applicant H Co-Applicant) x EG	0.240***	-1.105***
	[0.093]	[0.429]
(H Applicant Non-H Co-Applicant) x EG	-0.072	-0.031
	[0.155]	[0.700]
(Non-H Applicant H Co-Applicant) x EG	-0.240	0.400
	[0.159]	[0.557]
(B Applicant B Co-Applicant) x EG	-0.255***	-0.298
	[0.090]	[0.272]
(B Applicant O Co-Applicant) x EG	-0.132***	-0.292
	[0.047]	[0.181]
(W Applicant B Co-Applicant) x EG	-0.469	-0.116
	[0.328]	[1.875]
(W Applicant O Co-Applicant) x EG	0.045*	-0.149
	[0.024]	[0.133]
(O Applicant B Co-Applicant) x EG	-0.418	1.455
	[0.655]	[3.137]
(O Applicant O Co-Applicant) x EG	-0.207***	-0.401**
	[0.042]	[0.197]
State Fixed Effects	Yes	Yes
Constant	0.715***	0.383
	[0.060]	[441.598]
Observations	253,235	13,641
R-squared	0.097	0.094

Notes: The applicant/co-applicant abbreviations are as follows: Black (B), White (W), Other (O). The interaction terms are denoted with "x EG" next to the variable. The Efficiency Gap is represented by "EG." Robust standard errors are noted in the parentheses below each coefficient estimate. The asterisks next to the coefficient estimates are indicative of the statistical level of significance: * denotes significance at the 0.10 level; ** denotes significance at the 0.05 level; *** denotes significance at the 0.01 level. For formatting purposes, the state fixed effect variables have been hidden.

To further strengthen the regressions, state fixed effects were added to the model. State fixed effects eliminate omitted variable bias regarding factors that are the same for all applicants in a given state. The use of state fixed effects eliminates the need to control for the efficiency gap on its own, as it is a state-level variable and the regression sample only includes one year of data. Table 5 Columns 1 and 2 show the state fixed effects regressions. Oregon, a state with an Efficiency Gap measure of 0.197, had a vote distribution of 53.7% Democrat and 43% Republican. Their seat distribution was 80%

Democrat and 20% Republican, an even clearer example of gerrymandering than in the Nebraska case. For conventional loan applicants in a state with Oregon's efficiency gap, Black applicants applying with a Black co-applicant are 28.8 percentage points less likely to be approved than a White applicant with White co-applicant in the state fixed effects regression, where they were 30.8 percentage points less likely to be approved in the regression without state fixed effects. As for FHA-insure loan applicants in a state with Oregon's efficiency gap, Black applicants applying with a Black co-applicant are 15 percentage points less likely to be approved in the state fixed effects regression, while they were 16.8 percentage points less likely to be approved in the regression without state fixed effects. This slight decrease in the absolute magnitude of coefficient estimates suggests there were some unobserved state-level characteristics correlated with racial discrimination in the prior regressions, which are now controlled for by including state fixed effects.

Preapproved vs Non-Preapproved

Seeking pre-approval can have a large effect on being approved for a loan, thus the regressions were again split into different sets: those who were preapproved and those who were not preapproved. Table 6 Columns 1-4 shows the preapproved and not preapproved regressions. For those who were preapproved and applying for a conventional loan in a state like Florida, with an Efficiency Gap measure of 0.094, Black applicants applying with a Black applicant were 14.8

Table 6: Preapproved vs. Not-Preapproved

	1	2	3	4
VARIABLES	**Preapproved Conventional B,W,Other**	**Preapproved FHA-Insured B,W,Other**	**Not Preapproved Conventional B,W,Other**	**Not Preapproved FHA-Insured B,W,Other**
Loan Amount	-0.018***	-0.060*	-0.060***	-0.100***

	[0.004]	[0.035]	[0.001]	[0.013]
Income	0.102***	0.076**	0.096***	0.163***
	[0.006]	[0.033]	[0.002]	[0.011]
Female Applicant	0.009	-0.048*	-0.016***	0.009
	[0.006]	[0.025]	[0.002]	[0.009]
H Applicant H Co-Applicant	-0.043*	0.070	-0.164***	0.059
	[0.023]	[0.152]	[0.010]	[0.043]
H Applicant Non-H Co-Applicant	-0.041	0.323*	-0.025	-0.043
	[0.045]	[0.188]	[0.018]	[0.082]
Non-H Applicant H Co-Applicant	0.001	-0.062	-0.024	-0.002
	[0.038]	[0.202]	[0.018]	[0.071]
B Applicant B Co-Applicant	-0.086**	-0.040	-0.249***	-0.106***
	[0.039]	[0.099]	[0.011]	[0.033]
W Applicant B Co-Applicant	0.036	0.367**	-0.110***	-0.112
	[0.097]	[0.155]	[0.036]	[0.161]
B Applicant O Co-Applicant	-0.067***	-0.036	-0.315***	-0.099***
	[0.022]	[0.062]	[0.006]	[0.024]
W Applicant O Co-Applicant	-0.004	0.097***	-0.133***	-0.007
	[0.010]	[0.037]	[0.003]	[0.018]
O Applicant B Co-Applicant	-0.106	0.240	-0.229***	-0.400***
	[0.462]	[0.168]	[0.077]	[0.154]
O Applicant O Co-Applicant	-0.072***	-0.017	-0.149***	-0.079***
	[0.016]	[0.093]	[0.005]	[0.026]
(H Applicant H Co-Applicant) x EG	0.076	-1.612	0.239**	-1.071**
	[0.217]	[1.596]	[0.101]	[0.445]
(H Applicant Non-H Co-Applicant) x EG	0.154	-4.351	-0.090	0.087
	[0.382]	[3.254]	[0.169]	[0.711]
(Non-H Applicant H Co-Applicant) x EG	0.232	-2.557	-0.302*	0.443
	[0.323]	[2.311]	[0.169]	[0.546]
(B Applicant B Co-Applicant) x EG	-0.655**	0.375	-0.234**	-0.355
	[0.333]	[0.952]	[0.093]	[0.287]
(B Applicant O Co-Applicant) x EG	-0.614***	-0.193	-0.096**	-0.200
	[0.181]	[0.502]	[0.048]	[0.196]
(W Applicant B Co-Applicant) x EG	0.352	-4.440***	-0.504	1.032
	[0.726]	[1.586]	[0.337]	[2.065]
(W Applicant O Co-Applicant) x EG	-0.205***	-0.791*	0.059**	-0.036
	[0.072]	[0.414]	[0.025]	[0.141]
(O Applicant B Co-Applicant) x EG	-2.622		-0.408	1.712
	[8.185]		[0.665]	[2.847]
(O Applicant O Co-Applicant) x EG	-0.243*	-0.584	-0.205***	-0.390*
	[0.139]	[0.651]	[0.045]	[0.204]
State Fixed Effects	Yes	Yes	Yes	Yes
Constant	0.742***	0.030	0.569	0.905***
	[0.058]	[0.141]	[.]	[0.059]
Observations	18,522	1,372	234,713	12,269
R-squared	0.083	0.240	0.090	0.082

Notes: The applicant/co-applicant abbreviations are as follows: Black (B), White (W), Other (O). The interaction terms are denoted with "x EG" next to the variable. The Efficiency Gap is represented by "EG." Robust standard errors are noted in the parentheses below each coefficient estimate. The asterisks next to the coefficient estimates are indicative of the statistical level of significance: * denotes significance at the 0.10 level; ** denotes significance at the 0.05 level; *** denotes significance at the 0.01 level. For formatting purposes, the state fixed effect variables have been hidden. All 4 regressions were run with both robust and cluster standard errors and regression results were the same for both errors.

percentage points less likely to be approved for a loan than a White applicant with a White co-applicant, compared to those who were not preapproved being 27 percentage points less likely to be approved. As for those who were a applying for an FHA-insured loan in a state with Florida's efficiency gap, a Black applicant applying with a Black co-applicant was only 0.48 percentage points less likely to be approved if they were preapproved and 13.9 percentage points less likely to be approved if they were not preapproved. The preapproved FHA-insured loan regression coefficient was not statistically significant. While we can clearly see here that there is more discrimination in the group that does not have preapproval, this could be due in part to the fact that they were discriminated against in the preapproval process as well. This would further explain why discrimination seemed to decrease in the preapproved group. However, the hypothesis cannot be tested further because this data set does not give detailed information about the preapproval process.

Additionally, the R-squared values for these regressions were quite low. However, with each set of additions to the regressions, the explanatory power increased, with the exception of the last four regressions that split the sample by pre-approved status. The R-squared values for these regressions slightly decreased from the state fixed effects regressions, again with the exception of the preapproved FHA-insured loan regression having the highest explanatory power at 24% of the regression being able to predict the dependent variable. Values this low would suggest that a number of other factors could be added to the regression in order to improve the model. Ideally, an R-squared value of over 0.90 would suggest that the model is extremely reliable in explaining the relationship between gerrymandering and racial discrimination in mortgage lending.

Robustness

Categorizing Applicants by Race

The purpose of this paper is to explore the effects gerrymandering has on racial discrimination in mortgage lending. In order to construct the most parsimonious regressions, the race variables in the primary specifications (Tables 2-6) were consolidated into three categories: Black, White, or Other applicants and co-applicants. This decision was based on the fact that Black and non-disclosed racial categories showed the highest relevance in early specifications. And, while race not disclosed applicants had many statistically significant applicant/co-applicant pairings, the purpose of detailing applicant and co-applicant racial pairings is to discover which races are most heavily discriminated against in the mortgage lending process. Therefore, race not disclosed applicants were also put under the "Other" umbrella.

This section more carefully separates Other into more detailed racial categories for applicant and co-applicant pairings. Comparing the coefficients from Table 7 Columns 1 and 2 to Table 3 Columns 1 and 2, the FHA-insured loan regression coefficients stayed almost exactly the same. Black applicants who applied with a Black co-applicant are still 14.1 percentage points less likely to be approved for an FHA-insured loan than a White applicant with a White co-applicant while White applicants who applied with a Black co-applicant are now 4.2 percentage points less likely to be approved for an FHA-insured loan than a White applicant with a White co-applicant, a decrease from 4.5 percentage points with the more consolidated applicant/co-applicant variables. The conventional loan regression coefficient for a Black applicant with a Black co-applicant and a White applicant with a Black co-applicant were 26.5 and 13 percentage points, respectively, less likely to be approved for a conventional loan than a White applicant with a White co-applicant. Both coefficients decreased in the new regression from 26.5 to 19 percentage points for the Black applicant with a Black co-applicant and from 13 to 6.7 percentage points for the White applicant with a Black co-applicant. While the coefficients changed from the more concise regression applicant/co-applicant regression to the more detailed regression, their statistical significance remained the same as well as their overall all interpretation, which is that Black and White applicants with a Black co-applicant are less likely to be approved for a mortgage loan than a White applicant with a White co-applicant. Thus, the primary results using parsimonious racial categories are robust to alternative specifications with more detailed racial classifications.

Table 7: Detailed Co-Applicant Pairings

VARIABLES	1 Conventional w/ Co-Applicants	2 FHA-Insured w/ Co-Applicants
Loan Amount	-0.064***	-0.060***
	[0.001]	[0.011]
Income	0.105***	0.173***
	[0.001]	[0.010]
Preapproved	0.183***	0.161***
	[0.003]	[0.013]
Female Applicant	-0.025***	0.009
	[0.002]	[0.009]
H Applicant H Co-Applicant	-0.039***	-0.020
	[0.005]	[0.016]
H Applicant Non-H Co-Applicant	0.018	-0.051
	[0.011]	[0.049]
Non-H Applicant H Co-Applicant	0.011	-0.016
	[0.011]	[0.048]
AI Applicant AI Co-Applicant	-0.042*	0.110*
	[0.023]	[0.065]
AI Applicant A Co-Applicant	-0.095	0.462***
	[0.116]	[0.047]
AI Applicant B Co-Applicant	-0.144	
	[0.183]	
AI Applicant ND Co-Applicant	-0.272**	0.169
	[0.121]	[0.259]

AI Applicant No Co-Applicant	-0.154***	0.070
	[0.013]	[0.047]
AI Applicant PI Co-Applicant	-0.344**	0.411***
	[0.163]	[0.022]
A Applicant AI Co-Applicant	0.049	0.503***
	[0.154]	[0.009]
A Applicant A Co-Applicant	0.067***	-0.070
	[0.006]	[0.057]
A Applicant B Co-Applicant	-0.142*	-0.360**
	[0.079]	[0.147]
A Applicant ND Co-Applicant	0.045	-0.049
	[0.047]	[0.314]
A Applicant No Co-Applicant	-0.058***	-0.010
	[0.005]	[0.050]
A Applicant PI Co-Applicant	0.055	
	[0.100]	
B Applicant AI Co-Applicant	-0.332***	0.074
	[0.099]	[0.226]
B Applicant A Co-Applicant	0.021	-0.545***
	[0.056]	[0.011]
B Applicant B Co-Applicant	-0.190***	-0.141***
	[0.007]	[0.018]
B Applicant ND Co-Applicant	-0.245***	-0.085
	[0.033]	[0.074]
B Applicant No Co-Applicant	-0.247***	-0.131***
	[0.003]	[0.012]
B Applicant PI Co-Applicant	-0.119	0.400***
	[0.118]	[0.040]
ND Applicant AI Co-Applicant	-0.484***	
	[0.146]	
ND Applicant A Co-Applicant	-0.205**	
	[0.085]	
ND Applicant B Co-Applicant	-0.245***	-0.025
	[0.081]	[0.228]
ND Applicant ND Co-Applicant	-0.039***	-0.139***
	[0.006]	[0.032]
ND Applicant No Co-Applicant	-0.202***	-0.202***
	[0.005]	[0.026]
ND Applicant PI Co-Applicant	-0.070	
	[0.160]	
PI Applicant AI Co-Applicant	-0.235	0.371***
	[0.184]	[0.012]
PI Applicant A Co-Applicant	-0.237**	
	[0.108]	
PI Applicant B Co-Applicant	-0.266	
	[0.173]	
PI Applicant ND Co-Applicant	-0.140	-0.084
	[0.123]	[0.361]
PI Applicant No Co-Applicant	-0.156***	0.121*
	[0.014]	[0.069]
PI Applicant PI Co-Applicant	-0.053**	0.150
	[0.022]	[0.093]
W Applicant AI Co-Applicant	-0.065**	0.169*
	[0.028]	[0.088]
W Applicant A Co-Applicant	0.115***	0.157*
	[0.013]	[0.095]

W Applicant B Co-Applicant	-0.067***	-0.042
	[0.024]	[0.078]
W Applicant ND Co-Applicant	-0.050***	0.034
	[0.014]	[0.046]
W Applicant PI Co-Applicant	-0.011	0.129
	[0.034]	[0.183]
AI Applicant W Co-Applicant	-0.019	0.177**
	[0.029]	[0.078]
A Applicant W Co-Applicant	0.079***	0.218**
	[0.017]	[0.107]
B Applicant W Co-Applicant	-0.046**	0.059
	[0.020]	[0.062]
ND Applicant W Co-Applicant	-0.044*	0.019
	[0.026]	[0.103]
PI Applicant W Co-Applicant	0.024	0.064
	[0.041]	[0.163]
Constant	0.513***	0.137***
	[0.006]	[0.043]
Observations	255,699	13,792
R-squared	0.069	0.052

Notes: The applicant/co-applicant abbreviations are as follows: American Indian (AI), Asian (A), Black (B), Not Disclosed (ND), Pacific Islander (PI), White (W). Robust standard errors are noted in the parentheses below each coefficient estimate. The asterisks next to the coefficient estimates are indicative of the statistical level of significance: * denotes significance at the 0.10 level; ** denotes significance at the 0.05 level; *** denotes significance at the 0.01 level.

Conclusion

To conclude, the above regressions suggest that gerrymandering, on average, tends to increase the presence of racial discrimination in mortgage lending for a given state. Comparing the results from the regressions with the applicant/co-applicant interaction variables to the regressions without the Efficiency Gap, it is clear that the coefficients increased by at least a few percentage points as the models became stronger. The greater racial discrimination in mortgage lending in states with a high presence of gerrymandering has serious ramifications that are worth addressing. As it has been shown throughout this paper, racial discrimination in loan lending is still affecting minority applicants across the country. If the presence of gerrymandering exacerbates this issue, it begs the question of whether financial institutions in some states are complicit in the suppression of minority votes. As of the 26th Amendment passed in 1971, every 18-year-old citizen of the United States is guaranteed the right to vote. With harmful practices like loan discrimination and gerrymandering, politicians and institutions alike have found a way around the law so that for many minorities, their right to vote is under siege. Even though it seems trivial to pay attention to this issue because gerrymandering often only affects the election of one or two officials per state, over time and across the nation, this can drastically affect the legislation that is able to be passed at the national level.

While these models are cause for concern, further research and stronger models are necessary in order to identify causal effects and propose policy solutions. First, the base model of discrimination in the lending process could be strengthened by adding applicant's and co-applicant's credit and FICO scores into the model. As was previously mentioned, the Efficiency Gap is a general measure and is most certainly not an exact indication of whether a state has been gerrymandered. Gerrymandering is incredibly difficult to detect, therefore a more precise way to measure gerrymandering may not be available, as it is somewhat qualitative in nature whether district boundaries were manipulated. Even more difficult is the task of trying to show there were political or racial motivations in exploiting district plans and that those motivations in some way affected racially discriminatory practices of financial institutions. In order for reformation of the redistricting process to occur, it may take several more egregious offenses and a few more prominent court cases in order for all states to take actionable steps toward altering the way redistricting occurs.

As has been prominent in this country throughout time, when a law is passed to prohibit a certain practice, new structures are put in place so as to continue the harmful practice while going undetected by those aiming to enforce the law. It is the reason systemic racism has permeated almost every aspect of life. Even though one may not be an active participant in upholding the structural racism in this country, being passive is just as harmful. Standing by while institutions and politicians collaborate in some fashion under the table to deny minority individuals and families a mortgage loan so as to keep them in particular voting districts is what allows these practices to continue. Passing another law is not the solution; while that may help on a broad scale, the real change will come from the population's awareness on issues such as this one and their holding institutions and politicians alike accountable for affecting change.

Appendix A

Table 1: List of Variables and Data Sources

		Sources
Dependent Variable:	Approved	CFPB website (https://www.consumerfinance.gov/data-research/hmda/historic-data/?geo=nationwide&records=all-records&field_descriptions=labels)
Key Independent Variables:	Efficiency Gap	MIT Election Data Lab (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/IG0UN2)
	Black Applicant with Black Co-Applicant	Same as dependent variable
	Black Applicant with White Co-Applicant	Same as dependent variable
	Black Applicant with Other Co-Applicant	Same as dependent variable
	White Applicant with Black Co-Applicant	Same as dependent variable
	White Applicant with White Co-Applicant	Same as dependent variable
	White Applicant with Other Co-Applicant	Same as dependent variable
	Other Applicant with Black Co-Applicant	Same as dependent variable
	Other Applicant with White Co-Applicant	Same as dependent variable
	Other Applicant with Other Co-Applicant	Same as dependent variable
Other Independent Variables:	Loan Amount	Same as dependent variable
	Income	Same as dependent variable
	Preapproved	Same as dependent variable
	Female	Same as dependent variable
	Male	Same as dependent variable
	Hispanic Applicant with Hispanic Co-Applicant	Same as dependent variable
	Hispanic Applicant with Non-Hispanic Co-Applicant	Same as dependent variable
	Non-Hispanic Applicant with Hispanic Co-Applicant	Same as dependent variable
	Non-Hispanic Applicant with Non-Hispanic Co-Applicant	Same as dependent variable

Table 2: FHA-Insured/Conventional Summary Statistics

FHA-Insured Loan Applications			
Variables	**Obs.**	**Mean**	**Std. Dev.**
Approved	13,792	0.498	0.500
Efficiency Gap	13,792	0.092	0.076
Black Applicant with Black Co-Applicant	13,792	0.056	0.230
Black Applicant with White Co-Applicant	13,792	0.004	0.065
Black Applicant with Other Co-Applicant	13,792	0.149	0.356
White Applicant with Black Co-Applicant	13,792	0.003	0.054
White Applicant with White Co-Applicant	13,792	0.310	0.463
White Applicant with Other Co-Applicant	13,792	0.397	0.489
Other Applicant with Black Co-Applicant	13,792	0.001	0.024
Other Applicant with White Co-Applicant	13,792	0.006	0.077
Other Applicant with Other Co-Applicant	13,792	0.074	0.262
Conventional Loan Applications			
Approved	255,699	0.622	0.485
Efficiency Gap	255,699	0.095	0.086
Black Applicant with Black Co-Applicant	255,699	0.019	0.136
Black Applicant with White Co-Applicant	255,699	0.002	0.047
Black Applicant with Other Co-Applicant	255,699	0.094	0.291
White Applicant with Black Co-Applicant	255,699	0.002	0.039
White Applicant with White Co-Applicant	255,699	0.310	0.462
White Applicant with Other Co-Applicant	255,699	0.440	0.496
Other Applicant with Black Co-Applicant	255,699	0.0004	0.019
Other Applicant with White Co-Applicant	255,699	0.005	0.070
Other Applicant with Other Co-Applicant	255,699	0.129	0.335

Works Cited

Barreto, M. A., Nuño, S., Sanchez, G. R., & Walker, H. L. (2019). The racial implications of voter identification laws in america. *American Politics Research, 47(2)*, 238–249. Retrieved from https://journals.sagepub.com/doi/abs/10.1177/1532673X18810012?journalCode=aprb#articleCitationDownloadContainer

Charles, G. E., & Fuentes-Rohwer, L. (2018). Race and representation revisited: the new racial gerrymandering cases and section 2 of the VRA. *William & Mary Law Review, 59(5),* 1558-1600. https://scholarship.law.wm.edu/cgi/viewcontent.cgi?article=3749&=&context=wmlr&=&sei-redir=1&referer=https%253A%252F%252Fscholar.google.com%252Fscholar%253Fstart%253D10%2526q%253Dgerrymandering%252Band%252Brace%2526hl%253Den%2526as_sdt%253D0%252C36#search=%22gerrymandering%20race%22

Cohen, R. (2008, October 2). A structural racism lens on subprime foreclosures and vacant properties. Retrieved from http://kirwaninstitute.osu.edu/docs/pdfs/Rick_Cohen_paper.pdf

Fang, L. & Munneke, H. J. (2016, September). Gender equality in mortgage lending. Retrieved from http://www.fmaconferences.org/Vegas/Papers/Gender_Equality_in_Mortgage_Lending_Fang_Munneke_FMA.pdf

Federal Deposit Insurance Corporation. (2018). FDIC law, regulations, related acts. Retrieved from https://eprints.usq.edu.au/2551/1/Temple-Smith_Scheumack_Eddington_2000.pdf

Federal Reserve Bank of Boston. (1992). Mortgage lending in boston: interpreting HMDA data. Retrieved from https://www.bostonfed.org/publications/research-department-working-paper/1992/mortgage-lending-in-boston-interpreting-hmda-data.aspx

Glennon, D. & Stengel, M. (1994, April) An evaluation of the federal reserve bank of boston's study of racial discrimination in mortgage lending. (Report No. 94-2). Retrieved from https://ots.gov/publications-and-resources/publications/economics-working-papers/files/1990-1999/pub-econ-working-paper-1994-2.pdf

Gotham, K. F. (2012, November 19). Race, mortgage lending and loan rejections in a U.S. city. *Sociological Focus*. https://www.tandfonline.com/doi/abs/10.1080/00380237.1998.10571116

Hicks, W. D., McKee, S. C., Sellers, M. D., & Smith, D. A. (2015). A principle or a strategy? voter identification laws and partisan competition in the american states. *Political Research Quarterly, 68(1)*, 18–33. Retrieved from https://journals.sagepub.com/doi/abs/10.1177/1065912914554039?journalCode=prqb#articleCitationDownloadContainer

Ingraham, C. (2014, May 15). America's most gerrymandered congressional districts. Retrieved from https://www.washingtonpost.com/news/wonk/wp/2014/05/15/americas-most-gerrymandered-congressional-districts/

Kagan, J. (2020, February 14). *Personal finance loan basics: co-applicant*. Investopedia. Retrieved from https://www.investopedia.com/terms/c/co-applicant.asp#:~:text=A%20co%2Dapplicant%20is%20an,for%20more%20favorable%20loan%20terms.

Ladd, H. F. (1998). Evidence on discrimination in mortgage lending. *Journal of Economic Perspectives, 12(2)*, 41-62. Retrieved from https://www.jstor.org/stable/2646961?seq=1#metadata_info_tab_contents

Maldonado, C. (2018, July 27). 32% of applicants with less than perfect credit were denied mortgages in 2017. Retrieved from https://www.forbes.com/sites/camilomaldonado/2018/07/27/32-percent-of-applicants-without-perfect-credit-denied-in-2017/#6b19b4144b18

Massey, D. S., Rugh, J. S., Steil, J. P., & Albright, L. (2016, June) Riding the stagecoach to hell: a qualitative analysis of racial discrimination in mortgage lending. *City & Community 15(2)*, 118-136. Retrieved from https://onlinelibrary.wiley.com/doi/pdf/10.1111/cico.12179?casa_token=AMJicrynTFcAAAAA:SeEzcduzlvAP2-qMV69VFchhT84j0y5Tc2asgzrTUuGcm5NOoReGChbF5vwCzYtabl_-Lk95LUGZjg

Perry, V.G. (2019). A loan at last? Race and racism in mortgage lending. In Johnson, G. D., Thomas, K. D., Harrison, A.K., & Grier, S. A. (Eds.), *Race in the marketplace* (pp. 173-192). Cham, Switzerland: Springer Nature Switzerland AG.

Reynolds, R. (1976). Improving Access to Health Care among the Poor: The Neighborhood Health Center Experience. *The Milbank Memorial Fund Quarterly. Health and Society, 54(1)*, 47-82. Retrieved from https://www.jstor.org/stable/3349669?seq=1

Ross, S. L. & Yinger, J. (2002). The color of credit: mortgage discrimination, research methodology, and fair-lending enforcement. Retrieved from https://books.google.com/books?hl=en&lr=&id=ksyPNm1CYZYC&oi=fnd&pg=PP11&dq=discrimination+in+mortgage+loan+pre+approval&ots=aMHRy9vWdt&sig=zbOQXvImb5z81c0uWArZ4clKg4U#v=onepage&q&f=false

Smith, R. T., Scheumack, M., & Eddington, I. (n.d.). On the time lag between awareness of a public health problem and the enactment of preventative legislation. Retrieved from https://eprints.usq.edu.au/2551/1/Temple-Smith_Scheumack_Eddington_2000.pdf

Tigges, L. M., Browne, I., & Green, G. P. (2008). Social isolation of the urban poor: race, class, and neighborhood effects on social resources. *The Sociological Quarterly*, *39(1)*, 53–77. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1533-8525.1998.tb02349.x

Turner, M. A. & Skidmore, F. (1999, June). Mortgage lending discrimination: a review of existing evidence. *The Urban Institute*. Retrieved from https://www.urban.org/sites/default/files/publication/66151/309090-Mortgage-Lending-Discrimination.PDF

Warrington, G. S. (2018). Quantifying gerrymandering using the vote distribution. *Election law journal, 17(1)*, 39-57. Retrieved from: https://www.liebertpub.com/doi/pdf/10.1089/elj.2017.0447