Testing for Racial Discrimination in Mortgage Lending and Assessing the Community Reinvestment Act via Mortgage Default Equations

Acknowledgements

I am tremendously grateful to Professor Lawrence Summers for sharing his invaluable guidance and expertise throughout the production of this thesis. His commitment to the study of economics inspired me long before I had the opportunity to be his student, and I feel incredibly honored by the support I have received from him. I also extend my deepest thanks to Natasha Sarin for her patience and thoughtful guidance, which made this thesis possible. Her encouragement and confidence in me is the reason I felt capable of undertaking this project.

I would like to thank Vu Chau for providing valuable advice and Dr. Stacey Gelsheimer for helping me to think carefully about my research question. I am grateful for the support of the team at FAS Research Computing, who helped me learn how to use the Odyssey supercomputer to execute the analyses presented in this work. I extend immeasurable gratitude to my family for their unwavering support and love in every endeavor, and for instilling in me that there are truly "only solutions". Finally, I am endlessly thankful for my friends, whose genuine thoughtfulness and care inspire me every day.

Section 1: Introduction

Discrimination in the mortgage market has been a topic of concern in the United States for decades, as evidenced by a complex history of legislation in this arena informed by extensive academic research. Since the late 1960s, there have been a variety of legislative interventions related to the housing market beginning with the Fair Housing Act, which outlawed the refusal to rent or sell property to a person because of their race, religion, sex or national origin. Challenges associated with enforcing the Fair Housing Act led to further legislation targeting this issue, including the Equal Credit Opportunity Act of 1974 (ECOA), the Home Mortgage Disclosure Act of 1975 (HMDA) and the Community Reinvestment Act of 1977 (CRA). Each of these national policies represents an attempt to fairly regulate the quantity and price of credit by deeming inequitable treatment on behalf of mortgage lenders unlawful.

Despite the existence of legislation aimed to prevent discrimination in the housing market, this remains a prevalent issue and the presence (or lack thereof) of discrimination in lending continues to be studied by researchers, policymakers and regulators alike. One challenge for researchers in determining the nature of discriminatory lending is that racial discrimination can occur at various points in the process. For example, discrimination in the form of extending low quality credit to minority or low-income borrowers (e.g., disguised or excessive fees, poor resource availability), as discussed in Bayer et al. (2016), would be identified via different analyses than discrimination in the form of biased loan underwriting standards. Laws targeting discrimination like the ECOA and the CRA focus mainly on discrimination in the loan application process (Ladd, 1998). However, discrimination can occur at other stages as well: in the selection of the geographic service area chosen by a lending institution, the advertisement and marketing of loans, the prescreening of mortgage loan applicants and the setting of loan terms as evidenced by high interest rates or shorter maturities (Ladd, 1998).[1] In this paper I focus on drawing conclusions regarding a particular form of discrimination – the denial of loans to potential borrowers on the basis of race.

An extensive body of academic literature focuses on empirically identifying racial discrimination in mortgage lending in the context of underwriting decisions. Researchers in the past have approached this topic using one of three primary methods: applicant rejection equations, mortgage pricing equations or mortgage default equations.[2] I pursue the identification of racial discrimination at the point of loan underwriting via mortgage default equations. This approach, pioneered by Berkovec, Canner, Gabriel and Hannan (1994), compares the loan performance of minority borrowers to that of White borrowers in order to identify racial discrimination. If a minority group defaults at a lower rate than White borrowers after accounting for other borrower, loan, property and geographic characteristics, this methodology provides evidence for the existence of racial discrimination against that minority. I refer to this approach as "default methodology". Revisiting the default methodology employed by Berkovec et al. (1994) is valuable because it allows me to test if their results hold up with a more expansive dataset covering recent years and to learn whether mortgage default equations can be improved.

In addition to using performance equations to identify racial discrimination, I extend the work of Berkovec et al. (1994) to evaluate the impact of the Community Reinvestment Act (CRA), which is aimed at eradicating discrimination in the mortgage market. Specifically, I examine the impact of census tract CRA-eligibility on mortgage default rates. Put into law in

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[1] Recent research focusing on parts of the mortgage loan process other than underwriting decisions include Begley and Purnanandam (2017) who study discrimination in the servicing of credit, and Gurun, Matvos and Seru (2016) who study discrimination in the advertising of mortgage loans.
[2] See Yezer (2010).

1977, the CRA prohibits redlining (the practice of denying loans to borrowers based on the racial or ethnic composition of where they live) and aims to encourage lenders to meet the needs of all communities in which they are chartered while adhering to safe lending practices. In order to enforce this, a consortium of government entities, including the Board of Governors of the Federal Reserve System, the Federal Financial Institutions Examination Council, the Comptroller of the Currency, the Federal Deposit Insurance Corporation and the Office of Thrift Supervision, annually publish a list of census tracts that are designated as "underserved", "distressed" or below an income threshold and therefore are CRA-eligible. Every three to five years (depending on the size of the lender), these government institutions administer exams evaluating how thoroughly various lenders meet the needs of CRA-eligible census tracts. If a lender does not satisfactorily serve CRA-eligible communities, it risks not only reputational harm but also denial of merger, acquisition or branch-opening applications.

In this paper, I first assess racial discrimination in mortgage lending in the period of my sample. I construct an immense dataset of 19 million mortgage loans originated between 2006 and 2016 from datasets made public by Fannie Mae and the Federal Financial Institutions Examination Council. Understanding that the financial crisis may be relevant to underwriting decisions, I compare loans originated before the financial crisis of 2008 to those originated after the crisis to test whether default rates vary between these groups. This allows me to draw conclusions about the effect of the financial crisis on discriminatory lending. For example, if lenders became more discriminatory after the crisis due to more selective extension of credit or less discriminatory due to heightened regulator attention, my specification will yield insight into the direction of this shift.

My baseline specification therefore reflects the fundamental default approach implemented by Berkovec et al. (1994) but accounts for whether a loan was originated before or after the financial crisis. The estimate of this specification yields several meaningful relationships between loan-level characteristics and loan performance. Moreover, after controlling for these relationships, the estimate suggests that a one-unit increase in Hawaiian/Pacific Islander population in a county decreases the log odds of loan default by 104.5. This estimate thus predicts the existence of racial discrimination against this population at the point of loan underwriting in this sample. In contrast, Berkovec et al. (1994) find no evidence of discrimination against any of the racial groups included in their dataset. Further, I test whether the impact of post-crisis origination on loan default varies among counties with different proportions of minority borrowers. This analysis indicates that post-crisis origination generally alleviates large discrepancies in default rates between minority communities and White communities, although it does not necessarily eliminate discrimination against minorities.

After developing conclusions regarding the existence of racial discrimination in the sample of loans, I focus on understanding the impact of CRA-eligibility on the odds of loan default in a county. My estimates suggest that CRA-eligibility helped to eliminate discrepancies in the odds of default between Asian and White communities. For example, in pre-crisis, not CRA-eligible county-years, a one-unit increase in Asian population relative to White population increased the log odds of loan default in a county by 10.21. However, in pre-crisis, CRA-eligible county-years, this value was approximately zero. On the other hand, the estimates indicate an opposite effect for American Indian/Alaska Native communities when controlling for the explanatory variables considered in the baseline model. In post-crisis, not CRA-eligible county-years, a one-unit increase in American Indian/Alaska Native population relative to White population increased the log odds of default by 45.5; in post-crisis, CRA-eligible county-years, this value was 47.12. I also find that CRA-eligibility tends to increase the change in log odds of default associated with higher percentages of African American/Black residents in a county relative to White residents. Given these results, I conclude that CRA-eligibility had a mixed effect on racial discrimination in my sample of Fannie Mae loans.

The remainder of this paper is organized as follows. Section 2 overviews literature relating to (1) traditional methods of identifying discrimination in the mortgage market, (2) other examples of empirical applications of default studies, (3) the role of performance equations in identifying discrimination and (4) the assessment of the CRA. Section 3 describes the data and interprets descriptive statistics. Section 4 reviews the model underlying loan performance as a means of identifying discrimination and outlines my empirical approach. Section 5 discusses the results and Section 6 concludes.

Section 2: Literature Review

This paper contributes to three strands of literature. Primarily, it builds off of previous work focused on identifying racial discrimination in mortgage lending. Through the use of mortgage default equations, this paper is also in conversation with literature focused on default rate studies more generally as well as a body of work surrounding the use of performance equations to study discrimination. Finally, this paper contributes to the literature assessing the impact of housing-related policies like the CRA.

Traditional Approaches to Studying Discrimination in Mortgage Lending

There exists a detailed history of academic and policy-oriented research studying discrimination in mortgage lending. Many papers published on this topic implement one of the three empirical approaches briefly addressed in Section 1 to study discrimination at the point of loan underwriting decisions. Some recent papers have explored the possibility of discrimination in other parts of the loan offering, underwriting and servicing stages.[3]

The three traditional approaches to studying discrimination at the point of loan underwriting decisions—applicant rejection equations, mortgage pricing equations and mortgage default equations—each involve a single equation model in which the dependent variable is regressed on a series of explanatory variables related to loan terms, borrower characteristics or the underlying property.[4] For example, the dependent variable in applicant rejection equations is an indicator identifying whether a lender rejects a potential borrower's loan application. The race of the borrower is included as an explanatory variable. In this approach one would identify the presence of discrimination against racial minorities if the coefficient on an indicator for minority race is positive and significant, implying that the probability of a lender rejecting a potential borrower's application increases if the borrower is of a minority race when controlling for other loan-level characteristics.

Munnell, Tootell, Browne and McEneaney (1996) use applicant rejection equations in a piece colloquially known as the Boston Fed study, building on earlier work by Black, Schweitzer and Mandell (1978) and King (1980). Munnell et al. (1996) used an extensive dataset aggregated

[3] See Begley and Purnanandam (2017) and Gurun, Matvos and Seru (2016).
[4] See Yezer (2010).

directly from mortgage lenders to find that minority groups were more than twice as likely to be denied a mortgage than Whites.[5]

Regarding the second traditional approach, Boehm, Thistle and Schlottmann (2006); Courchane (2007); Haughwout, Mayer, Tracy, Jaffee, and Piskorski (2009) and Bayer, Ferreira and Ross (2016) focus on mortgage pricing equations in order to identify whether race is a factor in determining the interest rate charged on mortgage loans.

I test for discrimination using mortgage default equations, which is the third traditional approach. This approach takes a different angle by considering loan performance in order to identify racial discrimination in lenders' underwriting decisions. This methodology compares mortgage default rates of minority groups to those of White borrowers to examine the existence of racial discrimination; the dependent variable is an indicator for whether a borrower defaults on her loan. Controlling for factors of loan performance encapsulated in characteristics of the borrower, property, geography and loan terms, if minority borrowers default at lower rates than White borrowers, I can conclude that discrimination exists because lenders are holding minority borrowers to a higher standard of creditworthiness than White borrowers. However, if borrowers are defaulting at similar rates regardless of race, I cannot confirm the existence of racial discrimination at the point of lenders' underwriting decisions.

Two papers pioneering the use of default studies to study racial discrimination in mortgage lending were written by Berkovec, Canner, Gabriel and Hannan.[6] Their early paper, "Race, Redlining, and Residential Mortgage Loan Performance", adheres to a straightforward implementation of default methodology and establishes a thorough theoretical foundation

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[5] See Munnell, Tootell, Browne and McEneaney (1996).
[6] See Berkovec et al. (1994) and Berkovec et al. (1998).

specific to racial discrimination in mortgage lending. This paper received criticism by scholars who asserted that the results suffered from omitted variable bias, since neither lenders nor researchers were able to identify and control for all aspects of a borrower's creditworthiness, and these unobservable characteristics may be less favorable for minorities than Whites.[7] Economists were especially concerned with Berkovec et al.'s (1994) omission of a control variable for credit history, noting that this omission would bias the results away from finding discrimination (Ladd, 1998). Other scholars took issue with assumptions inherent in default methodology, such as that losses on minority defaults are at least as great as losses on White defaults (Yinger, 1996). These papers argue that the Boston Fed study avoided these issues by accounting for all variables considered by lenders in underwriting decisions via data provided directly from mortgage lenders. Finally, economists expressed concern regarding the dataset employed by Berkovec et al. because it consisted entirely of Federal Housing Administration (FHA) loans.[8]

In efforts to acknowledge potential bias, Berkovec et al. adjusted their approach to include the Herfindahl-Hirschmann index of market competition as an explanatory variable (Berkovec et al., 1998). The authors argued that using the interaction term between the Herfindahl-Hirschmann index and minority race to identify discrimination—instead of focusing on minority race alone—avoided some omitted variable bias because in more concentrated and thus less competitive markets, lenders have greater ability to exercise discretion in underwriting decisions and thus are more likely to discriminate. In both iterations of their research, Berkovec et al. were unable to reject the null hypothesis of no discrimination in mortgage lending.

[7] See Ladd (1998) and Yinger (1996).
[8] See Ladd (1998) for a discussion of the disadvantages of using FHA loans to study discrimination in mortgage lending.

Since the Berkovec et al. default studies of the 1990s, economists have not engaged much further with the default approach. In this paper, I replicate and update the methodology established in Berkovec et al. (1994) and use it to study the CRA. I alleviate large concerns regarding omitted variable bias by using a dataset that includes a variable denoting each borrower's FICO score, which is a standard measure of creditworthiness frequently considered in loan underwriting decisions. Moreover, this dataset consists only of conventional mortgage loans, mitigating scholars' concerns regarding the dataset of FHA loans employed by Berkovec et al. (1994). Revisiting default methodology using the present dataset—which, in addition to containing credit score information, is a factor of 85 times larger than that used in prior literature and reflects the mortgage market in recent years—offers valuable insight into whether the results of Berkovec et al. hold up under these rigorous conditions.

Default Rate Studies and Performance Equations

Default rates on residential mortgages have been widely studied in academia, policy and business for many purposes other than to identify discrimination. These studies have varied in approach depending on the perspective from which mortgage risk is analyzed: either by lender, borrower or institution.[9] For lenders and institutions, analysis has traditionally considered characteristics of the loan and borrower to predict default probabilities useful for measuring the risk level captured by a loan portfolio. From the borrower perspective, studies have focused on models of consumer behavior to determine under what circumstances it is rational for a borrower to default on a mortgage loan.

[9] See Quercia and Stegman (1992) for a review of default rate studies, including early measures of using default rates to determine the existence of racial discrimination.

As measured by default rates, loan performance was introduced as a method to study discrimination in mortgage lending following work on discrimination by Kenneth Arrow and Gary Becker in the early 1970s.[10] Default rate studies aimed at measuring discrimination are rooted in reverse regression analysis, which proposes that differential treatment discrimination can be identified by performance equations.[11] Introduced in the early 1980s, reverse regression analysis was critiqued by Arthur Goldberger, who reviewed issues associated with the method, such as omitted variable bias, in the context of salary discrimination.[12] Since then, versions of reverse regression analysis have been applied to measuring discrimination in a wide range of settings, including racial discrimination on sports teams.[13] Default methodology fundamentally relies on the reverse regression approach since it involves comparing the performance of various racial groups of borrowers to determine the presence of unfair treatment in loan underwriting.

<u>The Community Reinvestment Act</u>

In addition to a vast literature focused on identifying discrimination in the mortgage market, there is also a considerable literature engaged with understanding various effects of the CRA. Given the CRA's original implementation over 40 years ago, it is perhaps unsurprising

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[10] See Arrow (1971) and Becker (2010) for foundational publications in the economic theory of discrimination.
[11] See Yezer (2010).
[12] See Goldberger (1984) for a thorough review and critique of studies using the reverse regression approach to study discrimination.
[13] As highlighted by Anthony Yezer (2010), reverse regression analysis in the context of racial discrimination on sports teams reflects the following: if the weakest minority player on a team performs better than the weakest White player, racial discrimination may exist at the point of player selection. Mixon and Travino (2004) apply this theory to examine the existence of racial discrimination in the hiring of football coaches. The authors conclude that conditional on hiring a minority coach, colleges in their sample were more reluctant to fire a minority coach.

that there have been many attempts to evaluate its effectiveness and impact on minority and low-income communities.

Several papers have sought to determine whether the CRA has had a measurable impact on the quantity of credit extended to minority borrowers and borrowers in low-to-moderate income areas as the legislation was originally intended. For example, Bostic and Robinson (2003) measured the impact of the number of CRA agreements in a county on the change in lending volume in that county over a period of three years. The authors found that the presence of one or more agreements increased lending in the short term. Schwartz (1998) pursued a different approach by comparing the lending behavior of banks that are engaged in CRA agreements to those that are not. Schwartz found that banks with CRA agreements tend to be more responsive to the credit needs of minority and low-to-moderate income communities than other banks.

Other papers consider unintended consequences of the CRA. Bhutta (2011) used a regression discontinuity design to examine the indirect effects of the CRA on non-bank lending. Agarwal, Benmelech, Bergman and Seru (2012) considered whether the CRA encourages risky lending by comparing the lending behavior of banks undergoing CRA exams in a given census tract and year to the behavior of banks operating in the same census tract that did not face CRA exams in that year. These authors concluded that banks that are examined in a given year tend to originate riskier loans in that year. Most recently, Taylor Begley and Amiyatosh Purnanandam studied complaints issued by borrowers in CRA-eligible areas to evaluate the impact of the CRA on the *quality* of credit, given that the legislation is geared toward regulating the *quantity* of credit.[14]

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[14] See Begley and Purnanandam (2017).

In this paper, I specifically consider the CRA in the context of the 2008 financial crisis. This topic was the focus of Governor Randall Kroszner's speech at the Confronting Concentrated Poverty Policy Forum in 2008. In his speech, Kroszner reviewed two Federal Reserve studies, both of which concluded that lending in lower-income communities has performed similarly to other types of lending by banks covered by the CRA.[15] Governor Kroszner also discussed Federal Reserve research addressing concerns that the CRA was a principle cause of strain on the mortgage market. Pertinent to the analysis here, Kroszner noted that Fed researchers focused in part on loan performance in order to draw conclusions about the impact of the CRA on the mortgage crisis. Fed researchers compared subprime delinquency rates in lower-income neighborhoods to those in middle- and higher-income neighborhoods to see how CRA-related loans performed. As Governor Kroszner explained, this study found that subprime loans performed similarly regardless of neighborhood income level.

While the Federal Reserve study cited by Kroszner compared delinquency rates among neighborhoods with varying median incomes to examine whether the CRA encouraged fair lending across income brackets, I compare mortgage default rates in counties with differing racial compositions to examine the impact of the CRA on racial discrimination. By including a variable in one of my specifications describing whether a county is CRA-eligible in a given year, I draw conclusions regarding the impact of CRA-eligibility on default rates controlling for whether a loan was originated before or after the financial crisis. In further empirical tests, I study the specific impact of county CRA-eligibility on the default rates of borrowers of various races in that county and measure whether this impact varies before versus after the crisis.

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[15] See Kroszner (2008).

Section 3: Data

As briefly noted in Section 2, the default approach to studying discrimination in mortgage lending requires a loan-level dataset with information about the terms and performance of each mortgage loan as well as characteristics of the individual borrowers. In studying racial discrimination, it is, of course, necessary that race in some capacity be accounted for as a characteristic associated with each borrower.

Given the absence of a public database that includes both loan performance and race of the borrower on a loan-level basis, I use the percentage of minority populations in a county as a proxy for the race of an individual borrower. Therefore, instead of testing whether the default rate of minority borrowers is lower than that of White borrowers, I will effectively be testing whether of borrowers who live in predominantly minority counties default less frequently than those who live in predominantly White counties in order to determine the presence of racial discrimination. Using county-level racial composition as a proxy for individual race via the Fannie Mae and FFIEC datasets allows me to control for the credit score of each borrower, which significantly strengthens my analysis as compared to that of Berkovec et al. (1994).

Fannie Mae Data

I derive loan-level data, including loan terms, borrower financial characteristics and loan performance, from the Fannie Mae Single-Family Loan Performance Database. Each year since 2000 on a quarterly basis, Fannie Mae has published acquisition and performance data for a subset of Fannie Mae’s 30-year and less, fully amortizing, full documentation, conventional single-family mortgages. I have limited the dataset to loans originated after 2006 in order to accurately merge in census data. The Fannie Mae dataset spanning 2006 through 2016 contains over 19 million observations, each corresponding to a loan in the Fannie Mae portfolio. The variables associated with each loan are listed in Table 1, in addition to county-level census and CRA-related data.

Each variable included in the borrower, loan or property characteristics listed in Table 1 contain data sourced directly from the Fannie Mae database. Borrower characteristics include variables describing each borrower's home-buying history, with a dummy variable indicating whether the borrower is a first time or repeat home buyer, as well as variables describing the borrower's financial position at the time of loan origination. These variables include debt-to-income ratio and FICO score. A borrower's debt-to-income ratio is calculated by Fannie Mae by dividing a borrower's total monthly obligations (including housing expense) by his or her stable monthly income. Fannie Mae uses this metric to determine the size of the loan for which a borrower qualifies. I included debt-to-income ratio as a variable called DTI.

I included information about borrowers' credit scores as a series of indicator variables. Beginning in 2008, Fannie Mae has charged fees on mortgage loans based primarily on FICO score, LTV (loan-to-value ratio) and loan type. Given that the dataset is entirely made up of Fannie Mae loans, and Fannie Mae takes these three factors into account when calculating mortgage risk, I control for the ranges of FICO score and LTV that vary with Fannie Mae's assessment of risk.[16] (All of the loans included in the sample are of the same type: 30-year and less, fully amortizing, full documentation, conventional single-family mortgage loans). Thus, FICO score ($CSCORE$) is accounted for via 12 indicator variables (620-639, 640-659, … 780-799, etc.). For example, if a borrower associated with a given loan has a credit score of 710, the

[16] See Scharfstein and Sunderam (2016) for an implementation of this approach to accounting for FICO scores and LTV ratios in government sponsored enterprise (GSE) loans, and Hurst, Keys, Seru and Vavra (2016) for a derivation of this methodology.

variable $CSCORE700\_719$ would be equal to one, while the other 11 credit score-related indicators would be equal to zero.

I also consider how loan-specific characteristics included in the Fannie Mae dataset, such as loan term and amount, impact the probability of default. These characteristics are in line with those controlled for in the analysis of Berkovec et al. (1994). I account for loan-to-value ratios[17] at origination ($OLTV$) using a series of indicator variables structured similarly to the FICO score variables (50-54, 55-59, … 80-84, … 95-99, etc.). I also include indicator variables denoting whether the loan is for an investment property or if a borrower is using the loan to refinance an existing mortgage. The original property value at origination ($ORIG\_VAL$) and the original unpaid principal balance of the loan ($ORIG\_AMT$) are coded as logged values in the dataset. I also account for the original interest rate charged on the loan ($ORIG\_RT$) and the latest interest rate charged on the loan ($LAST\_RT$). Original loan term ($ORIG\_TRM$) is measured in number of months.

Property characteristics are unaltered from the Fannie Mae dataset. I include an indicator for whether the property is a condominium and a variable describing the number of units in the property. Loan performance, as derived from the Fannie Mae dataset, is summarized by an indicator for default. I consider a loan to have been in default if a loan payment is at least 30 days delinquent, if the loan has been repurchased or foreclosed upon, or if the collateral property has undergone an REO disposition.

[17] A loan-to-value (LTV) ratio is calculated by dividing the original loan amount by either the value of the mortgaged property at the time of sale (in the case of purchase) or the value of the mortgaged property at the time of refinancing (in the case of refinancing). LTV ratios capture a component of loan riskiness and thus are frequently employed by mortgage lenders in the underwriting process.

Census Data

I collected race and CRA-related data from the Federal Financial Institutions Examination Council (FFIEC). Each year since 2006, the FFIEC has released the data that it used to compile the CRA Aggregate and Disclosure Reports, which detail the components and results of the CRA examinations administered that year. For each census tract in the United States, the dataset made public annually by the FFIEC includes demographic information compiled from the American Community Survey (ACS) as well as data specific to census tract CRA-eligibility. The ACS is an ongoing survey administrated by the Census Bureau that collects data on the social, economic, demographic and housing-related status of Americans. It is published on a one-year, three-year and five-year basis. The FFIEC includes ACS five-year estimates in their dataset. Thus, the census and race-related variables vary for three different periods: (1) census data from 2000 is used in the FFIEC datasets from 2006-2011, (2) census data from 2010 is used in the FFIEC datasets from 2012-2016 and (3) census data from 2015 is used in the 2017 FFIEC dataset.

Each annual FFIEC dataset includes over 1,000 variables in total. I have chosen about 30 of these variables that are of central importance to the analysis. Several of these variables describe the racial composition of the population by census tract, including population estimates for White, Black or African American, American Indian and Alaska Native, Asian, Hawaiian and Other Pacific Islander and mixed-race citizens. Other variables I use from the FFIEC dataset describe census tract characteristics such as median income, median value of housing units and percentage of rental housing units in a census tract. The first two of these variables are transformed to a logarithmic scale in the dataset.

The Fannie Mae loan performance dataset includes variables noting the location of the collateral property of the mortgage loan in terms of both Metropolitan Statistical Area (MSA) and three-digit zip code. As noted above, the FFIEC data is compiled on the census tract level. In order to achieve geographic consistency to merge the Fannie Mae and FFIEC datasets, I manipulated both datasets to achieve county-level data. I aggregated the FFIEC data up to county level from the census tract level by averaging or summing component variables. I chose to define the variable describing county-level CRA-eligibility, CRA_FLG, as equal to one if any number of census tracts in that county were listed as CRA-eligible by the FFIEC.[18] In order to include county-level geographic information in the Fannie Mae loan-level dataset, I chose to represent each three-digit zip code by the largest county in the three-digit zip. I matched three-digit zip codes with counties using the HUD-USPS ZIP Crosswalk Files from 2010 through 2016.[19] For years 2006 through 2009, I used the 2010 crosswalk due to unavailability of prior years' crosswalks.

Once I attained county-level geographic data in both datasets, I merged the Fannie Mae dataset with the relevant FFIEC variables in order to match each loan in the sample with location-related characteristics. For each year from 2006 to 2016, I matched each loan originated

[18] I ran variations of the CRA-related regressions with alternate definitions of the CRA_FLG indicator variable: (1) a continuous CRA variable, set equal to the proportion of census tracts marked as CRA-eligible in a county; and (2) an indicator variable with a CRA-eligibility threshold of the median value of the continuous CRA-eligible variable. Both of these trials resulted in less significance in the CRA interaction terms than shown in the analysis in Section 5. The limited significance resulting from the inclusion of the continuous variable indicates that there is not a meaningful linear relationship between the odds of loan default and the number of CRA-eligible census tracts in a county. The limited significance resulting from the inclusion of the median-threshold CRA variable suggests that the existence of *any* CRA-eligible census tracts in a county has a more meaningful effect on default rates than the number of CRA-eligible census tracts in a county if that number is greater than one.

[19] This approach draws on Scharfstein and Sunderam (2016), who followed a similar methodology in their merging of Fannie Mae data with census data.

in that year from the Fannie Mae dataset to several FFIEC data points from that year using the county variable. After merging the Fannie Mae and FFIEC datasets, each loan in the Fannie Mae dataset contains several additional location-specific variables, such as percentage Asian population in the county where the collateral property is located, the median annual household income in that county and whether any census tracts in that county were CRA-eligible in the year the loan was originated.

The sample includes over 19 million observations, each of which corresponds to a loan in the mortgage portfolio held by Fannie Mae. Specifically, the sample includes 3.6 million loans originating between 2006 and 2008 and 15.4 million loans originating between 2009 and 2016. Definitions of the explanatory variables are listed in Table 1. Summary statistics in the form of means and standard deviations for these variables are included in Table 2, divided into three categories based on vintage year of the loan.

Summary Statistics

The summary statistics shown in Table 2 reveal important characteristics of the variables before and after the financial crisis. First, I address the variables reflective of borrower characteristics. In line with the tightening of lending and bank regulation after the financial crisis, the average credit score of borrowers included in the post-crisis group (757.53) is over 30 points higher than the average credit score of borrowers who received loans at the height of the mortgage bubble ($CSCORE$). The mean debt-to-income ratios of borrowers in the pre- and post-crisis periods also align with credit tightening. In the pre-crisis period the mean debt-to-income ratio is approximately 37.71, while in the post-crisis period the mean debt-to-income ratio is 32.23 (DTI). Since borrowers with higher debt-to-income ratios are more likely to default, this trend suggests a contraction in risk on behalf of mortgage lenders in the post-crisis period in line with my assumptions.

Next, I address descriptive statistics associated with loan characteristics. The mean value of $ORIG\_RT$, which signifies the interest rate charged on the loan at origination, fell from 6.24% in the pre-crisis period to 4.16% in the post-crisis period. Similarly, the value of $LAST\_RT$, the most recent interest rate charged on the loan, fell from 6.11% to 4.16%. These contractions in mortgage rates in large part reflect the depression of the 10-year Treasury rate after the crisis. The mean value of the 10-year Treasury rate was 4.36% in the pre-crisis period (2006-2008) as opposed to 2.49% in the post-crisis period (2009-2016).[20] Mortgage spreads remained similar in the pre- and post-crisis periods with values 1.88% and 1.67%, respectively, though this 10 percent decrease in spread may be evidence for a decrease in risk tolerated by lenders after the crisis.[21]

Summary statistics for the race-related variables derived from census data remain relatively constant between the pre- and post-crisis periods. This is consistent with intuition, as there is no compelling reason to expect the racial composition of counties in the United States to change significantly during this time frame. However, it should be noted that the mean value of CO_MED_HVAL, the logged mean of county-level median home value, grew from 11.81 in the pre-crisis period to 12.23 after the crisis. This indicates that lenders, on average, were extending mortgage loans to borrowers who were financing the purchase of higher-value homes in the post-crisis period.

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[20] FRED 10-Year Treasury Constant Maturity Rate data.

[21] Mortgage spreads, as used here, are calculated by subtracting the mean values of Treasury rates from the mean values of $ORIG\_RT$ in the pre- and post-crisis periods.

Section 4: Model and Empirical Approach

Model Overview

Berkovec et al. (1994, 1998) implement variations of default methodology to determine if racial discrimination is detectable in a set of approximately 220,000 records of Federal Housing Administration-insured mortgages originating between 1987 and 1989. This dataset includes loan-level performance data, borrower characteristics (including race), loan terms and characteristics of the neighborhood and the property of the mortgage.[22] Default methodology in its most thorough form would include a logit regression constructed in line with the following:

$$P(D) = f(F, R, T, C)$$

where probability of default serves as the dependent variable and the independent variables—represented in the above by vectors F, R, T and C—reflect characteristics of the borrower, loan and collateral property observed by the mortgage lender at application.[23] Specifically, the vector F includes financial characteristics of the borrower, R measures risks of default in the local housing market, T describes loan terms and C enumerates personal non-financial characteristics of the borrower, including race. Default methodology predicts that in the presence of discrimination, the coefficients of indicators for minority race on the right-hand side of the regression equation would be negative. Both papers written by Berkovec et al. found that default rates for minorities were higher than those of White borrowers and, thus, concluded that racial discrimination did not exist within their sample of loans.

A recent loan-level public dataset that includes information about both borrower race and loan performance, as Berkovec et al. are able to achieve using proprietary FHA data from 1987-

[22] For a thorough review of these studies, see Berkovec et al. (1994) and Berkovec et al. (1998).
[23] See Yezer (2010).

1989, does not appear to exist. Thus, I have constructed a dataset using multiple public sources that encapsulates as much information along the lines of vectors F, R, T and C as possible. These variables are listed and defined in Table 1. Summary statistics for these variables are included in Table 2 and discussed in Section 3 above.

One notable difference between the data that I use and that used by Berkovec et al. is that I do not have loan-level race of each borrower. This variable is key in Berkovec et al.'s study, as racial discrimination is the central concern and is measured via an indicator for each borrower's race. In order to conjecture default rates for various White and minority populations, I use the percentage minority population of the county in which the property is located, represented in census data, as a proxy for the race of each borrower.

In addition to measuring the impact of the crisis on loan performance, I also seek to understand the impact of anti-discrimination legislation, particularly the CRA, on the default rates of minority versus White borrowers. I break down the analyses into five models, each of which builds on each other by adding additional controls to the main specification. The first two regressions attempt to capture the effect of the financial crisis on default rates in counties with differing racial makeups while the final three regressions introduce analysis related to the CRA. In each of the following analyses, standard errors are clustered by state and county-level fixed effects are included. In all of the logit regressions, the estimated coefficient on each variable is the expected change in the log odds of loan default resulting from a one-unit increase in that variable, holding all other variables constant.

Equation (1): Controlling for Post-Crisis Origination Indicator

My baseline model mirrors that of Berkovec et al. to the extent possible. I estimate the impact of various loan, borrower, property and geographic characteristics on the probability a loan will default. In order to study the impact of the financial crisis on loan performance and to control for the macroeconomic and regulatory differences between the pre- and post-crisis periods, I introduce a variable, $POST_t$, that indicates whether a loan was originated before the crisis (2006-2008) or after the crisis (2009-2016). This analysis reflects that of Berkovec et al. (1994) except for the inclusion of a variable describing whether a loan was originated before or after the crisis. I estimate the following, equation (1):

$$D_{ikt} = \frac{e^{\alpha}}{1 + e^{\alpha}} \tag{1}$$

$$where \quad \alpha = \beta_1 X_{it} + \beta_2 Y_{it} + \beta_3 Z_{ikt} + \beta_4 C_{kt} + \beta_5 R_{kt} + \beta_6 POST_t + \varepsilon_{ikt}$$

where D_{ikt} is an indicator variable for whether the loan made by borrower i for a property located in county k during year t defaulted before 2017, when Fannie Mae made available the most recent loan performance data. X_{it} represents a vector of control variables specific to borrower i in period t; Y_{it} represents a vector of controls related to loan characteristics such as interest rate charged and loan amount for borrower i in period t; Z_{ikt} represents controls related to characteristics of the underlying property for borrower i in county k during period t; C_{kt} represents non-race locational characteristics for county k in year t, derived from census data; and R_{kt} represents race-related characteristics for county k in year t, also derived from census data. $POST_t$, an indicator variable, is equal to one if the loan was originated after the crisis, between 2009 and 2016 inclusive, and is equal to zero otherwise.

The independent variables of interest in identifying racial discrimination via this specification are the race-related variables that make up vector R_{kt}. According to the default methodology for identifying discrimination, in the presence of discrimination against a certain minority, I would expect the β_5 coefficient for the variable corresponding to the percentage population of that race in a county to be negative. I expect the β_6 coefficient of $POST_t$, which describes the effect of post-crisis origination on the probability of loan default, to be negative given the sharp decrease in risk tolerated by mortgage lenders after the crisis.[24] Regression results for equation (1) are listed in Table 3 and discussed in Section 5.

<u>Equation (2): Equation (1) + controls for Post-Crisis Origination Indicator interaction with Race Vector</u>

Next, I examine whether the relationship between the racial composition of a county and the log odds of default for loans originated in that county changed after the crisis relative to before the crisis. I build on equation (1) by adding terms describing the interaction of $POST_t$ with each of the race-related variables in vector R_{kt}, as in the following equation (2):

$$D_{ikt} = \frac{e^{\alpha}}{1 + e^{\alpha}} \tag{2}$$

$$where \quad \alpha = \beta_1 X_{it} + \beta_2 Y_{it} + \beta_3 Z_{ikt} + \beta_4 C_{kt} + \beta_5 R_{kt} + \beta_6 POST_t + \beta_7 POST_t \times R_{kt} + \varepsilon_{ikt}$$

If any coefficients of the interaction terms included in vector β_7 are significant, this demonstrates that the racial composition of a county had a different effect on loan performance in the pre-crisis period than in the post-crisis period.

To illustrate this, I estimate the impact of the percentage of African American/Black people living in a county on the probability of mortgage loan default for the pre- and post-crisis periods separately. β_5 is a vector of coefficients associated with each race-related variable alone, and β_7 is a vector of coefficients for each interaction term of race and $POST_t$. If the coefficient $\beta_{7,Black}$ is significant, this would indicate that the relationship between the proportion of Black

[24] See Ivashina and Scharfstein (2010) and Reinhart and Rogoff (2009) for a discussion of mortgage market regulation and credit tightening in the aftermath of the financial crisis.

population in a county and the default probability of mortgage loans in that county is different before versu after the crisis. If $\beta_{7,Black}$ is positive and significant, for example, this would suggest that the increase in default probability associated with a one-unit increase in Black population would be greater in the post-crisis period than in the pre-crisis period. Results for the estimate of equation (2) are shown in Table 4.

Discrimination is identified in equation (2) differently than in equation (1) by focusing on the sum of coefficients $\beta_{5,Black} + \beta_{7,Black}$ in addition to the coefficient of $\beta_{5,Black}$ alone. If Black borrowers were being discriminated against in our sample after controlling for whether loans were originated before or after the crisis, I would expect $\beta_{5,Black}$ to be negative and significant in equation (1). In equation (2), if $\beta_{5,black}$ is negative and significant, this would suggest that lenders were discriminating against Black communities *before* the crisis. On the other hand, I would conclude that lenders were discriminating against counties with larger proportions of Black residents *after* the crisis if the sum $\beta_{5,Black} + \beta_{7,Black}$ is negative and significant.

<u>Equation (3): Equation (2) + controls for County CRA-Eligibility Indicator</u>

In the above two specifications, I tested the impact of county-level racial composition on the probability of loan default from 2006 through 2016, as well as whether the relationship between race and the log odds of loan default changes before and after the crisis. In the third specification, I take into account legislation geared toward eliminating racial discrimination in the mortgage market: the Community Reinvestment Act. In the following regression, I look to see if county CRA-eligibility has had an impact on loan performance independent of county racial composition and whether loans were originated before or after the crisis. To do this, I have included in the dataset an indicator variable, CRA_{kt}, that labels county k "CRA-eligible" in year t if any census tracts in county k have been marked as "CRA-eligible" in year t. The following specification, adjusted from equation (2) to include CRA_{kt}, defines this CRA-focused analysis.

$$D_{ikt} = \frac{e^{\alpha}}{1 + e^{\alpha}} \tag{3}$$

$$where \quad \alpha = \beta_1 X_{it} + \beta_2 Y_{it} + \beta_3 Z_{ikt} + \beta_4 C_{kt} + \beta_5 R_{kt} + \beta_6 POST_t + \beta_7 POST_t \times R_{kt} + \beta_8 CRA_{kt} + \varepsilon_{ikt}$$

In equation (3), I focus on β_8 in order to understand the impact of county CRA-eligibility on loan performance. For example, a significantly positive β_8 suggests that CRA-eligibility in a given year t increases the log odds of loan default. In a given year, a census tract is marked as CRA-eligible if it is considered low- or moderate-income (if the median family income of the tract is between zero and 80% of the Metropolitan Statistical Area (MSA) median family income) or if it is a non-metropolitan middle-income tract designated by the FFIEC as "distressed" or "underserved" (defined signals of poverty, unemployment and demographics). I expect that county CRA-eligibility would limit lenders' discrimination toward borrowers residing in that county because the CRA instructs banks to lend fairly in CRA-eligible communities. In other words, if a county was being discriminated against, as evidenced by relatively low default rates (lenders holding borrowers in this community to higher standards of creditworthiness than other communities), I expect CRA-eligibility to eliminate this discrimination and increase default rates. The estimate of equation (3) is shown in Table 5.

<u>Equation (4): Equation (3) + controls for County CRA-Eligibility Indicator interactions with Race Vector</u>

In the fourth specification, I more closely examine the impact of the CRA on racial discrimination by considering whether county CRA-eligibility affects the relationship between the racial composition of a county and the log odds of default for loans originated in that county. I also compare this effect between the pre- and post-crisis periods. To achieve this, I introduce a second series of interaction terms by interacting the CRA indicator variable, CRA_{kt}, with each variable in the vector of race-related variables, R_{kt}, as in equation (4) below. The estimate of equation (4) is presented in Table 6.

$$D_{ikt} = \frac{e^{\alpha}}{1 + e^{\alpha}} \tag{4}$$

$$where \quad \alpha = \beta_1 X_{it} + \beta_2 Y_{it} + \beta_3 Z_{ikt} + \beta_4 C_{kt} + \beta_5 R_{kt} + \beta_6 POST_t + \beta_7 POST_t \times R_{kt} + \beta_8 CRA_{kt} + \beta_9 CRA_{kt} \times R_{kt} + \varepsilon_{ikt}$$

In addition to the interaction terms of the CRA indicator variable with the vector of race-related variables, this specification also accounts for the set of explanatory variables included in equation (3), including the interactions between $POST_t$ and R_{kt}. Therefore, equation (4) allows for examination of the effects of post-crisis origination and county CRA-eligibility in tandem. To make sense of the results, I consider whether the results corresponding to each race fit into one of four categories: racial groups for which neither β_7 nor β_9 are significant, for which only β_7 is significant, for which only β_9 is significant and for which β_7 and β_9 are significant. Table 6A below describes the interpretation of each relevant coefficient and their sums, taking the coefficients of variables relating to African American/Black populations as examples.

If neither β_7 nor β_9 are significant for a racial group, this indicates that the relationship between the population of this group and the odds of loan default in a county is not meaningfully impacted by post-crisis origination or CRA-eligibility. On the other hand, if β_9 is significant and β_7 is not significant for a racial group, the relationship between the population of that race and the log odds of default is impacted by county CRA-eligibility but not post-crisis origination. In this case, if β_5 is also significant, I will compare the β_5 coefficient for that race to the sum $\beta_5 +$

β_9 to assess how much discrimination varies between not CRA-eligible and CRA-eligible county-years. If β_5 is negative and significant, I would expect β_9 to be positive and significant, indicating the elimination of discrimination on behalf of the CRA. Relationships between β_5 and β_9 are described in the first and fifth rows of Table 6A.

I consider whether any components of vector β_7 are significant to understand whether the relationship between the racial composition of a county and the log odds of loan default in that county varies between the pre- and post-crisis periods. For racial groups for which β_7 is significant and β_9 is not significant, I compare the coefficients described the first and fourth rows of Table 6A to draw a conclusion regarding the extent of discrimination before versus after the crisis.

TABLE 6A

Interpretation of Logit Coefficients in Equation (4)

$\beta_{5,Black}$	Baseline increase in log odds of default associated with one percentage point increase in Black population
$\beta_{7,B}$	Additional increase in log odds of default when moving from pre- to post-crisis county-year
$\beta_{9,B}$	Additional increase in log odds of default when moving from not CRA-eligible county-year to CRA-eligible county-year
$\beta_{5,B} + \beta_{7,B}$	Increase in log odds of default associated with one percentage point increase in Black population for loans originated in post-crisis county-years
$\beta_{5,B} + \beta_{9,B}$	Increase in log odds of default associated with one percentage point increase in Black population for loans originated in CRA-eligible county-years
$\beta_{5,B} + \beta_{7,B} + \beta_{9,B}$	Increase in log odds of default associated with one percentage point increase in Black population for loans originated in post-crisis, CRA-eligible county-years

For racial groups for which both β_7 and β_9 are significant, I compare the effect of racial composition on the log odds of default for four groups of loans:

1. loans originated before the crisis in counties that are not CRA-eligible,

2. loans originated after the crisis in counties that are not CRA-eligible,
3. loans originated before the crisis in counties that are CRA-eligible and
4. loans originated after the crisis in counties that are CRA-eligible.

This approach compares the first, fourth, fifth and sixth rows, respectively, of Table 6A above.

Equation (5): Equation (4) + controls for Post-Crisis Origination Indicator interaction with CRA-Eligibility Indicator + controls for three-way interactions between Post-Crisis Origination Indicator, CRA-Eligibility Indicator and Race Vector

Finally, I add three-way interactions to the model to enhance the analysis of whether the effect of county-level CRA-eligibility on the relationship between race and default probability differed before the financial crisis versus after. This specification is very similar to equation (4), except for the addition of a series of three-way interactions between the CRA indicator, post-crisis origination indicator and vector of race-related variables and a two-way interaction between $POST_t$ and CRA_{kt}. The introduction of these three-way interactions specifically requires the comparison of post-crisis, CRA-eligible county-years with county-years that are either pre-crisis or not CRA-eligible. In other words, this regression separates the combined effect of post-crisis origination *and* CRA-eligibility from either of these individual effects. This refinement may improve the analysis by requiring more specific consideration of each of the main effects.

$$D_{ikt} = \frac{e^{\alpha}}{1 + e^{\alpha}} \tag{5}$$

$$\begin{aligned} where \quad \alpha = {} & \beta_1 X_{it} + \beta_2 Y_{it} + \beta_3 Z_{ikt} + \beta_4 C_{kt} + \beta_5 R_{kt} + \beta_6 POST_t + \beta_7 POST_t \times R_{kt} + \beta_8 CRA_{kt} \\ & + \beta_9 CRA_{kt} \times R_{kt} + \beta_{10} CRA_{kt} \times POST_t + \beta_{11} CRA_{kt} \times POST_t \times R_{kt} + \varepsilon_{ikt} \end{aligned}$$

Equation (5) can be analyzed using a very similar framework to that of equation (4): I draw conclusions regarding discrimination against each racial group based on which coefficients (e.g., β_7, β_9, β_{11}) are significant, if any. The coefficients included in vector β_{11} are of most interest in distinguishing this analysis from that of equation (4). If the β_{11} coefficient associated with any race is significant, I conclude that the relationship between the percentage of that race residing in a county and the log odds of default in that county is meaningfully impacted by both CRA-eligibility and post-crisis origination. I then look to the components of β_5, β_7 and β_9 to determine the complete impact of the proportion of that race in a county on the log odds of loan default. For racial groups for which β_{11} is not significant, I follow the analysis described in equation (4) above. Table 7A below describes the interpretations of combinations of these coefficients.

TABLE 7A
Interpretation of Logit Coefficients in Equation (5)

$\beta_{5,Black}$	Baseline increase in log odds of default associated with one percentage point increase in Black population
$\beta_{7,B}$	Additional increase in log odds of default when moving from pre- to post-crisis county-year
$\beta_{9,B}$	Additional increase in log odds of default when moving from not CRA-eligible county-year to CRA-eligible county-year
$\beta_{11,B}$	Additional increase in log odds of default when moving from any pre-crisis or not CRA-eligible county-year to post-crisis, CRA-eligible county-year
$\beta_{5,B} + \beta_{7,B}$	Increase in log odds of default associated with one percentage point increase in Black population for loans originated in post-crisis county-years
$\beta_{5,B} + \beta_{9,B}$	Increase in log odds of default associated with one percentage point increase in Black population for loans originated in CRA-eligible county-years
$\beta_{5,B} + \beta_{7,B} + \beta_{9,B} + \beta_{11,B}$	Increase in log odds of default associated with one percentage point increase in Black population for loans originated in post-crisis, CRA-eligible county-years

Using this specification, the identification of racial discrimination has become more nuanced than what was estimated in equation (4).[25] The results of the estimate of equation (5) are shown in Table 7.

Section 5: Results

<u>Equation (1): Controlling for Post-Crisis Origination Indicator</u>

My first specification regresses a default indicator on a series of borrower, loan, property and census characteristics as well as an indicator variable to control for whether a loan was originated before or after the crisis. As this is the baseline specification, I review the results regarding the majority of the control variables in addition to analyzing the race-related terms. This affords an understanding of many factors of loan performance in addition to the impact of race. The coefficients of these control variables, which are all measured at the borrower level, are significant at the 1% level in each of the specifications, and, thus, will only be reported and discussed in the context of equation (1). Estimates of the logit coefficients associated with all of the explanatory variables included in equation (1) are shown in Table 3.

Borrower Characteristics

<u>First-time vs. repeat buyers.</u> Considering first the variables related to borrower characteristics, the coefficient of $FTHB\_FLG$, -0.0312, is negative ($p < 0.001$). This indicates that if a borrower is a first-time homebuyer, she is slightly less likely to default than if she were a

[25] Because equation (5) estimates the same effects as equation (4) but with a more specific framework, the total effects of post-crisis origination and CRA-eligibility —achieved in equation (4) by the sum $\beta_5 + \beta_7 + \beta_9$ for each race, and equation (5) by the sum $\beta_5 + \beta_7 + \beta_9 + \beta_{11}$— should be approximately equal. I confirm this in Section 5.

repeat homebuyer. This could be a result of real estate investors making relatively risky investment decisions. Inherent in this speculation is that real estate investors are repeat homebuyers. This conjecture is also supported by the positive and significant coefficient of $INVEST\_FLG$, which indicates that investment properties were more likely to be defaulted on during this period than properties not bought as investments ($p < 0.001$).

Credit score. Results corresponding to the series of FICO score indicators are more intuitive to interpret in the context of odds ratios than logit coefficients since FICO score is coded as a categorical variable.[26] In this context, an odds ratio allows us to directly compare the odds of default for borrowers in different FICO score buckets.[27] It is important to note that among the FICO score-indicator variables, the omitted category of borrowers includes those with FICO scores of less than 620. Thus, odds ratios for the included FICO score categories compare each included category to the group of borrowers with FICO scores 620 and below. I begin with the first FICO score indicator variable, $CSCORE620\_639$, which has a significant coefficient of -0.0557 ($p < 0.001$). This coefficient yields an odds ratio of 0.9458, which represents the log odds of a borrower with FICO score between 620 and 639 defaulting on her loan divided by the odds of a borrower with FICO score less than 620 defaulting on her loan. Because this odds ratio is less than one, this value indicates that the odds of a borrower with FICO score between 620 and 639 defaulting on their mortgage loan are slightly smaller than the odds that a borrower with FICO score less than 620 will default. This aligns with what would be expected, since a

[26] The logit coefficients shown in Table 3 can be converted to odds ratios by raising e to the power of the coefficient.
[27] An odds ratio is equal to the odds that an outcome will occur given one condition divided by the odds that the outcome will occur given another condition. For example, consider a fair coin and a weighted coin. The fair coin has odds of 0.5 of landing heads-up and the biased coin has odds 0.25 of landing heads-up in a coin flip. The odds ratio between a fair coin landing heads-up and the biased coin landing heads-up is the ratio of these two odds: 2.

marginally more creditworthy borrower, identified by slightly higher FICO score, would be expected to be relatively less likely to default than a borrower with a lower FICO score.

The second credit score indicator variable, $CSCORE640\_659$, has a significant coefficient of -0.204 and an associated odds ratio of 0.815 ($p < 0.001$). This value is smaller in magnitude than 0.9458, the odds ratio associated with $CSCORE620\_639$. This is intuitive because a higher FICO score implies a higher level of creditworthiness, suggesting that the borrower is less likely to default. Therefore, the ratio of the odds of defaulting between borrowers with increasingly high FICO scores and borrowers with scores below 620 should continue to decrease as the FICO score range of the explanatory variable rises. This trend holds for 10 out of 12 cases (excluding $CSCORE820\_839$ and $CSCORE840\_$).

<u>Debt-to-income ratio.</u> I expect the probability of default to increase with borrowers' debt-to-income ratios (DTI) because a higher ratio indicates the borrower has a larger debt burden, requiring larger repayments perhaps across several debt obligations. This is reflected in the results: the positive and significant regression coefficient of 0.0163 associated with DTI indicates that having a higher debt-to-income ratio slightly increases a borrower's likelihood of defaulting on her mortgage loan ($p < 0.001$).

Loan Characteristics

<u>Number of borrowers.</u> The coefficient of the variable noting the number of borrowers associated with a loan, NUM_BO, also aligns with what I predict. The negative and significant coefficient of -0.591 signifies that the more borrowers signed onto a loan, the less likely the loan is to default ($p < 0.001$). This is intuitive because with each additional borrower, the pool of

collateral and income with which to repay the mortgage loan grows and a default therefore becomes less likely.

Loan-to-value ratio. Next, I again turn to odds ratios in the evaluation of the series of 10 categorical loan-to-value variables. The omitted category in this case constitutes loans with LTV ratios less than 50%. All 10 odds ratios are greater than one and significant, implying that for all borrowers with loan-to-value ratios above 50%, it is more likely she will default than a borrower with an LTV less than 50%, as would be expected. For example, the odds ratio of 1.206 associated with $OLTV50\_54$ implies that the odds that a borrower with LTV between 50% and 54% defaults on her mortgage loan relative to the odds that a borrower with LTV less than 50% defaults are about 12 to 10 ($p < 0.001$). Considering the highest LTV range, the odds of a borrower defaulting with LTV between 95% and 99% relative to the odds of a borrower with LTV less than 50% defaulting are approximately 40 to 10. In all 10 cases, the odds ratios associated with LTV increase in magnitude from the indicator for the lowest LTV range, $OLTV50\_54$, to the indicator for highest LTV range, $OLTV95\_99$. This is in line with what would be expected since higher loan-to-value ratios reflect lower borrower equity in the property and, thus, imply higher probability of default.

Loan terms and property value. Loans that were used to refinance existing mortgage debt were more likely to default than loans not used for refinancing, as signaled by a positive and significant coefficient on $REFIN\_FLG$ ($p < 0.001$). The coefficient of $ORIG\_VAL$, the home value at time of mortgage origination, is negative, suggesting that houses with higher property values at the time of mortgage origination are associated with lower probability of default ($p < 0.001$). The significant coefficient of $ORIG\_RT$, 0.711, yielding an odds ratio of 2.036, indicates that the odds of default doubles with a one-unit increase in the original interest rate charged at the time of loan origination ($p < 0.001$). The direction of this change is unsurprising, as a higher interest rate typically reflects increased default risk associated with a loan. The significant coefficient of 0.00284 associated with $ORIG\_TRM$ indicates that the original term of the loan has almost no bearing on whether a borrower defaults, but longer loan terms are associated with a slightly increased probability of default ($p < 0.001$). The negative and significant coefficient on $LAST\_RT$, the most recent interest rate charged on a loan, is surprising ($p < 0.001$). I expect this coefficient to be in line with that of $ORIG\_RT$, although the results indicate that it has the opposite sign.

Origination year. In order to demonstrate the effect of the crisis on mortgage default rates, I include a variable in the analysis that is equal to one for loans originated in years 2009 through 2016 and equal to zero otherwise. The significant coefficient of -0.782 associated with $POST_t$ indicates that the probability of default was much lower for loans originated after the financial crisis ($p < 0.001$). This could reflect credit tightening after the financial crisis or rising house prices in the pre-crisis period relative to the post-crisis period.

Census Data

Finally, I turn to the variables relevant to the conclusions regarding racial discrimination in mortgage lending, which are reflected in demographic data included in the Federal Financial Institutions Examination Council's annual dataset. I omit the variable describing the percentage of White population in a county, so that the default likelihoods associated with each race are relative to White borrowers. The coefficient of CO_BLACK_{kt}, or the percentage of African American/Black population in a county, as well as coefficients associated with variables measuring the percentage Asian, mixed-race and Hispanic populations in a county are not statistically significant. Thus, a null effect for these groups cannot be ruled out.

The coefficients of CO_AMIND_{kt} and CO_HPI_{kt} are statistically significant. The coefficient of CO_AMIND_{kt}, which represents the percentage American Indian/Alaska Native residents in a county, that is equal to 40.34 indicates an expected increase of 40.34 in the log odds of mortgage default with a one percentage point increase of this population in a county ($p = 0.052$). This result indicates that American Indian/Alaska Native populations were not discriminated against in the sample. However, the coefficient of CO_HPI_{kt}, -104.5, indicates an expected decrease of 104.5 in the log odds of mortgage default with a one percentage point increase in Hawaiian/Pacific Islander population in a county ($p = 0.031$). The results of equation (1) thus suggest that Hawaiian/Pacific Islander communities were heavily discriminated against by mortgage lenders at the point of loan underwriting decisions relative to White borrowers during the sample period. This is in contrast to the analysis in Berkovec et al. (1994), which reveals no evidence of racial discrimination against any group.

<u>Equation (2): Equation (1) + controls for Post-Crisis Origination Indicator interaction with Race Vector</u>

I now move onto studying the empirical results of equation (2). This specification is identical to the previous, but I have included interaction terms between each race variable and $POST_t$. In this specification, I test whether the relationship between the racial composition of a county and the log odds of default for loans originated in that county changed after the crisis relative to before the crisis. Thus, the main coefficients of interest are those associated with the interaction terms. As reviewed in Section 4, a significant coefficient is interpreted as evidence that the relationship between the racial composition of counties and the log odds of loan default in those counties is meaningfully different before versus after the crisis. Logit estimates for equation (2) are shown in Table 4.

The coefficients of $POST_t \times R_{kt}$ are statistically significant for Hawaiian/Pacific Islander and mixed-race groups. The coefficient of $POST_t \times CO\_HPI_{kt}$, reported to be 39.09, indicates that a one-unit increase in the percentage Hawaiian/Pacific Islander population in a county increased the log odds of default by 39.09 for loans originated in the post-crisis period relative to the pre-crisis period ($p = 0.079$). Because the coefficient of CO_HPI_{kt} is not significant in this estimate, I cannot draw conclusions as to the total effect of an increase in the Hawaiian/Pacific Islander population on the odds of default ($p = 0.255$).

I perform similar analysis regarding mixed race communities, given that the coefficient of $POST_t \times CO\_TWORACE_{kt}$, -24.95, is statistically significant ($p = 0.024$). This coefficient suggests that an increase in the mixed-race population in a county after the crisis decreased the log odds of default by 24.95 relative to before the crisis. However, the coefficient of $CO\_TWORACE_{kt}$ is not significant, indicating that I cannot draw conclusions as to the total effect of an increase in the mixed-race population on the log odds of default in a county or discrimination against mixed-race populations in either period ($p = 0.289$).

The fact that the coefficients of $POST_t$ interacted with CO_BLACK_{kt}, CO_AMIND_{kt}, CO_ASIAN_{kt} and CO_HISP_{kt} are not statistically significant imply that the relationships between the percentage of these races in a county and county-level default rates are not meaningfully different between the pre- and post-crisis periods.

I examine the coefficients of R_{kt} for the race variables whose interactions with $POST_t$ are not significant. I analyze these coefficients in light of the fact that I now directly control for the effect of the crisis on the relationship between county-level racial composition and default rates. Taking into account these interaction terms meaningfully changes several of the coefficients on the non-interaction race-related variables. The coefficient on CO_HISP_{kt}, for example, is now significant and equal to 5.880 ($p = 0.062$); in the estimate for equation (1), the coefficient of CO_HISP_{kt} was -0.336 and not at all statistically significant ($p = 0.930$). This implies that the estimate of equation (1) suffers from omitted variable bias, and the model was improved by including these interaction terms. This coefficient of CO_HISP_{kt} indicates that a one-unit increase in the percentage Hispanic population in a county increased the log odds of default by 5.880, implying that this community was not discriminated against at the point of loan underwriting during the sample period. The coefficient on CO_MISS_{kt} is highly statistically significant and equal to -14.85, compared to having little, if any, statistical significance in the results from equation (1) ($p < 0.001$ and $p = 0.108$, respectively). The negative sign of this coefficient suggests the existence of discrimination against individuals who do not report their race in loan applications.

In equation (1), the estimate reveals evidence of discrimination against Hawaiian/Pacific Islander communities. Via the estimate of equation (2) I find that an increase in the Hawaiian/Pacific Islander population in a county dramatically increases the probability of default in the county in the post-crisis period as compared to the pre-crisis period. However, this change between the pre- and post-crisis periods does not inform the total effect of an increase in Hawaiian/Pacific Islander population on default rates. Therefore, I cannot conclude via equation (2) whether post-crisis origination worked to eliminate discrimination (if this population were discriminated against in the pre-crisis period) or exacerbate discrepancies between the default rates of Hawaiian/Pacific Islander and White populations (if Hawaiian/Pacific Islander populations were previously defaulting at higher rates than White populations).

I conclude that increases in mixed-race populations in a county decreased the probability of default in the post-crisis period as compared to the pre-crisis period. However, similar to Hawaiian/Pacific Islander populations, I cannot conclude whether this change brought default rates of mixed-race populations in line with those of White populations or exacerbated the difference between them. Finally, the estimate of equation (2) allows the confirmation of a lack of discrimination against Hispanic populations in the sample according to this methodology and the existence of discrimination against individuals who do not report their race in loan applications.

<u>Equation (3): Equation (2) + controls for County CRA-Eligibility Indicator</u>

I now begin the discussion of results relating to the Community Reinvestment Act. In this third specification, I build on the second specification by adding an indicator variable for CRA-eligibility, CRA_{kt}, to the set of explanatory variables. Coefficients for this specification are shown in Table 5.

Taken alone, these results indicate that county CRA-eligibility did not significantly impact county-level default rates, as specified by the fact that the coefficient on the indicator for CRA-eligibility is not at all significant ($p = 0.648$). In order to fully understand the effects of CRA-eligibility on race-based discrimination, I build a fourth model, including interactions between the CRA indicator variable and the vector of race-related variables.

Equation (4): Equation (3) + controls for County CRA-Eligibility Indicator interactions with Race Vector

This fourth specification includes all of the explanatory variables in equation (3) but adds a series of interaction terms created by interacting CRA_{kt} with each race in vector R_{kt}. In this model I look to the coefficients on the interaction terms of $CRA_{kt} \times R_{kt}$ to test if the relationship between racial composition of a county and the odds of default in that county differs in counties that are CRA-eligible in a given year versus not CRA-eligible. I also examine the coefficients of $POST_t \times R_{kt}$ to learn whether the relationship between racial composition and default rates changes before versus after the crisis, now that I account for more specific effects of the CRA.

Considering the interaction terms of $CRA_{kt} \times R_{kt}$, the coefficient of $CRA_{kt} \times CO\_BLACK_{kt}$ is significant with value 2.131 ($p = 0.009$). Thus, only conclusions regarding the default rates of African American/Black communities can be refined in this specification. The significance of this interaction term suggests that CRA-eligibility impacts the relationship between the percentage Black residents and the log odds of loan default in a county. Specifically, the effect of a one-unit increase in the percentage of Black residents on the log odds of default in a county is 2.131 units larger in CRA-eligible counties than in not CRA-eligible counties. The coefficients of CRA_{kt} and CO_BLACK_{kt} are not significant, suggesting that the impact on the odds of default is concentrated in Black communities located in CRA-eligible areas ($p = 0.513$ and 0.149, respectively). Moreover, the insignificance of the coefficient of $POST_t \times CO\_BLACK_{kt}$ indicates that the relationship between the percentage Black population in a county and the odds of loan default in that county does not change before relative to after the crisis ($p = 0.266$).

The conclusions from equation (2) regarding the Hawaiian/Pacific Islander and mixed race communities still hold in this specification, as $POST_t \times CO\_HPI_{kt}$ and $POST_t \times CO\_TWORACE_{kt}$ maintain their significance and coefficient values.

Equation (5): Equation (4) + controls for Post-Crisis Origination Indicator interaction with CRA-Eligibility Indicator + controls for three-way interactions between Post-Crisis Origination Indicator, CRA-Eligibility Indicator and Race Vector

Finally, I conclude the analysis of the impact of the CRA on racial discrimination by adding a final term, $CRA_{kt} \times POST_t \times R_{kt}$, to the specification (an interaction term between CRA_{kt} and $POST_t$ is also added to account for all of the bilateral interactions encompassed by this three-way interaction term). The inclusion of these three-way interaction terms allows for refinement of the results as it controls directly for the combined effect of post-crisis origination and CRA-eligibility.[28] The coefficients on these terms, included in vector β_{11}, are significant for three races: American Indian/Alaska Native, Asian and mixed-race groups ($p = 0.052$, 0.055 and 0.021, respectively). Knowing this, I use the associated coefficients in vectors β_5, β_7, β_9 and β_{11} to understand racial discrimination against each of these races one at a time.

I begin with the variables relating to the percentage American Indian/Alaska Native individuals residing in a county. The coefficient of CO_AMIND_{kt} alone, $\beta_{5,AMIND}$, in equation (5) is 59.78; the coefficient of $CO\_AMIND_{kt} \times POST_t$, $\beta_{7,AMIND}$, is -14.28; the coefficient of $CO\_AMIND_{kt} \times CRA_{kt}$, $\beta_{9,AMIND}$, is -15.29 and the coefficient on the three-way interaction

[28] As a sense check to our estimate of equation (5), I take the sum $\beta_5 + \beta_7 + \beta_9 + \beta_{11}$ for each race in equation (5) and compare these totals to the sum $\beta_5 + \beta_7 + \beta_9$ for each race in equation (4). For each race, these sums are approximately equal. This confirms that equation (4) and equation (5) fundamentally measure the same effects—of post-crisis origination and CRA-eligibility on the relationship between county racial composition and default rates—as intended. Equation (5) is an improvement of equation (4) because it controls for the combined effect of these two conditions, allowing the potential for more significance in the results.

term, $\beta_{11,AMIND}$, is equal to 16.91 ($p = 0.006$, 0.068, 0.042 and 0.052, respectively). In order to understand the implications of these coefficients, I must consider them in various combinations. I number these combinations below to make interpretation as clear as possible.

1. Pre-crisis, not CRA-eligible: First, I look to the coefficient of CO_AMIND_{kt} alone, 59.78. This coefficient indicates that in pre-crisis county-years that are not CRA-eligible, a one-unit increase in percentage American Indian/Alaska Native residents in a county increases the log odds of loan default by 59.78.
2. Post-crisis, not CRA-eligible: Next, I consider the sum of $\beta_{5,AMIND}$ and $\beta_{7,AMIND}$, which is equal to 45.50. This indicates that in county-years that are post-crisis but not CRA-eligible, a one-unit increase in percentage American Indian/Alaska Native population causes the log odds of default to increase by 45.50 in a county. This increase is not as large as in pre-crisis, not CRA-eligible county-years, which suggests that after the crisis, banks lent to American Indian/Alaska Native communities more fairly relative to White communities than they had before the crisis in counties that were not CRA-eligible.
3. Pre-crisis, CRA-eligible: The sum of $\beta_{5,AMIND}$ and $\beta_{9,AMIND}$ is equal to 44.49. This suggests that in county-years that are pre-crisis and CRA-eligible, the increase in log odds of default caused by a one-unit increase in percentage American Indian/Alaska Native county population, 44.49, is smaller than in pre-crisis, not CRA-eligible county-years. Thus, in the pre-crisis period, loans were distributed more fairly among American Indian/Alaska Native and White borrowers in CRA-eligible communities than in not CRA-eligible communities.
4. Post-crisis, CRA-eligible: Finally, I consider the sum of $\beta_{5,AMIND}$, $\beta_{7,AMIND}$, $\beta_{9,AMIND}$ and $\beta_{11,AMIND}$, which equals 47.12. This sum indicates that in county-years that are post-crisis

and CRA-eligible, the increase in the log odds of default associated with a one-unit increase in percentage American Indian/Alaska Native population in a county is larger than that of county-years that are post-crisis and not CRA-eligible.

According to this analysis, the CRA seems to improve fairness in lending to American Indian/Alaska Native communities relative to White communities before the crisis but is counterproductive after the crisis. It is important to note that none of the values in the above four categories are negative, and therefore this analysis does not serve as evidence for discrimination against American Indian/Alaska Native communities at the point of loan underwriting during the sample period.

I execute this process again to understand racial discrimination against Asian communities. The coefficients $\beta_{5,Asian}$, $\beta_{7,Asian}$, $\beta_{9,Asian}$ and $\beta_{11,Asian}$ are 10.21 ($p = 0.084$), -8.319 ($p = 0.022$), -10.31 ($p = 0.004$) and 9.085 ($p = 0.055$) respectively. These coefficients suggest that in pre- and post-crisis, not CRA-eligible county-years, Asian communities witnessed higher odds of default relative to White communities. In both pre- and post-crisis, CRA-eligible county-years, Asian and White communities defaulted at approximately the same rates. Thus, it appears that CRA-eligibility has brought upon fairer lending to Asian communities as compared to White communities, although according to this analysis, Asian communities were not discriminated against to begin with at the point of loan underwriting.

I carry out a similar analysis for mixed-race communities. The coefficients on mixed-race related variables are -24.40 ($p = 0.362$), 36.53 ($p = 0.092$), 46.42 ($p = 0.054$) and -61.19 ($p = 0.021$) for $\beta_{5,TWORACE}$, $\beta_{7,TWORACE}$, $\beta_{9,TWORACE}$ and $\beta_{11,TWORACE}$ respectively. Because $\beta_{5,TWORACE}$ is not significant, I cannot conclude whether mixed-race populations were discriminated against in pre-crisis, not CRA-eligible county-years. Therefore, conclusions can only be drawn regarding changes in the log odds of default between the pre- and post-crisis periods and between CRA-eligible counties and not CRA-eligible counties. As evidenced by the positive value of $\beta_{7,TWORACE}$, a one-unit increase in the mixed-race population in a county increased the log odds of default in the post-crisis period relative to the pre-crisis period by 36.53. Similarly, the value of $\beta_{9,TWORACE}$ suggests that a one-unit increase in the percentage of mixed-race population in a county increased the log odds of loan default by 46.42 in CRA-eligible counties relative to not CRA-eligible counties. The value of $\beta_{11,TWORACE}$ suggests that considering the combined effect of post-crisis origination and CRA-eligibility, a one-unit increase in the percentage mixed-race population in a county decreased the log odds of default by 61.19.

Also of note in the estimate of equation (5) is increased significance in several of the two-way interaction terms. This implies an improvement in the model in equation (5) by adding terms that previously may have been a source of omitted variable bias. For example, though the coefficient of the three-way interaction term $POST_t \times CRA_{kt} \times CO\_BLACK_{kt}$ is not statistically significant ($p = 0.309$), the results from equation (5) indicate that the coefficients of $CRA_{kt} \times CO\_BLACK_{kt}$ and $POST_t \times CO\_BLACK_{kt}$ are significant ($p = 0.012$ and 0.033, respectively). The positive values of these two coefficients suggest that the log odds of default in Black communities increased in the post-crisis period relative to the pre-crisis period and in CRA-eligible counties relative to not CRA-eligible counties.

Taking the results from equation (5) in sum, I draw a few central conclusions. After controlling for several combinations of interactions between CRA_{kt}, $POST_t$ and the race-related variables, I refine my conclusions about the existence of racial discrimination in this sample of mortgage loans for the final time. For several racial groups, I have documented changes in default rates between the pre- and post-crisis periods as well as between counties containing CRA-eligible census tracts and those containing none. However, these changes are not consistent across racial groups. According to this methodology, the CRA seems to be effective in eliminating default rate discrepancies between Asian and White communities but exaggerates differences in default probabilities between American Indian/Alaska Native and White communities after the crisis. Neither of these cases confirms evidence of the CRA alleviating discrimination against a racial group. Estimates of both equations (4) and (5) indicate that CRA-eligibility increases the odds of loan default in Black communities, but this does not yield conclusions regarding discrimination against Black communities. Overall, via the analysis outlined in this paper, I cannot come to a definitive conclusion regarding the effect of the CRA on racial discrimination.

It does appear that post-crisis origination tends to bring the odds of default across racial minorities more in line with White borrowers, since magnitudes of logit coefficients describing the log odds of default between minority relative to White borrowers tend to shrink when considering the effect of post-crisis origination. Though this effect occasionally results in some discrimination against minority communities, this overall trend may suggest that tighter regulation after the crisis led to a more equitable distribution of loans across racial groups.

Section 6: Conclusion

In this paper I set out to learn about racial discrimination in the mortgage market by evaluating loan performance in a sample of 19 million Fannie Mae loans. While including several loan-level characteristics as factors of loan performance in the analysis, I specifically focus on evaluating the effects of post-crisis origination and the Community Reinvestment Act on loan default. The results yield conclusions regarding borrower, loan and property characteristics in line with what I expect.

Given the variety of results regarding racial discrimination obtained by estimating five specifications, the conclusions about discrimination are not clear-cut. However, various estimates indicate lower odds of default for Hawaiian/Pacific Islander populations relative to White populations when controlling for loan-level characteristics, suggesting this population was not treated fairly by mortgage lenders. In addition, the results indicate that post-crisis origination generally worked to alleviate large disparities in the log odds of default between minority and White communities. However, the convergence of these magnitudes did not consistently provide evidence for the elimination of discrimination against minority groups.

I hoped the data would speak clearly to the impact of the CRA on loan performance and perhaps the differential impact of the CRA before and after the financial crisis. I find mixed evidence regarding the impact of the CRA on the default rates of minority populations. Given the intention of the CRA to encourage fair lending, I expected the presence of CRA-eligibility in a county to eliminate existing racial discrimination by raising default rates in minority communities until they were equal to those in White communities. However, this did not play out precisely for any of the racial groups included in this analysis. In some cases, particularly for Asian communities who previously were defaulting at higher rates than White communities, CRA-eligibility helped bring the log odds of default in Asian communities in line with the log odds of default in White communities. In another example, CRA-eligibility in the post-crisis period seemed to overcorrect for potential racial discrimination against American Indian/Alaska Native populations, resulting in much higher default rates in these communities relative to White communities. I find evidence in two of the estimates that CRA-eligibility increased the odds of default in Black communities relative to White communities but cannot conclude whether this impact worked to eliminate discrimination or exacerbate higher odds of default in Black communities relative to White communities.

It is crucial to recognize that my analyses only provide insight into racial discrimination at the point of loan underwriting in the mortgage market. Thus, my conclusions do not extend to the many other phases of loan advertisement, application and extension that could be subject to various forms of racial discrimination. Moreover, it is important to acknowledge the limitations of my analyses. Though I included as many control variables as were available, it is likely that the analyses suffer from some degree of omitted variable bias, since I do not know exactly which variables lenders consider when choosing to accept or reject a loan application. Uncertainty may also arise from my matching of geographies between the Fannie Mae and FFIEC datasets. Since the loan-level Fannie Mae dataset does not include the county in which a loan was originated, I imputed this information based on the assumption that a loan extended in a three-digit zip code belonged to the largest county in that three-digit zip code. This assumption may have distorted the results. A potential robustness check for my results would be to test whether they hold up for alternate definitions of loan default.

A central limitation of my analysis arose from the unavailability of a public, loan-level dataset including variables describing borrower, loan and property characteristics, loan performance *and* loan-level race. Future implementations of default methodology would heavily benefit if such a dataset were made available. Because I accounted for race at the county-level instead of the loan-level, I did not achieve significance in the majority of the race-related variables (despite 19 million loan-level observations, only about 1,000 counties were represented in the dataset). Loan-level race data would alleviate this issue and likely yield more significant results regarding discrimination.

One broad implication to draw from this study is the potential benefit of including a framework in CRA examinations to specifically evaluate whether communities with higher proportions of minority populations are treated fairly by mortgage lenders. According to my understanding of the current implementation of the CRA, CRA exams focus on metrics of financial stability and security in order to label census tracts as CRA-eligible. However, one of the stated goals of the CRA is to prohibit redlining.[29] It is not clear whether racial differences in census tracts are explicitly considered when evaluating fairness in the mortgage market via the CRA. Further research would be useful to understand in what way racial discrimination could be more thoroughly accounted for in CRA regulation.

While there currently exists a developed literature studying discrimination in the mortgage market, research in this area remains as important as 40 years ago when the CRA was put into place. Just recently, concerns about changes to the enforcement of civil rights laws prompted critics to argue that the pursuit of fairness in mortgage lending may be in jeopardy.[30] Recent weakening of this federal enforcement highlights the importance and urgency of research surrounding discrimination.[31] This paper contributes to the effort of identifying discrimination so that it can be addressed by those who manage policy and regulation.

[29] As described on the website of the Office of the Comptroller for the Currency, the definition of redlining applicable with regard to the CRA is “denying or increasing the cost of banking to residents of racially defined neighborhoods”. See Office of the Comptroller for the Currency (2018).
[30] The New York Times Editorial Board (2018).
[31] The U.S. Commission on Civil Rights (2017).

TABLE 1
Variable Definitions

Borrower Characteristics	
FTHB_FLG	1 if borrower is a first-time home buyer, 0 otherwise
CSCORE620_639	1 if minimum FICO score among co-borrowers is between 620 and 639, 0 otherwise
CSCORE640_659	1 if minimum FICO score among co-borrowers is between 640 and 659, 0 otherwise
...	
CSCORE820-839	1 if minimum FICO score among co-borrowers is between 820 and 839, 0 otherwise
*CSCORE840_*	1 if minimum FICO score among co-borrowers is above 840, 0 otherwise
DTI	Borrower's debt-to-income ratio
NUM_BO	Number of borrowers associated with the mortgage loan
Loan Characteristics	
OLTV50_54	1 if original loan-to-value ratio is between 0.50 and 0.54, 0 otherwise
OLTV55_59	1 if original loan-to-value ratio is between 0.55 and 0.59, 0 otherwise
...	
OLTV90_94	1 if original loan-to-value ratio is between 0.90 and 0.94, 0 otherwise
OLTV95_99	1 if original loan-to-value ratio is between 0.95 and 0.99, 0 otherwise
INVEST_FLG	1 if investment property, 0 otherwise
REFIN_FLG	1 if loan is a refinance, 0 otherwise
ORIG_VAL	Original home value
ORIG_RT	Original interest rate
ORIG_AMT	Original unpaid principal balance
ORIG_TRM	Original loan term
LAST_RT	Most recent interest rate
Property Characteristics	
CONDO_FLG	1 if property is a condominium, 0 otherwise
NUM_UNIT	Number of units, 1-4
Census Data	
CO_BLACK	Percentage of county population that is Black/African American
CO_AMIND	American Indian/Alaska Native percentage of county population
CO_ASAIN	Asian percentage of county population
CO_HPI	Percentage of county population that is Native Hawaiian and Other Pacific Islander
CO_MISS	Percentage of county population with race or ethnicity unknown
CO_TWORACE	Percentage of county population that is mixed race of two races
CO_HISP	Percentage of county population that is of Hispanic ethnicity
CO_HOUSEINC	Household median income within the county
CO_RENTRATE	Percentage of housing units in the county that are rental
CO_HOUSEAGE	Median house age, in years, within the county
CO_MED_HVAL	Median house value within the county
CO_URBAN	1 if property is located in an urban county, 0 otherwise
CRA-Related Data	
CRA_FLG	1 if at least one census tract in the county is CRA-eligible
Loan Performance	
DEFAULT_FLG	1 if borrower defaults on the loan, 0 otherwise

TABLE 2

Means and Standard Deviations of Explanatory Variables

	2006-2016		2006-2008		2009-2016	
	Means	S.D.	Means	S.D.	Means	S.D.
Borrower Characteristics						
FTHB_FLG	0.13	0.33	0.11	0.31	0.13	0.34
CSCORE	751.11	48.67	725.01	58.62	757.53	43.56
DTI	33.28	10.68	37.71	12.52	32.23	9.91
NUM_BO	1.56	0.51	1.55	0.51	1.57	0.51
Loan Characteristics						
OLTV	70.07	17.36	70.60	17.10	69.93	17.43
INVEST_FLG	0.08	0.27	0.08	0.28	0.08	0.27
REFIN_FLG	0.63	0.48	0.61	0.49	0.63	0.48
ORIG_VAL_LOG	12.53	0.63	12.43	0.60	12.55	0.63
ORIG_RT	4.57	1.05	6.24	0.52	4.16	0.67
ORIG_AMT_LOG	12.13	0.59	12.05	0.58	12.15	0.59
ORIG_TRM	309.98	81.49	329.69	66.39	305.13	84.08
LAST_RT	4.55	1.04	6.11	0.76	4.16	0.67
Property Characteristics						
CONDO_FLG	0.09	0.28	0.09	0.29	0.08	0.28
NUM_UNIT	1.03	0.23	1.04	0.24	1.03	0.23
Census Data						
CO_BLACK	0.13	0.12	0.13	0.12	0.13	0.11
CO_AMIND	0.01	0.01	0.01	0.02	0.01	0.01
CO_ASIAN	0.06	0.07	0.04	0.05	0.06	0.07
CO_HPI	0.00	0.01	0.00	0.01	0.00	0.01
CO_MISS	0.07	0.06	0.05	0.06	0.07	0.06
CO_TWORACE	0.03	0.02	0.03	0.02	0.03	0.02
CO_HISP	0.16	0.15	0.13	0.13	0.16	0.15
CO_RENTRATE	0.36	0.09	0.35	0.09	0.36	0.09
CO_HOUSEINC	10.84	0.22	10.71	0.18	10.87	0.22
CO_HOUSEAGE	34.37	10.12	30.99	9.07	35.20	10.19
CO_MED_HVAL	12.15	0.56	11.81	0.40	12.23	0.56
CO_URBAN	0.59	0.33	0.64	0.25	0.58	0.34
CRA-Related Data						
CRA_FLG	0.98	0.13	0.97	0.16	0.99	0.12
Loan Performance						
DEFAULT_FLG	0.02	0.15	0.08	0.27	0.01	0.09
No. of Observations	*19,381,385*		*3,825,084*		*15,556,301*	

Source: Fannie Mae Single-Family Loan Performance Data and demographic files for use with CRA by the Federal Financial Institutions Examination Council from 2006-2016.

TABLE 3
Logit Estimates of Equation 1

Borrower Characteristics		Loan Characteristics		Property Characteristics	
FTHB_FLG	-0.0312***	OLTV50_54	0.187***	CONDO_FLG	0.0802
	(0.00784)		(0.0224)		(0.0578)
CSCORE620_639	-0.0557***	OLTV55_59	0.308***	NUM_UNIT	0.177***
	(0.00985)		(0.0213)		(0.0277)
CSCORE640_659	-0.204***	OLTV60_64	0.417***		
	(0.0158)		(0.0363)	Census Data	
CSCORE660_679	-0.408***	OLTV65_69	0.543***	CO_BLACK	1.126
	(0.0205)		(0.0427)		(2.388)
CSCORE680_699	-0.660***	OLTV70_74	0.697***	CO_AMIND	40.34*
	(0.0293)		(0.0504)		(20.73)
CSCORE700_719	-0.881***	OLTV75_79	0.779***	CO_ASIAN	-3.117
	(0.0375)		(0.0536)		(3.127)
CSCORE720_739	-1.106***	OLTV80_84	0.941***	CO_HPI	-104.5*
	(0.0481)		(0.0568)		(48.54)
CSCORE740_759	-1.374***	OLTV85_89	1.159***	CO_MISS	-6.892
	(0.0602)		(0.0589)		(4.284)
CSCORE760_779	-1.686***	OLTV90_94	1.277***	CO_TWORACE	16.38
	(0.0599)		(0.0592)		(12.56)
CSCORE780_799	-2.034***	OLTV95_99	1.435***	CO_HISP	-0.336
	(0.0715)		(0.0642)		(3.804)
CSCORE800_819	-2.215***	INVEST_FLG	0.343***	CO_RENTRATE	-4.033
	(0.0652)		(0.0483)		(3.228)
CSCORE820_839	-2.123***	REFIN_FLG	0.617***	CO_HOUSEINC	3.780**
	(0.0783)		(0.0247)		(1.904)
CSCORE840_	-0.361***	ORIG_VAL	-0.847***	CO_HOUSEAGE	0.0485
	(0.129)		(0.0918)		(0.0327)
DTI	0.0163***	ORIG_RT	0.711***	CO_MED_HVAL	-2.188***
	(0.000983)		(0.0424)		(0.683)
NUM_BO	-0.591***	ORIG_AMT	0.652***	CO_URBAN	0.0453
	(0.0208)		(0.132)		(0.0944)
		ORIG_TRM	0.00284***		
			(0.000125)		
		LAST_RT	-0.321***		
			(0.0515)		
		POST	-0.782***		
			(0.183)		
No. of Observations					*19,156,828*

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 4

Logit Estimates of Equation 2

CO_BLACK	-2.236
	(2.978)
CO_AMIND	44.58**
	(19.66)
CO_ASIAN	-0.518
	(5.684)
CO_HPI	-52.22
	(45.85)
CO_MISS	-14.85***
	(4.081)
CO_TWORACE	22.02
	(20.77)
CO_HISP	5.880*
	(3.154)
POST	-0.201
	(0.175)
POST * CO_BLACK	0.462
	(0.410)
POST * CO_AMIND	2.779
	(2.904)
POST * CO_ASIAN	0.851
	(2.308)
POST * CO_HPI	39.09*
	(22.29)
POST * CO_MISS	0.423
	(1.472)
POST * CO_TWORACE	-24.95**
	(11.06)
POST * CO_HISP	-1.018
	(0.987)
No. of Observations	*19,156,828*

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE 5

Logit Estimates of Equation 3

CO_BLACK	-2.239
	(2.979)
CO_AMIND	44.41**
	(19.66)
CO_ASIAN	-0.538
	(5.690)
CO_HPI	-51.84
	(46.16)
CO_MISS	-14.89***
	(4.100)
CO_TWORACE	22.04
	(20.78)
CO_HISP	5.879*
	(3.155)
POST	-0.202
	(0.176)
POST * CO_BLACK	0.464
	(0.412)
POST * CO_AMIND	2.780
	(2.903)
POST * CO_ASIAN	0.841
	(2.306)
POST * CO_HPI	39.04*
	(22.31)
POST * CO_MISS	0.431
	(1.473)
POST * CO_TWORACE	-24.90**
	(11.09)
POST * CO_HISP	-1.021
	(0.988)
CRA_ FLG	0.0421
	(0.0922)
No. of Observations	*19,156,828*

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE 6
Logit Estimates of Equation 4

	__	POST * __	CRA _FLG * __
CO_BLACK	-4.469	0.462	2.131***
	(3.097)	(0.415)	(0.813)
CO_AMIND	35.77*	2.755	8.918
	(21.70)	(2.895)	(6.674)
CO_ASIAN	-0.646	0.858	0.230
	(6.367)	(2.320)	(2.148)
CO_HPI	-121.8	38.96*	70.04
	(151.3)	(22.35)	(152.9)
CO_MISS	-5.682	0.414	-9.224
	(7.332)	(1.481)	(7.169)
CO_TWORACE	44.32	-24.89**	-22.41
	(29.58)	(11.12)	(20.38)
CO_HISP	2.011	-1.021	3.970
	(3.321)	(0.990)	(2.909)
POST	-0.202		
	(0.176)		
CRA_ FLG	0.177		
	(0.270)		
No. of Observations			*19,156,828*

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 7
Logit Estimates of Equation 5

	__	POST * __	CRA_FLG * __	POST * CRA_FLG * __
CO_BLACK	-4.767	1.361**	2.481**	-0.861
	(3.006)	(0.637)	(0.992)	(0.846)
CO_AMIND	59.78***	-14.28*	-15.29**	16.91*
	(21.64)	(7.823)	(7.514)	(8.701)
CO_ASIAN	10.21*	-8.319**	-10.31***	9.085*
	(5.911)	(3.634)	(3.579)	(4.736)
CO_HPI	34.16	-130.6	-86.99	169.9
	(197.8)	(161.8)	(188.7)	(166.6)
CO_MISS	-3.276	-2.602	-11.70	3.084
	(10.71)	(7.408)	(10.44)	(7.418)
CO_TWORACE	-24.40	36.53*	46.42*	-61.19**
	(26.78)	(21.71)	(24.07)	(26.50)
CO_HISP	0.102	0.503	5.856	-1.522
	(4.344)	(3.503)	(4.181)	(3.456)
POST	-0.403**			
	(0.178)			
CRA_FLG	-0.248	0.183		
	(0.309)	(0.276)		
No. of Observations				*19,156,828*

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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