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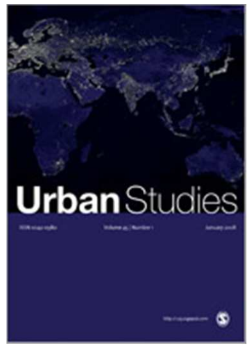
Nolan Kopkin
University of Wisconsin - Milwaukee, kopkin@uwm.edu



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Abstract
Many studies have shown the existence of disparities in loan denial rates between blacks and whites that cannot be accounted for by observable applicant characteristics. Examining the link between racial gaps in home loan denial rates and prejudicial attitudes toward blacks measured by questions in the General Social Survey, this article shows that blacks are not only more likely to be denied conventional home mortgages but that denial rates among blacks for these loans are also geographically correlated with racial prejudice, particularly among first-lien home purchase loans and loans from depository lenders. However, among Federal Housing Administration-insured loans guaranteed by the government in the event of borrower default, this study finds no evidence of a statistical relationship between racial prejudice and loan denials among black applicants. Results are consistent with taste-based discrimination by discriminatory lenders, however one cannot rule out that statistical discrimination is at least partially driving the results.

Keywords: Housing, Race/Ethnicity, Real Estate, discrimination, home mortgages

Introduction

The 2008 financial crisis left many homes foreclosed on or abandoned and threatened a total collapse of the U.S. mortgage market. From 2006-2010 the fraction of properties foreclosed on nearly quadrupled and hundreds of lending institutions went bankrupt or were acquired (RealtyTrac Staff, 2011). In the wake of the crisis, lenders have been increasingly selective. Many require higher credit scores and larger down payments for conventional mortgages and it is more difficult to refinance one's home or adjust an existing mortgage (Appelbaum, 2012; Palmer, n.d.). The Urban Institute estimates that lenders forwent 6.3 million mortgage loans from 2009-2015 that would have been provided under more ordinary lending circumstances (Goodman et al., 2016b).

In the current lending environment discrimination may make it even more difficult for minorities to secure home financing. However, there is debate about the existence of lender discrimination in the mortgage market since it is unclear whether higher denial rates for minorities are driven by market forces or taste-based discrimination. Additionally, the majority of past studies finding disparities in denial rates between whites and minorities omit important explanatory variables such as credit history, wealth, and debt burden that may be important in the lending decision (Black et al., 1978; King, 1980; Schafer and Ladd, 1981; Maddala and Trost, 1982; Canner and Gabriel, 1992). Since minorities have more undesirable credit histories and less wealth than whites on average, failure to control for these variables has resulted in stronger estimated relationships between denial rates and applicant race (Munnell et al., 1996).

This article focuses on the spatial relationship between black-white mortgage denial rate disparities and an index measuring racial prejudice toward blacks. The analysis shows racial denial rate disparities in the conventional market are largest in counties where racial prejudice is greatest conditional on observable individual- and county-level characteristics including county-level differences in wealth and creditworthiness. It may be difficult to interpret these conditional correlations as proof of discrimination since racial prejudice is not randomly assigned and important individual-level characteristics such as wealth and credit history are unobserved. However, this study contributes to the literature by providing the first empirical evidence that mortgage denial disparities are spatially correlated with racial prejudice conditional on all individual- and county-level characteristics that can be observed.

Discussion and Related Literature

Central to the study of lender discrimination in the mortgage market is the difference between statistical and taste-based discrimination. Statistical discrimination is driven by profit-seeking, possibly unprejudiced, lenders who use race to proxy for the unobservable characteristics of a group (Arrow, 1973). On the other hand, taste-based discrimination is prejudicial in nature and should result in lower profits for lenders who engage in it (Becker, 1957). The finding that denial rates are higher for blacks than for whites could be consistent with statistical discrimination if loans to blacks are riskier.

Previous studies have found evidence of discrimination in the mortgage market by studying differences in denial rates between blacks and whites (Black et al., 1978; King, 1980; Schafer and Ladd, 1981; Maddala and Trost, 1982; Canner and Gabriel, 1992; Munnell et al., 1996). However, these studies are unable to determine whether differences in denial rates result from statistical or taste-based discrimination and most omit key determinants of loan denials.

In an effort to overcome limitations in Home Mortgage Disclosure Act (HMDA) data, namely the omission of variables such as applicant wealth and credit history, members of the Federal Reserve Bank of Boston collected additional information from mortgage applicants in the Boston area (Munnell et al. 1996). After controlling for these additional characteristics, Munnell et al. (1996) found that minority applicants continued to have higher denial probabilities than whites though inclusion of the additional characteristics substantially attenuated the gap. A number of other studies have used data from the Boston Fed Study in support of these findings (Carr and Megbolugbe, 1993; Browne and Tootel, 1995; Glennon and Stengel, 1995; Tootel, 1996).

Critics of the Boston Fed study argue that denial rate disparities between whites and minorities do not prove the existence of discrimination if loans to minorities are riskier (Becker, 1993; Brimelow, 1993; Brimelow and Spencer, 1993; Roberts, 1993); however, it is worth noting this would constitute statistical discrimination. Theoretically, if lenders use taste-based discrimination to set higher credit cutoffs for black applicants, then the marginal black borrower should be more creditworthy than the marginal white borrower. Using this justification, researchers have attempted to rule out discrimination in the lending market by showing that blacks have higher – not lower –default rates (Van Order et al., 1993; Berkovec et al., 1994, 1996). There are a couple major problems with these studies of loan performance: they (1) compare average, not marginal, black and white borrowers, and (2) fail to include factors such as credit history that may be negatively correlated with minority status and default rates. [1,2,3]

This study adds to the existing literature by providing the first evidence that blacks not only have higher conditional mortgage denial rates, but also that conventional loan denial disparities are geographically correlated with racial prejudice conditional on all individual- and county-level characteristics that can be observed.

Data

The data used in this study come primarily from the 1993-2008 General Social Survey (GSS) and 2009-2015 HMDA. Additionally, the study supplements these sources with data from the 2006-2010 American Community Survey (ACS) 5-year Estimates, 2008 Federal Reserve Economic Data (FRED), 2004 and 2008 Survey of Income and Program Participation (SIPP), 2010 Department of Housing and Urban Development's Neighborhood Stabilization Program (HUDNSP3), and 2010 Environmental Systems Research Institute (ESRI) Home Affordability Index. Due to data limitations, the analysis is limited to a 189 county sampling frame for which

[1] Other studies have found evidence of redlining in loan originations (Bradbury et al., 1989), loan rejections (Dedman, 1988), the types of creditors in the market (Avery and Buynak, 1981), and the types of loans used to finance home purchases (Gabriel and Rosenthal, 1991). However, studies controlling for applicant characteristics generally conclude that individuals in minority neighborhoods are no less likely to be granted loans (Bentson et al., 1978; Schafer and Ladd, 1981; Schill and Wachter, 1993) or use conventional financing when purchasing a home (Canner et al., 1991). Additionally, Tootel (1996) finds that lenders do not appear to be redlining neighborhoods based on racial composition or average income, but instead deny loans to minorities with a higher frequency regardless of neighborhood characteristics. However, Ross and Tootel (2004) conclude that lenders are withholding home loans from individuals in certain neighborhoods for those who do not purchase private mortgage insurance.

[2] More recently, Hansen et al. (2016) use a field experiment to show that lenders are less likely to respond to or send follow-up emails to inquiries from blacks – a response effect equivalent to having a credit score 71 points lower. In a follow-up they further show that blacks are more likely to obtain subprime loans when borrowing from lenders more responsive to them (Hansen et al., 2017).

[3] For a more extensive treatment of the housing market discrimination literature see Goering and Wienk (1996), Ladd (1998), and Ross and Yinger (2002).

county-level estimates pertaining to racial prejudice, racial demographic gaps, and state-level wealth gaps for metropolitan and nonmetropolitan areas could be estimated concurrently; more information is discussed below.[4] This 189 county sampling frame covers 41.4% of the U.S. population and 39.9% of housing units. The years for which data are used were selected to maximize the accuracy of the covariates while minimizing the extent of reverse causality whereby racial denial gaps could impact independent variables in the model.

GSS Sensitive Data Files

This study measures racial prejudice across counties using the GSS Sensitive Data Files consisting of responses to demographic, behavioral, and attitudinal questions for each individual and containing county-level geographic identifiers.[5] In each year, the survey contains an independently drawn sample of roughly 2,000-3,000 English or Spanish speaking persons 18 years of age or over living in non-institutional arrangements within the U.S. GSS data are designed to be representative at the primary sampling unit (PSU) level, with each PSU being either a metropolitan area consisting of one or more counties or a single nonmetropolitan county (NORC, 2017).[6] In order to measure prejudicial attitudes across counties survey results from 1993-2008 are pooled, as representativeness should improve by pooling additional years of the

[4] There are 224 counties in the GSS consisting of at least 25 sampled white individuals. Of these 224 counties, there are 23 where racial demographic gaps in the ACS cannot be estimated, 10 where racial wealth gaps from SIPP cannot be estimated, and 2 where conditional denial gaps from HMDA cannot be estimated.

[5] Some of the data used in this analysis are derived from Sensitive Data Files of the GSS, obtained under special contractual arrangements designed to protect the anonymity of respondents. These are restricted-access data files maintained by the National Opinion Research Center at the University of Chicago. These data are not available from the author. Persons interested in obtaining GSS Sensitive Data Files should contact the GSS at GSS@NORC.org.

[6] Segments within PSUs are first sorted with regard to state, place, percent minority, census tract, and whether they fall within the central city, and then sampled proportional to the number of housing units contained within (NORC, 2017).

GSS due to the addition of decade-specific sampling frames and more individual observations each year (NORC, 2017).[7]

The GSS asks many questions focused on determining white individuals' attitudes toward blacks. However, many questions include components not directly related to racial prejudice, such as feelings about government assistance for blacks or affirmative action. Including only questions that one-dimensionally focus on attitudes toward blacks, a racial prejudice index is compiled for each white individual. The study then estimates the average prejudice of whites towards blacks in each county by estimating the pooled average of the racial prejudice index across the 1993-2008 surveys. The analysis is limited to counties where at least 25 white respondents are sampled from 1993-2008 in order to exclude counties where average white prejudice cannot be accurately estimated. Similar indices have been used to show that taste-based racial prejudice is conditionally correlated with wages (Charles and Guryan, 2008) and business ownership (Kopkin, 2017). For more details on the calculation of the index used in this article, see the Supplemental Appendix.

HMDA Data

Given sufficient credit, a homebuyer generally has the option of financing a home purchase with either a conventional or FHA-insured loan.[8] Conventional loans are generally intended for homebuyers with decent credit and income and enough savings to support down payment requirements of 5%-20% of the purchase price. According to John Councilman, federal housing

[7] Due to data limitations, this study is only able to include census tracts from the 1993, 1994, and 1996 waves in the 1990s sampling frame that can be matched to primary sampling unit segments in the 1998-2004 waves since census tracts were unreported prior to 1998.

[8] Conventional and FHA-insured loans comprised 77.0% and 16.1% of the mortgage market from 2009-2015. The remaining 6.9% is comprised of Veterans Administration-guaranteed, Farm Service Agency, or Rural Housing Service-guaranteed loans available to individuals meeting specialized criteria.

chairman for the National Association of Mortgage Brokers, in the current climate only individuals with credit scores above 620 should expect to succeed in acquiring conventional mortgages and those with scores below 740 should expect to be charged exceptionally higher interest rates (Santiago, n.d.).

FHA-insured loans on the other hand are generally targeted at moderate to low income homebuyers who cannot meet credit score or down payment requirements for conventional loans. These loans are backed by the FHA in the event of borrower default but are granted by independent lenders. The FHA generally places lower credit score and down payment requirements on these loans than on comparable conventional loans though lenders may set higher requirements if they choose. Additionally, FHA-insured loans may sometimes offer lower interest rates than comparable conventional loans but include an annual mortgage insurance premium and an upfront fee (which may be financed into the loan) to pay for the FHA-provided mortgage insurance (Da Costa, 2011). According to Brian Gould, Chief Operating Officer for private mortgage insurance firm United Guaranty, “a conventional loan generally is less expensive” (Da Costa, 2013). However, an analysis by the Urban Institute shows FHA loans may be a lower-cost option than conventional loans with private mortgage insurance for individuals with minimal down payments and low credit scores (Goodman et al., 2016a). In the aftermath of the housing crisis subprime lending has largely ceased and FHA loans now account for a much larger fraction of home purchase and refinancing loans made to blacks, raising serious concerns about racial steering into FHA loans (Furman Center, 2010).

HMDA was enacted into U.S. law in 1975, requiring covered financial institutions to “maintain, report, and publically disclose” information pertaining to home mortgages (Consumer Financial Protection Bureau, 2017). These data were requested to help lenders better serve their communities' housing needs, aid policymakers, and help uncover discriminatory lending practices (Consumer Financial Protection Bureau, 2017). HMDA consists of data from all covered financial institutions in response to applications, originations, and purchases of home loans in each calendar year and contains over 112 million observations from 2009-2015. These data cover home purchase, refinancing, and home-improvement loans and include many applicant, loan, and property characteristics. These characteristics include the race, ethnicity, gender, and income of the applicant and co-applicant, the loan amount and type, information about the property and location (census tract identifiers), and the action taken by the financial institution. In HMDA, a loan application is either originated, approved but not accepted, denied by the financial institution, withdrawn by the applicant, or closed for incompleteness. This study defines a loan as approved if it is either originated or approved but not accepted and defines a loan as denied if it is denied by the lender; loan applications withdrawn by the applicant or closed for incompleteness are disregarded. This study includes in its primary analysis the 19.5 million observations within the 189 county sampling frame where the applicant and co-applicant are both either non-Hispanic black or non-Hispanic white of the same race.[9,10,11,12]

[9] While there are over 112 million loans in HMDA over this period, over 20 million of these were purchases by financial institutions on the secondary market, and over 14 million were either pre-approval requests, were closed due to incompleteness, or were withdrawn by the applicant; this leaves 77.9 million loans that were either approved or denied. Of these, 8.5 million were mail, telephone, or internet applications that do not contain race information. All in-house applications contain race information. If an applicant does not volunteer their race or ethnicity, the loan officer is supposed to make a determination on her own accord. Lenders failing to follow correct procedure may incorrectly list race, gender, or ethnicity as 'not applicable.' It is unclear what impact this may have on HMDA analysis. Of the 68.6 million loan applications including race and ethnicity, 55.7 million represent applicants who are non-Hispanic and either Black or White alone. An additional 1.3 million observations omit income because income is not required for multifamily units or when not considered in the loan decision. Of the remaining observations, 19.5 million are in the 189 county sampling frame.

[10] While there is information on preapproval requests denied or accepted, preapproval denial analysis is not possible because reporting for acceptances is optional.

[11] HMDA also provides information on loan purchases by financial institutions on the secondary market; this study does not make use of these observations.

[12] Because HMDA has been used in litigation resulting in the payment of fines, to avoid reporting loan denials to minorities there is incentive for lenders to dissuade less-qualified minority applicants from completing applications. Such behavior could understate conditional correlations between loan denial rates and racial prejudice if prospective

Panel A of Table 1 summarizes HMDA loan applications by race for the primary sample. It shows that 18.6% of loans applied for by whites were denied and 39.1% of loans applied for by blacks were denied; these rates compare with national denial rates of 19.8% and 39.9%. Additionally, the table shows white applicants apply for larger loans, have higher gross income, are less likely to be female, and are more likely to have co-applicants than blacks. Furthermore, the table shows blacks are more likely to apply for home purchase or home improvement loans and less likely to apply for refinancing loans than whites; blacks are also more likely to seek second mortgages and less likely to use conventional home financing.

Other Data

This study supplements the GSS and HMDA with county-level demographic data from the 2006-2010 ACS 5-year Estimates, 2008 county-level subprime credit data from FRED, state-level metropolitan and nonmetropolitan area wealth data from the SIPP 2004 Wave 6 and 2008 Wave 4, tract-based racial delinquency gap estimates from HUDNSP3, and the 2010 Home Affordability Index published by ESRI. From the 2006-2010 ACS, the study makes use of county-level data on the fraction of blacks and whites with at least a bachelor's degree, the fraction of blacks and whites unemployed, and the fraction of blacks and whites self-employed; it also makes use of the fraction of the population that is black and the population density in each county. Some counties consist of too few black observations for the ACS to publically disclose an estimate; for these counties the study is unable to compute racial demographic gaps.

The study includes data from FRED over the four quarters of 2008 on the percentage in each county with subprime credit. Unfortunately, race-specific data on the subprime credit population

minority applicants are observably similar to qualified white applicants and the behavior is correlated with racial prejudice.

in each county is unavailable. However, by including an interaction term between the percentage with subprime credit and the fraction black, the study is able to flexibly allow the conditional correlation between denial rates and the percentage with subprime credit to vary linearly with the fraction black in each county. Additionally, the study uses SIPP to uncover state-level metropolitan and nonmetropolitan area estimates of net assets per capita for blacks and whites. To do so, wave 6 of the 2004 SIPP (collected in late 2005 to early 2006) is merged with wave 4 of the 2008 SIPP (collected in early 2010); merging data from multiple samples helps ensure the aggregated sample is not biased. Unfortunately, the finest level of geography available in the SIPP is state within either metropolitan or nonmetropolitan areas. Because the SIPP does not contain more detailed geographic information, the analysis is forced to operate under the assumption that the average wealth gap is homogeneous across all metropolitan counties and across all nonmetropolitan counties within a state. While the assumption is not ideal this is the best available estimate of the racial wealth gap.

From HUDNSP3, the study estimates a tract-based county-level racial delinquency gap. To do so, it first determines the fraction of the race-specific county population living in each tract. Then, by assuming the average delinquency rate for each racial group in a tract is the same as the overall average delinquency rate in the tract, the study calculates a weighted average for each racial group over all tracts in each county. Therefore, the estimate of the racial gap provided in each county is the result of racial location differences within county and likely underestimates true differences in delinquency rates within county. However, this is the best available estimate of the race-specific county-level delinquency gap. Lastly, the study includes the 2010 Home Affordability Index published by ESRI. As a guide, the Supplemental Appendix lists the source of each variable used in the analysis in Table A1 and provides additional rationale for the use of the specific years of data chosen for analysis. Panels B and C of Table 1 provide county-level estimates of conditional black-white denial gaps and county-level covariates used in the analysis that follows.

Methodology

The aim of this study is to test whether racial denial disparities are geographically correlated with racial prejudice. Studies such as Munnell et al. (1996) show that disparities in loan denial rates between blacks and whites exist conditional on observable applicant, loan, property, and neighborhood characteristics. This study augments previous analysis by showing that conditional loan denial gaps are geographically correlated with racial prejudice controlling for observable county-level differences in creditworthiness, wealth, unemployment, education, and other demographic differences between blacks and whites.

In the first step of the analysis, the study estimates a separate regression for each county of whether a loan applicant is denied her loan on an indicator variable that takes a 1 if the applicant is black and a 0 otherwise. Each regression includes control variables for the applicant's income-to-loan ratio, the loan amount, the gender of the applicant and co-applicant, the property type, the purpose of loan, the loan type, information on occupancy and lien status, and census tract and lender fixed effects.[13] Additionally, each regression includes the ratio of the loan-to-median housing value using race-specific county-level ACS data on the median value of owner-occupied units. Formally, the study estimates the following regression for each county:

$$P\left(y_{iclpnt(j)} = 1\right) = f\begin{pmatrix} \varphi_0 + \varphi_{1j} Black_{i(j)} + \varphi_{2j}\mathbf{X}_{i(j)} + \varphi_{3j}\mathbf{W}_{c(j)} + \varphi_{4j}\mathbf{L}_{l(j)} \\ +\varphi_{5j}\mathbf{P}_{p(j)} + \sum \tau_{t(j)} + \sum \theta_{n(j)} + \sum \pi_{n(j)} + u_{iclpnt(j)} \end{pmatrix}, \qquad (1)$$

[13] Lender fixed effects can explain significant racial differences in loan denial rates (Munnell et al., 1996; Ross and Yinger, 2002) and loan pricing (Bayer et al., 2014; Bhutta and Ringo, 2014).

where y is equal to 1 if applicant i and co-applicant c who apply for loan l on property p in census tract n in year t in county j are denied the loan, $Black$ is an individual-specific indicator variable equal to 1 if applicant i in county j is black and equal to 0 if i is white, **X** is a vector of applicant characteristics including gender and the income-to-loan ratio, and **W** is a vector of co-applicant characteristics. Additionally, each regression includes **L**, a vector of loan characteristics, **P**, a vector of property characteristics, τ, year fixed effects, θ, census tract fixed effects, and π, lender fixed effects; u is an error term. When f is a linear function, φ is the county-specific black-white denial rate gap controlling for observable applicant, loan, and, property characteristics.

In the second step of the analysis, the study estimates a regression of county-level gaps in loan denials on the average prejudice of whites in each county. Specifically, the study estimates the following regression:

$$\widehat{\varphi_{1j}} = \delta_0 + \delta_1 Prej_j + \delta_2 \mathbf{Z}_j + v_j, \tag{2}$$

where $\hat{\varphi}$ is the estimated county-level loan denial gap between blacks and whites from estimation of equation (1), $Prej$ is the average prejudice of whites in county j, **Z** is a vector of county-level characteristics, and v is a county-level error term. The vector **Z** includes all variables shown in Panel C of Table 1 aside from the index of prejudicial attitudes labeled Avg. White Prejudice.

Identification of the coefficient δ_1 in equation (2) is based on the covariance between the county-level loan denial gap and the average prejudice of whites in those counties conditional on the county-specific characteristics in **Z**. $100\delta_1$ can be interpreted as the percentage point increase in the racial denial gap associated with a one standard deviation increase in the average prejudice of whites within a county. This estimate controls for all observable applicant, co-applicant, loan, property, lender, and census tract characteristics and those characteristics observable at the county level. Note that performing the analysis in two steps is equivalent to performing the analysis in a single step with county and census tract fixed effects, county-specific coefficients for each individual-level characteristic, and interactions between the black indicator variable and each county-level variable. However, by performing the estimation in two steps the study is able to more easily compute coefficient estimates from over 20 million HMDA observations, more accurately estimate standard errors that account for both county-level clustering and imprecision in the prejudice index, and display county-level coefficients with a more simplistic interpretation. For more information on two-stage feasible generalized least squares estimation, see Borjas (1982), Hanushek (1974), Lewis and Linzer (2005) and Leoni (2009).[14,15]

Results

In this section, the study first shows correlations between racial denial gaps and racial prejudice in the conventional and FHA loan markets conditional on observable applicant, property, and loan characteristics available in HMDA and county-level data from other sources. The study then extends this analysis to more segmented markets: conventional and FHA first-lien home purchase markets, conventional and FHA refinancing markets, and conventional lending from depository institutions and non-depository institutions regulated by HUD. Lastly, the study notes potential biases and provides suggestive evidence that these biases are unlikely driving the results based on an analysis of observable county-level characteristics.

[14] A non-linear binary model such as a logit or probit could be used to estimate equation (1), however the estimate of the coefficient δ_1 in equation (2) would be difficult to interpret. For ease of interpretation, this study uses a linear probability model to estimate equation (1).

[15] See the Supplemental Index for a note on the methodology used to estimate standard errors.

Column 1 of Table 2 shows estimates from the county-level regression of the conditional racial denial gap in the conventional market on the index of racial prejudice. A one standard deviation increase in average white prejudice is associated with a 1.07 percentage point increase in the racial denial gap that is statistically significant at the 5% level. Racial gaps in unemployment and self-employment are significantly correlated with the racial denial gap at the 1% level suggesting that a one percentage point increase in the black-white unemployment gap is associated with a 0.91 percentage point increase in the racial denial gap and a one percentage point increase in the black-white self-employment gap is associated with a 0.61 percentage point increase in the racial denial gap. Additionally, the racial denial gap is conditionally correlated with home affordability at the 0.1% level suggesting that the racial denial gap is greater in counties with more affordable housing. Supplemental Appendix Table A4 shows that the coefficient of interest in the conventional market specification shown is relatively robust to the inclusion or exclusion of controls for racial gaps in education, wealth, unemployment, delinquencies, etc., as the bivariate correlation remains relatively unchanged after the inclusion of the full set of controls.[16]

To understand the magnitude of the conditional correlation between the racial denial gap in the conventional market and racial prejudice, the analysis relates the coefficient estimate on racial prejudice in the conventional market to the difference in the average amount of racial prejudice and the average racial denial gap in the conventional market across quartiles of the county-level distribution of racial prejudice. This analysis shows that racial prejudice accounts

[16] The analysis excludes a measure of segregation as a county-level covariate because segregation may be endogenously determined if lenders in more racially prejudiced counties are more likely to deny loans from black applicants in largely-white census tracts. However, substantively similar conclusions can be drawn including the black-white dissimilarity index over census tracts, a widely used measure of segregation. For more details, see the Supplemental Appendix and Supplemental Appendix Table A5.

for 2.65 percentage points of the average racial denial gap difference in the conventional market (approximately 61% of the gap) between counties in the least and most prejudiced quartiles.

The estimate in column 1 of Table 2, showing the conditional correlation between racial prejudice and the racial denial gap in the conventional market, can be directly compared to the estimate in column 2 showing no statistical relationship between racial prejudice and the black-white denial gap in the FHA-insured market: the coefficient on average white prejudice in column 2 is less than one-fifth the size of the estimate in the conventional market and is statistically insignificant. If no relationship exists between the racial denial gap in the FHA market and racial prejudice it may be because greater government oversight in the FHA market makes it more costly for lenders to discriminate for fear of fair lending litigation. Additionally, because FHA-insured loans generally have more standardized terms than conventional loans it may be easier for government agencies to use HMDA to uncover evidence of discrimination at the bank level. However, this study finds a large albeit statistically insignificant relationship between the racial denial gap in the FHA first-lien home purchase market and racial prejudice. Therefore, it is unclear if there is actually no relationship in the FHA market or if there is simply not enough power to uncover the relationship.

Estimates in columns 3 and 4 show conditional correlations between racial prejudice and racial denial gaps in the conventional and FHA first-lien home purchase markets. The estimate of the conditional correlation between racial prejudice and the racial denial gap in the conventional first-lien home purchase market is somewhat more pronounced than the estimate in the conventional market as a whole and is statistically significant at the 5% level. The estimate in the FHA first-lien home purchase market, though statistically insignificant, is even more pronounced than the estimate in the conventional first-lien home purchase market.

Estimates in columns 5 and 6 show conditional correlations between racial prejudice and racial denial gaps in the conventional and FHA refinancing markets. The estimate of the conditional correlation in the conventional refinancing market is somewhat smaller than the estimate in the conventional market as a whole and the conditional correlation in the FHA refinancing market is essentially zero; neither is statistically significant. Estimates in columns 7 and 8 further examine conventional loans by depository institutions and non-depository institutions covered by HUD. The estimate of interest is large and statistically significant at the 5% level for conventional loans by depository institutions but is negative and statistically insignificant for conventional loans by non-depository institutions.[17,18]

An extension of the analysis, provided in Supplemental Appendix Table A6, shows the fraction of the conditional racial denial gap that can be attributed to racial prejudice between the 1st and 2nd quartile, 1st and 3rd quartile, and 1st and 4th quartile of the prejudice distribution separately by market type based on coefficients in Table 2. Furthermore, Supplemental Appendix Table A8 provides estimates of the conditional relationship between racial prejudice and racial gaps in the prevalence of high-priced loans, providing additional evidence that racial prejudice has a statistical impact in the conventional market.

[17] Exceptionally tight credit in the current environment has been partially tied to concerns about mortgage put-backs from government-sponsored enterprises or the FHA (Goodman et al., 2016b). Concern about put-backs is particularly large for high loan-to-value loans to low credit borrowers. While put-back risk may affect the magnitude of the conditional correlations between racial denial gaps and racial prejudice in conventional markets it is particularly relevant to FHA markets. Despite the fact that conditional correlations between racial denial gaps and racial prejudice in all observed FHA markets is statistically insignificant, put-back risk may be one driver of the relatively large estimate found in the FHA first-lien home purchase market. However, the magnitude of the impact of put-back risk ultimately depends on the distribution of creditworthiness among black and white applicants.

[18] One potential criticism of the primary analysis is that the county-level prejudice index is estimated using the distribution of all whites in each county but lenders are the only individuals whose tastes for discrimination influence the lending decision. Thus, to more accurately assess the impact of 'lender' prejudice, the study reweights the sample from the GSS by the propensity to work in a managerial occupation in a banking, savings, and loan organization. Adjusting the prejudice index in this manner provides substantively similar results. For more information refer to the Supplemental Index and Supplemental Index Table A7.

Potential Biases

Because the conditional correlation between racial prejudice and the racial denial gap is statistically significant in the conventional market but not the FHA market, it is possible that the marginal black applicant might opt for FHA-based home financing in more prejudiced counties to circumvent taste-based discrimination in the conventional market. Additionally, it is possible that lenders in more prejudiced counties might be more likely to steer black applicants toward FHA loans. If black applicants whose conventional loans would be accepted in the absence of prejudice choose to instead apply for FHA-insured loans in more prejudiced counties, perhaps because lenders steer them toward these loans, then estimates presented may understate the conditional correlation between racial prejudice and the racial denial gap in the conventional market. In this vein, this study explores how racial prejudice is correlated with the likelihood of applying for FHA-based financing. Table 3 shows that there is no statistical relationship between racial prejudice and the probability that blacks apply for FHA-insured loans instead of conventional loans. While this analysis provides no evidence of selection into the FHA-insured market for the average black applicant, it does not necessarily preclude the possibility that some marginal black applicants do self-select into the FHA-insured market or finance homes using other methods, cash payment upfront for example.

Another potential issue in the analysis is that unobservable characteristics of black applicants may be negatively correlated with racial prejudice. If black applicants in more prejudiced counties are lower quality applicants in ways unobservable to the researcher, then conditional correlations between racial denial gaps and racial prejudice may be overstated. However, there is also reason to believe that black applicants in more prejudiced counties would be more likely to avoid applying for a loan (or apply for a smaller loan) if they believe they will be discriminated against or if steered from applying by a racially prejudiced lender.

In an effort to explore these issues, the study next considers how the observable characteristics of blacks in each county are correlated with racial prejudice. Table 4 shows bivariate regressions of county-level racial gaps in the income-to-loan ratio and log income of applicants in the conventional and FHA-insured markets against the average prejudice of whites in each county. In addition, among the entire population, the table shows how county-level gaps in the fraction with a bachelor's degree, the unemployment rate, the self-employment rate, wealth, delinquency, the percent owning their home free and clear, and the percent with housing costs exceeding 35% of income are correlated with racial prejudice. All bivariate correlations aside from the correlation between racial prejudice and the bachelor's degree gap are statistically insignificant and the correlation between racial prejudice and the bachelor's degree gap takes the opposite sign expected. Lack of statistical significance does not formally prove there are no relationships between racial prejudice and other covariates as it may be the case that there is not enough power to uncover the relationships. Nonetheless, if racial gaps in the income-to-loan ratio and log income of applicants are uncorrelated with racial prejudice then any omitted variable can only be correlated with prejudice if the part of the unobservable correlated with prejudice is uncorrelated with both of these variables.

On the whole, evidence shows no observable bias in the quality of black conventional loan applicants. What cannot be known, however, is how the individual wealth and credit histories of black applicants compare to observably comparable white applicants; if black applicants have lower wealth and poorer credit than can be explained with observable county-level differences and these omitted variables are correlated with racial prejudice, then these unobservable characteristics may explain part of the racial difference in denial rates across counties attributed in the model to racial prejudice.

Conclusion

Many studies have shown the existence of disparities in loan denial rates between blacks and whites that cannot be explained by observable characteristics. In contrast, this study examines the link between these conditional racial denial gaps and prejudicial attitudes toward blacks. Findings show that an increase in the average prejudice of whites at the county level is conditionally correlated with a widening in the black-white denial rate gap in the conventional market. Separately examining the conventional first-lien home purchase market and the conventional refinancing market, the study finds that the conditional correlation between racial prejudice and the racial denial gap is relatively large in both markets though statistically insignificant in the conventional refinancing market. Splitting the sample by depository and non-depository lenders, the study further shows that the conditional correlation between racial prejudice and the racial denial gap is large and statistically significant among depository institutions but negligible and statistically insignificant among non-depository institutions.

In contrast to findings in the conventional market, the study finds no evidence of statistical relationships between racial prejudice and racial denial gaps in the FHA-insured market. On the whole, details presented in this article provide evidence that racial denial gaps in the conventional market, particularly in the first-lien home purchase market, are conditionally spatially correlated with racial prejudice such that blacks are more likely denied home financing in more prejudiced counties.

Provided that racial prejudice is having an adverse impact on the ability of blacks to obtain home loans, many blacks are being wrongfully kept from achieving positive outcomes associated with homeownership regardless of ability to pay. Such behavior by lenders has negative implications for wealth creation, income tax benefits (mortgage interest and property tax deductions, preferential treatment of gains at sale), and emotional satisfaction for blacks. If racial prejudice is partially responsible for the existence of racial denial gaps, policies targeted at reducing racial prejudice could improve home loan outcomes for blacks. Such policies could include reducing barriers to outside competition in particularly prejudiced jurisdictions or implementing stricter enforcement of anti-discrimination laws in jurisdictions where racial prejudice is prevalent.

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Table 1 Summary Statistics

Panel A. In-Sample Individual-Level Statistics from 2009-2015 HMDA

	Black	White		Black	White
Denied	0.3909	0.1855	Refinancing Loan	0.5304	0.6262
	(0.4880)	(0.3887)		(0.4991)	(0.4838)
Loan Amount	146,237.30	194,013.70	Owner-Occupied	0.9229	0.9061
	(130,814.20)	(187809.40)		(0.2668)	(0.2916)
Gross Income	71,771.33	107,044.90	Secured by First Lien	0.8973	0.9488
	(105,922.40)	(155,117.00)		(0.3036)	(0.2204)
Female Applicant	0.4679	0.2740	Conventional Loan	0.5733	0.7926
	(0.4990)	(0.4460)		(0.4946)	(0.4054)
Co-applicant Present	0.2572	0.5275	FHA Loan	0.3028	0.1442
	(0.4371)	(0.4992)		(0.4595)	(0.3513)
Home Purchase Loan	0.3549	0.3147	Single Family Home	0.9571	0.9692
	(0.4785)	(0.4644)		(0.2027)	(0.1727)
Home Improvement Loan	0.1147	0.0591	Preapproval Requested	0.0235	0.0219
	(0.3187)	(0.2358)		(0.1515)	(0.1465)
Number of Observations	1,554,616	19,476,140			

Panel B. In-Sample County-Level Conditional Black-White Denial Gaps

All Conventional Loans	0.1463	Conventional Refinance Loans	0.1329
	(0.0683)		(0.1016)
All FHA Loans	0.0804	FHA Refinance Loans	0.1349
	(0.1471)		(0.3536)
Conventional First Lien Purchase Loans	0.1320	Conventional HUD Loans	0.0378
	(0.0932)		(1.2037)
FHA First Lien Purchase Loans	0.0810	Conventional Non-HUD Loans	0.1522
	(0.2388)		(0.0726)

Panel C. In-Sample County-Level Covariates

Avg. White Prejudice	2.3334	Delinquency Gap	2.2554
	(1.0000)		(2.1593)
Fraction Black	0.1301	Owned Free/Clear Gap	-10.3529
	(0.1257)		(9.6836)
Log Population Density	6.2169	Housing Costs Exceed 35% Gap	12.8963
	(1.4912)		(9.8632)
Bachelor's Degree Gap	-14.8032	Home Affordability Index	161.7349
	(9.6623)		(48.2393)
Unemployment Gap	-6.2240	Central Metropolitan County	0.7937
	(1.4865)		(0.4058)
Self-Employment Gap	-2.8941	Outlying Metropolitan County	0.0741
	(2.8645)		(0.2626)
Percent Subprime Credit	32.3949	Micropolitan County	0.1005
	(7.3738)		(0.3015)

Table 2 Conditional Correlations between Denial Gaps and Racial Prejudice, Seperately by Loan Type

	All Conv. (1)	All FHA (2)	Conv. First Lien Purchase (3)	FHA First Lien Purchase (4)	Conv. Refinance (5)	FHA Refinance (6)	Conv. HUD (7)	Conv. Non-HUD (8)
Avg. White Prejudice	0.0107*	0.0020	0.0132*	0.0156	0.0090	-0.0001	-0.0013	0.0107*
	(0.0044)	(0.0071)	(0.0052)	(0.0138)	(0.0061)	(0.0199)	(0.0361)	(0.0049)
Fraction Black	0.2290	0.0058	0.1690	-0.3080	0.5610	0.1210	-0.7290	0.2610
	(0.1960)	(0.3480)	(0.2350)	(0.6410)	(0.310)	(1.3090)	(1.5660)	(0.220)
Log Population Density	0.0007	0.0078	-2.65e-05	0.0212	-0.0033	0.0323	-0.0114	0.0004
	(0.0044)	(0.0077)	(0.0050)	(0.0109)	(0.0058)	(0.0291)	(0.0365)	(0.0048)
Bachelor's Degree Gap	-0.0007	0.0007	3.40e-05	0.0011	2.95e-05	0.0006	-0.0058	-0.0010
	(0.0006)	(0.0012)	(0.0008)	(0.0017)	(0.0010)	(0.0030)	(0.0084)	(0.0007)
Unemployment Gap	0.0091**	0.0046	0.0010	0.0011	0.0093*	0.0332*	-0.0080	0.0081*
	(0.0030)	(0.0053)	(0.0035)	(0.0082)	(0.0038)	(0.0157)	(0.0376)	(0.0032)
Self-Employment Gap	0.0061**	0.0039	0.0121**	-0.0028	0.0020	-0.0085	0.0318	0.0050
	(0.0023)	(0.0056)	(0.0037)	(0.0080)	(0.0046)	(0.0132)	(0.0230)	(0.0028)
Percent Subprime Credit	-0.0008	0.0006	-0.0003	-0.0011	-0.0016	0.0142*	0.0049	-0.0009
	(0.0009)	(0.0019)	(0.0012)	(0.0028)	(0.0014)	(0.0068)	(0.0087)	(0.0011)
Percent Subprime Credit*Black	-0.0033	-0.0006	-0.0016	0.0080	-0.0104	-0.0177	0.0213	-0.0039
	(0.0046)	(0.0088)	(0.0057)	(0.0162)	(0.0075)	(0.0310)	(0.0330)	(0.0052)
Wealth Gap	-4.51e-05	0.0002	0.0003	0.0002	-0.0007	0.0013	0.0006	-0.0001
	(0.0004)	(0.0009)	(0.0005)	(0.0015)	(0.0005)	(0.0019)	(0.0021)	(0.0004)
Delinquency Gap	-0.0001	-0.0016	0.0039	-0.0006	-0.0034	-0.0045	-0.0087	-0.0003
	(0.0022)	(0.0035)	(0.0026)	(0.0057)	(0.0029)	(0.0119)	(0.0248)	(0.0023)
Owned Free/Clear Gap	0.0012	0.0029*	0.0011	0.0041	0.0021*	0.0016	-0.0031	0.0010
	(0.0006)	(0.0013)	(0.0007)	(0.0024)	(0.0009)	(0.0041)	(0.0074)	(0.0007)
Housing Costs Exceed 35% Gap	0.0003	0.0027	0.0007	0.00407*	0.0008	0.0002	-0.0055	0.0004
	(0.0007)	(0.0018)	(0.0008)	(0.0020)	(0.0010)	(0.0036)	(0.0083)	(0.0007)
Home Affordability Index	0.0004***	0.0002	-0.0001	0.0001	0.0003**	0.0010*	-0.0007	0.0004***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0004)	(0.0011)	(0.0001)
R-Squared	0.40	0.15	0.29	0.11	0.26	0.16	0.04	0.36
Counties	189	189	187	187	189	189	187	189

[a] Bootstrap standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

[b] The table reports the coefficients from a regression of the black-white loan denial gap in each county on an index of the average prejudice of whites in those counties. The dependent variable is the coefficient on the black indicator variable from separate linear probability models that control for the income and gender of the applicant, the gender of the co-applicant if applicable, the amount of the loan, the purpose of the loan, the type of the property, information on occupancy and lien status, and census tract, lender, and year fixed effects; additionally, each linear probability model controls for the ratio of the loan amount to the median housing value of homes owned by members of the individual's racial group in the county of interest. The weights for each county are explained in the text.

[c] Each regression shown also includes indicator variables representing whether the county is a central metropolitan county, outlying metropolitan county, or micropolitan county, with rural county being the omitted category.

Table 3 Conditional Correlations between Selection Into FHA Loans and Racial Prejudice

	Includes Lender Fixed Effects (1)	Excludes Lender Fixed Effects (2)
Avg. White Prejudice	-0.0059	-0.0040
	(0.0049)	(0.0059)
Fraction Black	0.0422	-0.0535
	(0.2180)	(0.2750)
Log Population Density	0.0009	0.0042
	(0.0049)	(0.0061)
Bachelor's Degree Gap	-0.0015*	-0.0014
	(0.0007)	(0.0009)
Unemployment Gap	-0.0004	0.0018
	(0.0028)	(0.0033)
Self-Employment Gap	0.0011	0.0015
	(0.0017)	(0.0020)
Percent Subprime Credit	-0.0013	-0.0021
	(0.0010)	(0.0012)
Percent Subprime Credit*Black	-0.0002	0.0018
	(0.0053)	(0.0068)
Wealth Gap	0.0003	0.0005
	(0.0003)	(0.0004)
Delinquency Gap	0.0028	0.0026
	(0.0032)	(0.0040)
Owned Free/Clear Gap	-0.0006	-0.0006
	(0.0007)	(0.0009)
Housing Costs Exceed 35% Gap	-0.0004	-0.0006
	(0.0006)	(0.0007)
Home Affordability Index	0.0004***	0.0005***
	(0.0001)	(0.0001)
R-Squared	0.289	0.302
Counties	189	189

[a] Bootstrap standard errors in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$

[b] The table reports the coefficients from a regression of the black-white gap in FHA to conventional loans in each county on an index of the average prejudice of whites in those counties. The dependent variable is the coefficient on the black indicator variable from separate linear probability models that control for the income and gender of the applicant, the gender of the co-applicant if applicable, the amount of the loan, the purpose of the loan, the type of the property, information on occupancy and lien status, and census tract, lender (in column 1), and year fixed effects; additionally, each linear probability model controls for the ratio of the loan amount to the median housing value of homes owned by members of the individual's racial group in the county of interest. The weights for each county are explained in the text.

[c] Each regression shown also includes indicator variables representing whether the county is a central metropolitan county, outlying metropolitan county, or micropolitan county, with rural county being the omitted category.

Table 4 Bivariate Regression of Racial Gaps in Observable Characteristics on Average White Prejudice

	Income-to-Loan Conv. (1)	Log Income Conv. (2)	Income-to-Loan FHA (3)	Log Income FHA (4)	Bachelor's Degree (5)	Unemployment (6)
Avg. White Prejudice	0.0438	-0.0163	-0.00231	-0.00357	2.777*	-0.202
	(0.0535)	(0.0135)	-0.0073	-0.0093	(1.270)	(0.196)
R-Squared	0.004	0.008	0.001	0.001	0.060	0.014
Counties	189	189	189	189	189	189

	Self-Employment (7)	Wealth (8)	Delinquency (9)	Owned Free/Clear (10)	Excess Housing Costs (11)
Avg. White Prejudice	0.315	-1.345	0.326	-1.594	0.399
	(0.187)	(0.998)	(0.336)	(1.127)	(0.506)
R-Squared	0.024	0.017	0.011	0.028	0.004
Counties	189	189	189	189	189

[a] Bootstrap standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.5

[b] The table reports the coefficients from a regression of the black-white gap in each characteristic on an index of the average prejudice of whites in those counties. The dependent variable in columns 1 and 2 are the black-white income-to-loan ratio gap and the log income gap, respectively, for conventional loan applicants. The dependent variable in columns 3 and 4 are the black-white income-to-loan ratio gap and the log income gap, respectively, for FHA-issured loan applicants. The regressions in columns 1-4 are estimated by FGLS, and the weights for each state are explained in the text. The dependent variables in columns 5-11 represent state-level gaps calculated from ACS, SIPP, and HUD data. The regressions in columns 5-8 are weighted by the state black and white population and regressions in columns 9-11 are weighted by the number of housing units occupied by blacks or whites.

Supplemental Appendix

Data Sources

The article discusses that the years of data were selected to maximize the accuracy of the covariates and minimize the extent of reverse causality. Hence, the dataset includes independent variables closest to and preferably prior to 2009 and dependent variables from 2009 onward. Again, the prejudice index includes the years 1993-2008 because representativeness improves when additional years of the GSS are pooled due to the inclusion of additional sampling frames and additional individual observations each year. In a set of robustness checks, a more current measure of racial prejudice was estimated that limited the sample to the years 2000-2008 and included the sub-sample of the 189 counties with at least 20 observations in this period. This reanalysis finds substantively similar albeit more imprecise estimates: statistical significance at the 10% level in the conditional market as a whole and in the conditional first-lien home purchase market and statistical significance at the 5% level in the conditional refinancing market. Another set of robustness checks was estimated that separated the time period of observation of the dependent variables into the periods 2009-2011 and 2012-2015. This reanalysis finds substantively similar estimates in each period, though standard errors are larger when the time periods are separated due to increased imprecision in the gaps.

As mentioned, the dataset also includes covariates closest to and preferably prior to 2009. American Community Survey 5-year estimates are included from 2006-2010 because 5-year estimates minimize the number of censored data points and some relevant 5-year estimates lack availability prior to 2010. Similarly, the 2010 location-based delinquency gap is used because 2010 is the first year delinquency data is included in the Neighborhood Stabilization Program. Likewise, the 2010 home affordability index is used since ESRI releases the index only once every five years. In addition, estimating the wealth gap by aggregating separate survey periods in the SIPP improves representativeness of the estimates. In addition to the data sources discussed in the main text, within the robustness checks subsection this study also makes use of the black-white dissimilarity index calculated over census tracts within county using the 2006-2010 ACS 5-year Estimates and the variance of the home price index over the period of 2004-2008 from the Federal Housing Finance Agency.[i]

[Insert Table A1 here]

Prejudice Index Methodology

To create a racial prejudice index for each white individual in the GSS, this study uses the method introduced by Charles and Guryan (2008) and utilized by Kopkin (2017). Table A2 shows the years that each question was asked for questions included in the index.[ii] First, this study codes higher values to correspond to more prejudiced answers and then normalizes the response to each question by the mean and standard deviation in 1993.[iii] The study normalizes each response by the 1993 value of the standard deviation so that the relative weight of each question does not change over time. Formally, let d_{it}^{q} be respondent *i*'s response to question *q* in year *t.* Then respondent *i*'s normalized response to question *q* in year *t*, $\tilde{d}_{it}^{q}$, is given by:

$$\tilde{d}_{it}^{q} = \frac{d_{it}^{q} - E[d_{i,93}^{q}]}{\sqrt{Var(d_{i,93}^{q})}}. \tag{A1}$$

i The county-level home price index is a developmental index discussed in Bogin et al. (2016). For the purposes of calculating the variance, the analysis rebases all counties so that 2004 takes the value 100 in the index.

ii Where available, this study uses the same questions that Charles and Guryan (2008) use with a few notable exceptions. For one, Charles and Guryan (2008) use GSS waves from 1972-2004 while this study uses GSS waves from 1993-2008 to more accurately assess current prejudice; their study also uses some questions no longer asked post-1991. Moreover, Charles and Guryan (2008) include the question "Irish, Italians, Jewish and many other minorities overcame prejudice and worked their way up. Do you believe blacks should do the same without special favors?" This study excludes the question as it also focuses on views pertaining to the appropriate role of government and affirmative action. In addition, this study uses two questions that ask "On the average blacks have worse jobs, income, and housing than white people. Do you think these differences are because most blacks have less in-born ability to learn?" and "On the average blacks have worse jobs, income, and housing than white people. Do you think these differences are because most blacks just don't have the motivation or will power to pull themselves up out of poverty?" that were not used by Charles and Guryan (2008).

iii Three of the questions were not asked in 1993. Answers to these questions are normalized by the mean and standard deviation from the first year the question was asked.

Figure A1 shows how normalized responses to each question have changed over time from 1993-2008. While prejudice has generally fallen over time there is variation in the decline across questions. For instance, the fraction of respondents stating they would vote for a qualified black candidate for president in 2008 is much larger than in 1993 but the fraction of respondents stating they believe that blacks have less motivation, willpower, and in-born ability to learn has declined at a much slower rate.

[Insert Table A2 here]

[Insert Fig. A1 here]

After normalizing the response to each question for each individual, the study then calculates the average of each individual's normalized responses. Formally, let $D_{it}^{q} = \sum \tilde{d}_{it}^{q}/Q_t$, where Q_t is the total number of prejudice questions in year *t.* To separate the county-specific component of racial prejudice from the time-specific component, the study then estimates a regression of D_{it}^{q} on individual year fixed effects to find the residual $\widetilde{D}_{it}^{q}$, referred to in this study as the individual-level prejudice index.

Using the individual-level prejudice index and standardized responses to each question, the study then estimates a regression of each outcome on age, years of education, and an indicator variable for male, as well as state and year fixed effects, to determine how prejudice varies across the population. Regressions describing the individual-level prejudice index and the standardized responses to each question are shown in Table A3. It is a commonly held belief that older people, the less educated, and men tend to be more prejudiced. On average, the individual-level prejudice index increases with age, decreases with education, and is larger for males. The study cannot reject that the same is true of the standardized responses to each question. Furthermore, answers to all of the normalized prejudice questions are positively correlated – most highly correlated – with other questions and with the individual-level index. These results are consistent with Charles and Guryan (2008) and provide confidence that the individual-level prejudice index is an accurate measure of prejudicial attitudes.

[Insert Table A3 here]

Once the individual-level prejudice index, $\widetilde{D}_{it}^{q}$, is obtained for each individual, the study calculates the average $\widetilde{D}_{it}^{q}$ in each county to create the county-level index.[iv,v] Although this study uses a county-level index of racial prejudice, contractual arrangements with NORC prohibit the study from displaying any summary statistics from the GSS Sensitive Data Files at a more narrow geography than the census division. Thus, Figure A2 shows the distribution of prejudice across census divisions. The East South Central division (AL, KY, MI, TN) is the most prejudiced, followed by the West South Central (AR, LA, OK, TX) and South Atlantic divisions (DE, DC, FL, GA, MD, NC, SC, VA, WV). The New England (CT, ME, MA, NH, RI, VT), Mountain (AZ, CO, ID, NM, MT, UT, NV, WY), and Pacific divisions (AK, CA, HI, OR, WA) are the least prejudiced. These tabulations follow closely with generally held beliefs. Additionally, Figure A3 shows how prejudice has changed over time in each census division. In the majority of census divisions there is not much movement in the prejudice index over time. It is important to note that fluctuations in the prejudice index over time might occur not only because prejudice is changing but also because the mix of questions asked and the individuals sampled in each year are changing. Stability of the prejudice index within each census division

[iv] To perform this calculation observations are weighted by the number of adults in the household and the weights are corrected for survey non-response where possible (2004-2008). This is done because the full-probability GSS samples are designed to give each household an equal probability of inclusion in the sample, and each adult in the household then has an equal probability of inclusion in the survey. Left unweighted, this would serve to under-represent individuals from large households and over-represent individuals from small ones. As a robustness check, an alternative specification is estimated in which the state-level prejudice index is calculated using unweighted GSS data. The use of weights has no substantive impact on the estimate of the conditional correlation between average white prejudice and the black-white conventional loan denial rate gap.

[v] Additionally, individuals are reweighted so that each county-year combination takes equal weight in the county-level index. This convention was chosen because the sample size from each county is changing over time and one would prefer not to overweight some years over others when calculating racial prejudice. Despite the fact that the data is time-detrended, it is possible that prejudice is falling at a different rate across counties. Without this adjustment the results are substantively similar.

over time further supports the use of the average county-level prejudice index over this time span.

[Insert Fig. A2 here]

[Insert Fig. A3 here]

Standard Error Estimation

Since the dependent variable in equation (2) is estimated, the error term, v_j, can be decomposed into two components: sampling error, τ_j, and standard regression error, ε_j. It is then immediate that the error term is heteroskedastic since estimates from larger counties will generally have less sampling variance associated with them. Thus, weighted least squares with weights equal to the inverse of the standard deviation of the error term, $1/\sqrt{(\sigma^2 + \omega_j^2)}$, where σ^2=Var(ε_j) and ω_j^2=Var(τ_j), will produce the most efficient parameter estimates for equation (2). ω_j^2 is approximated using the estimate of the sampling variance of $\widehat{\varphi_{1j}}$ from equation (1). However, given that σ^2 is not observed, it must be estimated by feasible generalized least squares (FGLS). Using FGLS, σ^2 is approximated by estimating equation (2) by unweighted ordinary least squares (OLS) regression. Next, the residuals, $\hat{v}_j$, are retrieved from the unweighted OLS regression. Then, given that equation (1) is estimated using a linear probability model, σ^2 can be estimated by:

$$\hat{\sigma}^2 = \frac{\sum_j \hat{v}_j^2 - \sum_j \hat{\omega}_j^2 + tr\left(\left(\mathbf{X'X}\right)^{-1}\mathbf{X'GX}\right)}{J-k}, \qquad \text{(A2)}$$

where $\hat{v}_j$ is the residual for county *j* from the second-step unweighted OLS regression, $\widehat{\omega}_j^2$ is the estimated sampling variance of $\hat{\varphi}_{1j}$, $\mathbf{Z}$ is the matrix of state-level independent variables, $\mathbf{G}$ is the diagonal matrix with ω_j^2 as the diagonal elements, *J* is the number of counties, and *k* is the number of county-level independent variables including the constant. Equation (2) is then re-estimated, weighted by $1/\sqrt{(\hat{\sigma}^2 + \widehat{\omega}_j^2)}$.[vi]

As a separate and unrelated issue, the variable of interest in equation (2), $Prej_j$, is estimated. In a regression framework failure to account for estimation of a covariate could result in substantially understated standard errors. The issue is especially important in this context because the estimated covariate comes from a dataset, the GSS, with relatively few observations per county. Thus, to correct for imprecision in the estimated regressor this study bootstraps standard errors stratified on GSS year and primary sampling unit; bootstrapping produces much more conservative standard errors.[vii]

Select Robustness Checks

This section discusses a number of select robustness checks of the conditional correlation between racial prejudice and the racial denial gap in the conventional market. In total, the takeaway from this section is that the estimate of the conditional correlation between racial prejudice and the racial denial gap in the conventional market is relatively robust to the inclusion or exclusion of controls for racial gaps in education, wealth, unemployment, delinquencies, etc.,

[vi] Robustness checks were performed using unweighted OLS and weighted least squares with weights equal to the inverse of the estimated sampling variance associated with $\hat{\varphi}_{1s}$ from equation (1). The choice of weights has no substantive impact on the estimates of interest or the standard errors associated with these estimates.
[vii] Each bootstrapped standard error is calculated using 1000 replications.

as the bivariate correlation remains relatively unchanged after the inclusion of the full set of controls.

Table A4 shows estimates of the correlation between racial prejudice and the racial denial gap in the conventional market adding additional covariates across columns to show how the addition of variables changes the estimate. A one standard deviation increase in average white prejudice is associated with an increase in the racial denial gap in the conventional market by between 0.91 and 1.43 percentage points in columns 1-6 and each estimate is statistically significant at the 5% level. Exclusion of lender fixed effects, as shown in column 6, increases the size of the estimate by approximately 34%, thereby revealing that the conditional correlation between racial prejudice and the racial denial gap in the conventional market is smaller within lender than across all loan applications in a county.

[Insert Table A4 here]

Table A5 shows a series of other select robustness checks of the estimated conditional correlation between racial prejudice and the racial denial gap in the conventional market. The specification in column 1 includes the variance of the house price index in each county between 2004 and 2008 from the Federal Housing Finance Agency as a measure of home price volatility in the local market. Home price volatility may affect perceived lender risk and thus dictate how broadly lenders are willing to lend. When home price volatility is included, the estimated correlation between racial prejudice and the racial denial gap in the conventional market is attenuated but remains statistically significant at the 5% level.

[Insert Table A5 here]

The specification in column 2 includes the black-white dissimilarity index, a measure of racial segregation, as an explanatory variable. The study omits this variable from in its main analysis because it is potentially endogenous. For example, if lenders in more racially prejudiced counties are more likely to deny loan applications from black applicants in largely-white census tracts this would result in more racially segregated counties. Thus, this variable may be an outcome of racial prejudice and is not a suitable input variable in the model. Nonetheless, when the dissimilarity index is included the conditional correlation between the racial prejudice and the racial denial gap in the conventional market is only slightly attenuated (as compared to the result shown in column 1 of Table 2) and remains statistically significant at the 5% level.

The specifications in columns 3 and 4 include indicator variables representing whether an applicant is included in the Private Mortgage Insurance Companies (PMIC) database in the first-step regression. If a conventional loan applicant cannot afford a down payment of 20% of the purchase price a lender will require the applicant apply for private mortgage insurance. The private mortgage insurance company will protect the lender in the case of borrower default in exchange for an annual premium of between 0.3%-1.15% of the purchase price. Therefore, individuals found in the PMIC database are those that had a down payment of less than 20% and have applied for private mortgage insurance. PMIC may be matched to HMDA using observable applicant characteristics. Those applicants matched to the PMIC database are generally less likely to be denied a loan regardless of the county in which they reside. The indicator variable in the specification in column 3 includes all possible matches as indicated by a fuzzy matching algorithm while the one in column 4 includes only exact matches.[viii] In both cases the inclusion

[viii] Of the 2.24 million in-sample observations found in PMIC, approximately 52% can be matched exactly on observable applicant and co-applicant characteristics and an additional 24% can be matched based on a fuzzy matching algorithm. For applicants without exact matches, it is first assumed that the applicant and co-applicant have been swapped. For remaining unmatched applicants, it is then assumed that PMIC applicants have the amount of the loan mismeasured by as much as $1,000. For remaining unmatched applicants, it is then assumed that unmatched applicants have income miusmeasured by as much as $5,000. For remaining unmatched applicants, it is then assumed that PMIC applicants have the amount of the loan mismeasured by as much as $5,000. For remaining unmatched applicants, it is then assumed that PMIC applicants have income and the amount of the loan both mismeasured by as much as $5,000. Remaining unmatched applicants are then matched on county instead of census

of the PMIC indicator variable in the first stage has no substantive impact on the estimate of interest.

The specification in column 5 omits from all first-step regressions loan observations with missing census tracts. This results in 15,583 additional applications dropped from the 189 county sampling frame. Further, the specification in column 6 drops all but the first occurrence of all observations identical across all observed covariates aside for the lender to account for the filing of multiple applications by the same applicant. This results in an additional 37,407 applications dropped from the 189 county sampling frame. In both cases the estimates are substantively similar to the main result in column 1 of Table 2 and remain statistically significant at the 5% level.

The specifications in columns 7 and 8 show that the results are robust to alternative methods of calculating the prejudice index. In the primary analysis each GSS observation is weighted by the number of adults in household and weights are corrected for survey non-response where possible (2004-2008). Observations are weighted in this way because the full-probability GSS samples are designed to give each household an equal probability of inclusion in the sample. Each adult in the household then has an equal probability of inclusion in the survey. Left unweighted, the index would under-represent respondents from large households and over-represent respondents from small ones. In the specification in column 7 the conditional correlation between racial prejudice and the racial loan denial gap in the conventional market is estimated using unweighted GSS data. This adjustment has no substantive impact on the estimate. Additionally, in the primary analysis the prejudice index gives all county-year combinations equal weight in the county-level index. The study chooses this conventional

tract. Any remaining unmatched applicants are then matched on the characteristics of the applicant and ignore co-applicant characteristics.

because the sample size from each county is changing over time and one would prefer not to overweight some years over others when calculating racial prejudice. Despite the fact that the data are time-detrended it is possible that prejudice is falling at a different rate across counties. Therefore, in the specification in column 8 the conditional correlation between racial prejudice and the racial denial gap in the conventional market is estimated without this adjustment to the prejudice index. Once again, this adjustment has no substantive impact on the estimate.

While not shown for the sake of brevity, additional robustness checks of the second-step regression were estimated using unweighted OLS regression and weighted least squares regression with weights equal to the inverse of the standard error of the estimated racial denial gap in the conventional market. Under unweighted OLS regression the resulting conditional correlation is substantively similar to the main result found in column 1 of Table 2. Under weighted least squares regression with inverse standard error weights the resulting conditional correlation is more pronounced and is statistically significant at the 0.1% level.[ix]

Average Black-White Denial Gaps by Loan Type and Prejudice Quartile

Table A6 shows the fraction of the conditional racial denial gap that can be attributed to racial prejudice between the 1st and 2nd quartile, 1st and 3rd quartile, and 1st and 4th quartile of the prejudice distribution separately by market type based on coefficients in Table 2. This information can help one better understand the results presented in Table 2 of the main text. For example, the article discusses the fact that racial prejudice can account for approximately 61% of the average black-white denial gap difference in conventional loans between counties in the least and most prejudiced quartiles; this estimate is shown in column 1 of Table A6. Table A6 further shows that racial prejudice can account for approximately 40% of the difference between the 2nd

[ix] These results are available from the author upon request.

and 4th quartiles and 39% of the difference between the 3rd and 4th quartiles of the prejudice distribution in the market for conventional loans.

Table A6 further shows estimates for the other loan types discussed in the article. Most notably substantively similar and precisely estimated impacts are found in the conventional first-lien home purchase market and conventional non-HUD market. Substantively smaller estimated impacts are found in the FHA-insured market, FHA first-lien home purchase market, FHA refinancing market, and conventional HUD market.

[Insert Table A6 here]

Reconciling Average Prejudice and Lender Prejudice

The primary analysis uses the distribution of prejudice among all whites that reside within a county to estimate conditional correlations between racial prejudice and racial denial gaps. However, lenders are the only agents whose tastes for discrimination influence the lending decision. Since the primary analysis includes the prejudice of non-lenders when calculating average prejudice in each county, the primary analysis implicitly assumes that the average prejudice of whites in each county is the same as the average prejudice of white lenders in that county. Based on Table A3 this assumption is unlikely to be correct.

In the GSS the 171 individuals identified as working in managerial occupations in banking, savings, and loan organizations have 1.7 years of additional education, are 13.2 percentage points more likely to be female, and are nearly a full year younger.[x] Since Table A3 shows that older people are more prejudiced, more educated people less prejudiced, and men significantly more prejudiced than women, lenders should on average be less prejudiced toward blacks than

[x] Differences in education and the likelihood of being female are statistically significant at the 5% level. The difference in age is not statistically significant.

the rest of the population. The data shows that bank managers are indeed less prejudiced than non-lenders and the difference is statistically significant at the 5% level.

Since only 171 individuals in the GSS can be identified in managerial positions in the banking, savings, and loan industry, estimating the average prejudice of 'lenders' in each county with such a small sample would be futile. The goal then is to extrapolate observable information about these 'lenders' to the rest of the white population. To more closely match the distribution of racial prejudice among white 'lenders' with the distribution of prejudice across the entire white population this study uses propensity score reweighting. To determine which individuals most closely resemble 'lenders' the analysis uses age, years of education, gender, and all 4th degree polynomials and interaction terms. The analysis then up-weights individuals that closely resemble managers in the banking, savings, and loan industry based on age, education, and gender and down-weights individuals that do not.

Figure A4 shows the distribution of prejudice among whites in managerial positions in the banking, savings, and loan industry, among the entire white population, and among the entire white population reweighted by the propensity score. While the distribution of prejudice among the entire population is clearly to the right of the distribution of 'lender' prejudice, reweighting by the propensity score brings the distribution of prejudice among the populace much closer to that of 'lenders.' Next, the study re-estimates the conditional correlations between racial prejudice and racial denial gaps in the mortgage market using the average prejudice among the reweighted population in each county.

Table A7 shows the conditional correlations between racial prejudice and racial denial gaps in each market using the reweighted prejudice index. The estimates from Table A7 are substantively similar to those presented in Table 2 with a couple of notable exceptions. While the conditional correlation between racial prejudice and the racial denial gap in the conventional market is substantively similar, the conditional correlation in the FHA market is much larger than in Table 2 though still statistically insignificant; the same can be said of the conditional correlation between racial prejudice and the racial denial gaps in the conventional and FHA first-lien home purchase markets. Among refinancing loans, the estimate of the conditional correlation is somewhat smaller in the conventional market than in Table 2 and the estimate of the conditional correlation is much, much larger in the FHA-insured market than in Table 2, though both remain statistically insignificant. The conditional correlation between racial prejudice and the racial denial gap among non-depository institutions in the conventional market remains statistically insignificant though it is now much larger in magnitude.

[Insert Table A7 here]

Evidence of Racial Prejudice in the Prevalence of High-Priced Loans

Lastly, this study analyzes the conditional correlations between racial prejudice and the prevalence of high-priced loans in each of the specified mortgage markets. HMDA does not provide the interest rate on all loans. Instead, the most relevant variable related to the interest rate is the rate spread. The rate spread is the spread between the Annual Percentage Rate (APR) of a loan and the average APR offered on a comparable prime mortgage loan. However, reporting of the rate spread in HMDA is less than ideal since the rate spread is reported only for loans that are originated, secured by a lien, and have a rate spread exceeding a pre-defined threshold (1.5 percentage points for loans secured by a first lien and 3.5 percentage points for loans secured by a subordinate lien). Nonetheless, it is worth exploring whether the prevalence of high-price loans is conditionally correlated with racial prejudice. To do so, the study uses the methodology discussed in the article using the sample of originated loans replacing the dependent variable in Eq. 1 by an indicator variable equal to 1 if an originated loan is above the rate spread threshold and equal to 0 otherwise.

Table A8 shows estimates from county-level regressions of the conditional racial gap in the prevalence of high-priced loans in each of the specified markets on the index of racial prejudice. The estimate in column 1 shows that a one standard deviation increase in average white prejudice is associated with a 0.40 percentage point increase in the racial gap in the prevalence of high-priced loans in the conventional market that is statistically significant at the 5% level. The estimate in column 2 in the FHA market is of a similar magnitude but is statistically insignificant. Estimates in columns 3 and 4 show the conditional correlations between racial prejudice and racial gaps in the prevalence of high-priced loans in the conventional first-lien home purchase market and FHA first-lien home purchase market; in comparison to the conditional correlation between racial prejudice and racial gaps in the prevalence of high-priced loans in the conventional market shown in column 1 both estimates are substantively large but statistically insignificant.

Estimates in columns 5 and 6 show the comparable conditional correlations in the conventional refinancing market and FHA refinancing market; the estimate in the conventional refinancing market shows that a one standard deviation increase in average white prejudice increases the racial gap in the prevalence of high-priced loans in the conventional refinancing market by 0.61 percentage points and is statistically significant at the 5% level while the estimate in the FHA refinancing market is relatively small and statistically insignificant. Lastly, estimates in columns 7 and 8 further examine the conditional correlations between racial prejudice and racial gaps in the prevalence of high-priced loans in the conventional market by depository institutions and non-depository institutions covered by HUD. Both estimates are substantively similar to the estimate in the conventional market as a whole but neither is statistically significant.[xi]

Estimates of the conditional correlations between racial prejudice and racial gaps in the prevalence of high-priced loans shown in Table A8 may be understated for a number of reasons. First, these estimates only account for loans that exceed the rate spread threshold. Therefore, smaller differences in interest rates charged to comparable black and white borrowers, which would theoretically occur more often in more racially prejudiced counties, go uncaptured. Second, because the rate spread is only reported for originated loans the sample does not capture approved loan applications that are not accepted by the applicant. Sensibly, an applicant would be more likely to refuse the terms of a loan charging an exceptionally high interest rate. If there are more high-priced loans charged to blacks in more racially prejudiced counties that go unaccepted by the applicant this would understate the estimates. Third, the article shows evidence that blacks are more likely to be denied loans in racially prejudiced counties. Therefore, it is worth questioning whether discriminatory lenders deny loans as an alternative to charging blacks higher interest rates, as discrimination in loan pricing is easier for government agencies to verify than discrimination in denials. Nevertheless, despite the possibility of downward bias in the estimates, Table A8 shows that racial disparities in the prevalence of high-priced loans in the conventional market are largest in counties where racial prejudice is greatest conditional on observable individual- and county-level characteristics. However, Table A8 shows no statistical evidence that the same is true in the FHA-insured market.

[xi] Research shows that non-depository institutions are much more likely to target blacks with high-interest loans (Ghent et al., 2014). However, this analysis shows no statistical evidence that blacks are more likely to be charged higher interest rates than whites by non-depository institutions as compared to depository institutions in more prejudiced counties.

Additional References

Bogin A, Doerner W. and Larson W (2016) Local house price dynamics: New indices and stylized facts. Working Paper, Federal Housing Finance Agency. Available at: http://www.fhfa.gov/papers/wp1601.aspx (accessed 29 September 2017).

Ghent AC, Hernández-Murillo R, and Owyang MT (2014) Differences in subprime loan pricing across races and neighborhoods. Regional Science and Urban Economics 48(September): 119–215.

Table A1 Data Sources

Variable	Source	Years
Black-White Loan Denial Gaps	Home Mortgage Disclosure Act	2009-2015
Avg. White Prejudice	General Social Survey	1993-2008
Fraction Black	American Community Survey	2006-2010 5-year Estimates
Population Density	American Community Survey	2006-2010 5-year Estimates
Bachelor's Degree Gap	American Community Survey	2006-2010 5-year Estimates
Unemployment Gap	American Community Survey	2006-2010 5-year Estimates
Self-Employment Gap	American Community Survey	2006-2010 5-year Estimates
Percent Population Subprime Credit	Federal Reserve Economic Data	2008 Q1 - 2008 Q4
Wealth Gap	Survey of Income & Program Participation	2004 Wave 6 & 2008 Wave 4
Location-Based Delinquency Gap	Neighborhood Stabilization Program	2010
Owned Free/Clear Gap	American Community Survey	2006-2010 5-year Estimates
Housing Costs Exceed 35% Gap	American Community Survey	2006-2010 5-year Estimates
Home Affordability Index	Environmental Systems Research Institute	2010
Dissimilarity Index	American Communiy Survey	2006-2010 5-year Estimates
Home Price Volatility	Federal Housing Finance Agency	2004-2008

Table A2 General Social Survey Prejudice Questions, Years Asked

Year	1993	1994	1996	1998	2000	2002	2004	2006	2008
In general, how close do you feel to blacks?			✓	✓	✓	✓	✓	✓	✓
In general, how warm or cool do you feel towards blacks?						✓			
If you and your friends belonged to a social club that would not let blacks join, would you try to change the rules so that blacks could join?	✓	✓							
Blacks have worse jobs, income, and housing than white people. Do you think these differences are because most blacks have less in-born ability to learn?	✓	✓	✓	✓	✓	✓	✓	✓	✓
Do you think most blacks just don't have the motivation or will power to pull themselves up out of poverty?	✓	✓	✓	✓	✓	✓	✓	✓	✓
Do you think there should be laws against marriages between blacks and whites?	✓	✓	✓	✓	✓	✓			
Do you agree that a homeowner should be able to decide for himself whom to sell his house to, even if he prefers not to sell to blacks?	✓	✓	✓				✓	✓	✓
If your party nominated a black for President, would you vote for him if he were qualified for the job?	✓	✓	✓						✓
Do you agree that blacks shouldn't push themselves where they're not wanted?		✓	✓	✓	✓	✓			
Would you yourself have any objection to sending your children to a school where a few/half/most of the children are black?	✓	✓	✓						
Do you agree that white people have a right to keep blacks out of their neighborhoods if they want to, and blacks should respect that right?	✓	✓	✓						

Table A3 Determination of Prejudice at the Individual Level

Variables	(1) PREJ INDEX	(2) RACDIF2	(3) RACDIF4	(4) CLOSEBLK	(5) RACMAR	(6) RACOPEN
Age	0.00767***	0.00901***	0.00601***	0.00541***	0.00993***	0.00839***
	(0.000327)	(0.000663)	(0.000544)	(0.000924)	(0.000795)	(0.000897)
Education	-0.0513***	-0.0581***	-0.0711***	-0.0240***	-0.0658***	-0.0205***
	(0.00255)	(0.00477)	(0.00370)	(0.00588)	(0.00619)	(0.00515)
Male	0.105***	0.0492**	0.0742***	0.0768***	-0.00132	0.174***
	(0.0120)	(0.0183)	(0.0217)	(0.0229)	(0.0212)	(0.0309)
Observations	17,477	10,540	10,184	7,591	7,497	6,467
R-squared	0.122	0.074	0.088	0.046	0.158	0.067

Variables	(7) RACPUSH	(8) RACPRES	(9) RACSEG	(10) RACSCHL	(11) FEELBLKS	(12) RACCHNG
Age	0.0134***	0.00253**	0.0135***	0.00527***	0.00607***	0.00856***
	(0.000856)	(0.000946)	(0.00210)	(0.000908)	(6.05e-11)	(0.00160)
Education	-0.0877***	-0.0484***	-0.0706***	-0.0223***	-0.0442***	-0.0423***
	(0.00929)	(0.00536)	(0.0111)	(0.00605)	(3.98e-10)	(0.00829)
Male	0.182***	0.0937***	0.0657**	0.0276	0.262***	0.109
	(0.0242)	(0.0246)	(0.0288)	(0.0437)	(1.51e-09)	(0.0736)
Observations	6061	4,177	3221	3,117	2151	1,212
R-squared	0.188	0.066	0.163	0.054	0.079	0.134

Robust standard errors clustered on state and year in parenthesis.

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

[a]All GSS prejudice questions are standardized by the mean and standard deviation of the first year that each question is asked. Each regression controls for state and year fixed effects.

[b]CLOSEBLK- In general, how close do you feel to blacks?, FEELBLKS- In general, how warm or cool do you feel towards blacks?, RACCHNG- If you and your friends belonged to a social club that would not let blacks join, would you try to change the rules so that blacks could join?, RACDIF2- On the average blacks have worse jobs, income, and housing than white people. Do you think these differences are because most blacks have less in-born ability to learn?, RACDIF4- On the average blacks have worse jobs, income, and housing than white people. Do you think these differences are because most blacks just don't have the motivation or will power to pull themselves up out of poverty?, RACMAR-Do you think there should be laws against marriages between blacks and whites?, RACOPEN-Do you agree that a homeowner should be able to decide for himself whom to sell his house to, even if he prefers not to sell to blacks?, RACPRES- If your party nominated a black for President, would you vote for him if he were qualified for the job? RACPUSH- Do you agree that blacks shouldn't push themselves where they're not wanted?, RACSCHL- Would you yourself have any objection to sending your children to a school where a few/half/most of the children are black?, RACSEG- Do you agree that white people have a right to keep blacks out of their neighborhoods if they want to, and blacks should respect that right?

Table A4 Conditional Correlations between Conventional Loan Denial Gaps and Racial Prejudice

	(1)	(2)	(3)	(4)	(5)	(6)
Avg. White Prejudice	0.0112*	0.0091*	0.0130**	0.0132**	0.0096*	0.0143*
	(0.0044)	(0.0045)	(0.0043)	(0.0045)	(0.0042)	(0.0056)
Fraction Black		0.128***	0.0945**	0.3440	0.2590	0.3810
		(0.0284)	(0.0293)	(0.2160)	(0.2230)	(0.2470)
Log Population Density		0.0032	-0.0003	-0.0012	0.0022	-0.0010
		(0.0036)	(0.0038)	(0.0051)	(0.0045)	(0.0052)
Bachelor's Degree Gap			-0.0011	-0.0010	-0.0006	-0.0012
			(0.0006)	(0.0006)	(0.0006)	(0.0007)
Unemployment Gap			0.0082**	0.0080*	0.0087**	0.0101**
			(0.0028)	(0.0033)	(0.0031)	(0.0036)
Self-Employment Gap			0.0080**	0.0076**	0.0064*	0.0056*
			(0.0027)	(0.0029)	(0.0026)	(0.0027)
Percent Subprime Credit				0.0008	-0.0005	-0.0006
				(0.0011)	(0.0010)	(0.0012)
Percent Subprime Credit*Black				-0.0064	-0.0047	-0.0065
				(0.0053)	(0.0054)	(0.0059)
Wealth Gap				-0.0003	-0.0003	0.0001
				(0.0003)	(0.0003)	(0.0004)
Delinquency Gap					0.0005	-0.0009
					(0.0022)	(0.0026)
Owned Free/Clear Gap					0.0013	0.0017*
					(0.0007)	(0.0008)
Housing Costs Exceed 35% Gap					0.0002	-4.51e-05
					(0.0007)	(0.0009)
Home Affordability Index					0.0003***	0.0004***
					(0.0001)	(0.0001)
Lender Fixed Effects in First Step	Yes	Yes	Yes	Yes	Yes	No
County Type Fixed Effects in Second Step	No	No	No	No	No	Yes
R-Squared	0.035	0.120	0.274	0.285	0.368	0.393
Counties	189	189	189	189	189	189

[a] Bootstrap standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

[b] The table reports the coefficients from a regression of the black-white loan denial gap in each county on an index of the average prejudice of whites in those counties. The dependent variable is the coefficient on the black indicator variable from separate linear probability models that control for the income and gender of the applicant, the gender of the co-applicant if applicable, the amount of the loan, the purpose of the loan, the type of the property, information on occupancy and lien status, and census tract, lender (in columns 1-5), and year fixed effects; additionally, each linear probability model controls for the ratio of the loan amount to the median housing value of homes owned by members of the individual's racial group in the county of interest. The weights for each county are explained in the text.

[c] The regression shown in column 6 also includes indicator variables for county type, representing whether the county is a central metropolitan county, outlying metropolitan county, or micropolitan county, with rural county being the omitted category.

Table A5 Selected Robustness Checks of Conventional Loan Specifications

	Include Home Price Volatility (1)	Include Dissimilarity Index (2)	PMIC All Matches (3)	PMIC Exact Matches (4)	Omit HMDA Missing (5)	Omit Duplicate Observation (6)	Use Unweighted GSS Data (7)	GSS Years Not Reweighted (8)
Avg. White Prejudice	0.00882*	0.0094*	0.0111*	0.0112*	0.00972*	0.00998*	0.0118**	0.0113**
	(0.0043)	(0.0044)	(0.0048)	(0.0048)	(0.0044)	(0.0043)	(0.0043)	(0.0043)
Fraction Black	0.1940	0.2530	0.3510	0.3520	0.1910	0.1910	0.2310	0.2110
	(0.180)	(0.1840)	(0.2030)	(0.2030)	(0.190)	(0.1890)	(0.1960)	(0.1950)
Log Population Density	0.0013	-0.0012	0.0016	0.0016	0.0016	0.0016	0.0008	0.0008
	(0.0044)	(0.0042)	(0.0049)	(0.0049)	(0.0043)	(0.0043)	(0.0043)	(0.0044)
Bachelor's Degree Gap	-0.0006	-0.0005	-0.0006	-0.0006	-0.0006	-0.0006	-0.0007	-0.0007
	(0.0006)	(0.0005)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Unemployment Gap	0.0086**	0.0098***	0.0087**	0.0087**	0.0096**	0.0096**	0.0089**	0.0096**
	(0.0031)	(0.0029)	(0.0033)	(0.0033)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Self-Employment Gap	0.0065**	0.0060*	0.0046	0.0047	0.0063**	0.0063**	0.0061**	0.0062**
	(0.0023)	(0.0024)	(0.0027)	(0.0027)	(0.0023)	(0.0023)	(0.0023)	(0.0024)
Percent Subprime Credit	-0.0003	-0.0006	-0.0005	-0.0004	-0.0006	-0.0007	-0.0009	-0.0009
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0010)
Percent Subprime Credit*Black	-0.0028	-0.0036	-0.0059	-0.0060	-0.0026	-0.0026	-0.0033	-0.0029
	(0.0043)	(0.0043)	(0.0048)	(0.0048)	(0.0045)	(0.0044)	(0.0046)	(0.0045)
Wealth Gap	-0.0001	3.96e-05	0.0001	0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
Delinquency Gap	0.0003	-0.0035	-0.0023	-0.0024	0.0002	0.0002	-0.0003	-0.0002
	(0.0022)	(0.0032)	(0.0024)	(0.0024)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Owned Free/Clear Gap	0.0012	0.0012	0.0010	0.0010	0.0013*	0.0013*	0.0012	0.0012
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Housing Costs Exceed 35% Gap	0.0004	0.0001	0.0002	0.0001	0.0004	0.0003	0.0002	0.0003
	(0.0006)	(0.0006)	(0.0008)	(0.0008)	(0.0006)	(0.0006)	(0.0007)	(0.0007)
Home Affordability Index	0.0003**	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Home Price Index Volatility	-0.0001							
	(3.66e-05)							
Black-White Dissimilarity Index		0.0010						
		(0.0006)						
R-Squared	0.418	0.421	0.305	0.305	0.407	0.411	0.407	0.405
Counties	189	189	189	189	189	189	189	189

[a] Bootstrap standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

[b] The table reports the coefficients from a regression of the black-white loan denial gap in each county on an index of the average prejudice of whites in those counties. The dependent variable is the coefficient on the black indicator variable from separate linear probability models that control for the income and gender of the applicant, the gender of the co-applicant if applicable, the amount of the loan, the purpose of the loan, the type of the property, information on occupancy and lien status, and census tract, lender, and year fixed effects; additionally, each linear probability model controls for the ratio of the loan amount to the median housing value of homes owned by members of the individual's racial group in the county of interest. The weights for each county are explained in the text.

[c] Each regression shown also includes indicator variables representing whether the county is a central metropolitan county, outlying metropolitan county, or micropolitan county, with rural county being the omitted category.

[e] Column 1 includes the variance of the county-level House Price Index from 2004-2008. The specification in column 2 includes the black-white dissimilarily index. Specifications in columns 3 and 4 include an indicator variable in the first-step regression describing whether an individual from HMDA is included in PMIC. The indicator variable in column 3 indicates all possible matches, while the indicator variable in column 4 includes only exact matches. The specification in column 5 deletes from the first-step regressions all observations with missing census tract data while the specification in column 6 deletes from the first-step regressions all observations with identical data on a number of covariates. The speicifcation in column 7 uses a racial prejudice index calculated using unweighted GSS data, while the specification in column 8 does not weight all years evenly in the racial prejudice index. More details are discussed in the text.

Table A6 Fraction of Difference in Black-White Denial Gaps Due to Racial Prejudice

	All Conv. (1)	All FHA (2)	Conv. First Lien Purchase (3)	FHA First Lien Purchase (4)	Conv. Refinance (5)	FHA Refinance (6)	Conv. HUD (7)	Conv. Non-HUD (8)
1st Quartile-4th Quartile	0.614**	0.183	0.654**	0.439	0.644	-0.002	0.012	0.635**
	(0.195)	(0.223)	(0.241)	(0.305)	(0.361)	(0.002)	(0.015)	(0.227)
2nd Quartile-4th Quartile	0.400**	0.046	0.388**	0.296	0.352	-0.001	0.007	0.441*
	(0.147)	(0.025)	(0.141)	(0.207)	(0.195)	(0.001)	(0.009)	(0.183)
3rd Quartile-4th Quartile	0.389*	-4.609	0.249*	0.284	1.718	-0.001	0.005	0.399
	(0.196)	(345.8)	(0.010)	(0.338)	(6.640)	(0.001)	(0.006)	(0.220)

[a] Bootstrap standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

[b] Each fraction shown in the table is the fraction of the difference between conditional black-white denial gaps in specified prejudice quartiles estimated to be due to differences in racial prejudice between quartiles. Standard errors are estimated under the assumption that the estimated coefficients on 'Avg. White Prejudice' taken from Table 2 are the true population parameters.

Table A7 Conditional Correlations between Denial Gaps and Racial Prejudice, Seperately by Loan Type
Prejudice Reweighted by the Propensity that Individual is in a Managerial Occupation in the Banking, Savings, and Loan Industry

	All Conv. (1)	All FHA (2)	Conv. First Lien Purchase (3)	FHA First Lien Purchase (4)	Conv. Refinance (5)	FHA Refinance (6)	Conv. HUD (7)	Conv. Non-HUD (8)
Avg. White Prejudice	0.0103*	0.0105	0.0117*	0.0340	0.0075	0.0263	0.0155	0.0097*
	(0.0042)	(0.0076)	(0.0052)	(0.0186)	(0.0058)	(0.0205)	(0.0417)	(0.0046)
Fraction Black	0.2250	0.0754	0.1420	-0.1640	0.5490	0.3560	-0.5780	0.2520
	(0.20)	(0.3510)	(0.2330)	(0.6710)	(0.3150)	(1.280)	(1.6490)	(0.2240)
Log Population Density	0.0007	0.0079	0.0002	0.0212	-0.0033	0.0322	-0.0115	0.0004
	(0.0044)	(0.0077)	(0.0051)	(0.0109)	(0.0058)	(0.0290)	(0.0365)	(0.0048)
Bachelor's Degree Gap	-0.0006	0.0005	0.0001	0.0008	0.0001	0.0002	-0.0060	-0.0009
	(0.0006)	(0.0012)	(0.0008)	(0.0016)	(0.0010)	(0.0030)	(0.0087)	(0.0007)
Unemployment Gap	0.0095**	0.0051	0.0019	0.0026	0.0096*	0.0341*	-0.0073	0.0086**
	(0.0030)	(0.0053)	(0.0036)	(0.0082)	(0.0038)	(0.0157)	(0.0373)	(0.0032)
Self-Employment Gap	0.0064**	0.0039	0.0124***	-0.0021	0.0021	-0.0083	0.0322	0.0052
	(0.0023)	(0.0056)	(0.0037)	(0.0075)	(0.0047)	(0.0134)	(0.0238)	(0.0028)
Percent Subprime Credit	-0.0008	0.0006	-0.0002	-0.0010	-0.0015	0.0141*	0.0050	-0.0009
	(0.0010)	(0.0019)	(0.0012)	(0.0028)	(0.0014)	(0.0068)	(0.0089)	(0.0011)
Percent Subprime Credit*Black	-0.0032	-0.0024	-0.0011	0.0043	-0.0101	-0.0235	0.0175	-0.0037
	(0.0046)	(0.0088)	(0.0056)	(0.0169)	(0.0076)	(0.0304)	(0.0346)	(0.0052)
Wealth Gap	7.06e-06	0.0002	0.0003	0.0003	-0.0006	0.0015	0.0006	-0.0001
	(0.0004)	(0.0009)	(0.0005)	(0.0015)	(0.0005)	(0.0019)	(0.0021)	(0.0004)
Delinquency Gap	-1.47e-05	-0.0026	0.0041	-0.0030	-0.0032	-0.0077	-0.0108	-0.0002
	(0.0022)	(0.0036)	(0.0027)	(0.0061)	(0.0029)	(0.0118)	(0.0269)	(0.0023)
Owned Free/Clear Gap	0.0013*	0.0030*	0.0012	0.0043	0.0022*	0.0016	-0.0031	0.0011
	(0.0006)	(0.0013)	(0.0007)	(0.0024)	(0.0009)	(0.0041)	(0.0075)	(0.0007)
Housing Costs Exceed 35% Gap	0.0003	0.0027	0.0007	0.00389*	0.0009	4.87e-05	-0.0057	0.0004
	(0.0007)	(0.0017)	(0.0008)	(0.0020)	(0.0010)	(0.0036)	(0.0086)	(0.0007)
Home Affordability Index	0.0004***	0.0002	-0.0001	0.0001	0.0004**	0.0009*	-0.0008	0.0004***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0004)	(0.0012)	(0.0001)
R-Squared	0.40	0.16	0.28	0.13	0.26	0.17	0.04	0.36
Counties	189	189	187	187	189	189	187	189

[a] Bootstrap standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

[b] The table reports the coefficients from a regression of the black-white loan denial gap in each county on an index of the average prejudice of whites in those counties. The dependent variable is the coefficient on the black indicator variable from separate linear probability models that control for the income and gender of the applicant, the gender of the co-applicant if applicable, the amount of the loan, the purpose of the loan, the type of the property, information on occupancy and lien status, and census tract, lender, and year fixed effects; additionally, each linear probability model controls for the ratio of the loan amount to the median housing value of homes owned by members of the individual's racial group in the county of interest. The weights for each county are explained in the text.

[c] Each regression shown also includes indicator variables representing whether the county is a central metropolitan county, outlying metropolitan county, or micropolitan county, with rural county being the omitted category.

[d] The average prejudice of whites in each state is calculated using the reweighted population, where the weights are proportional to the propensity that the individual is in a managerial occupation in the banking, savings, and loan industry. More information is presented in the text.

Table A8 Conditional Correlations between Racial Gaps in High-Priced Loan Prevalence and Racial Prejudice, Seperately by Loan Type

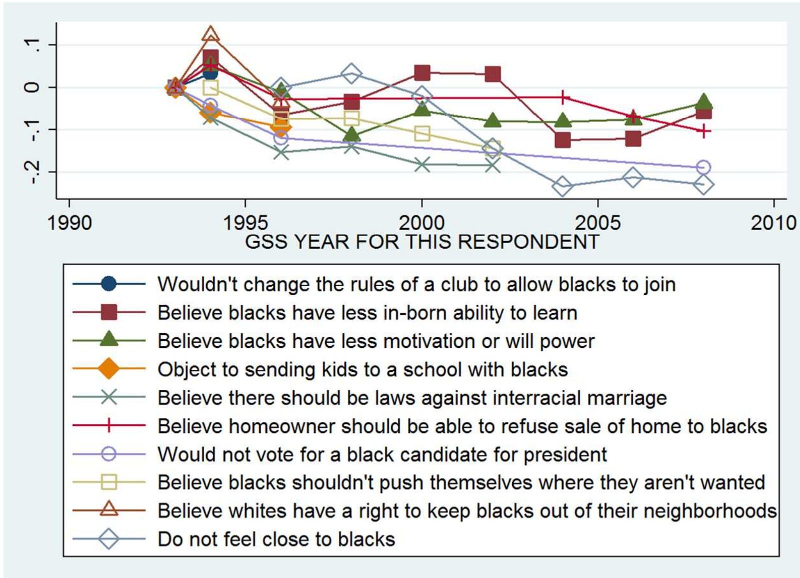
	All Conv. (1)	All FHA (2)	Conv. First Lien Purchase (3)	FHA First Lien Purchase (4)	Conv. Refinance (5)	FHA Refinance (6)	Conv. HUD (7)	Conv. Non-HUD (8)
Avg. White Prejudice	0.0040*	0.0038	0.0068	0.0051	0.0061*	0.0259	0.0042	0.0035
	(0.0017)	(0.0050)	(0.0055)	(0.0113)	(0.0025)	(0.0171)	(0.0037)	(0.0018)
Fraction Black	0.0674	0.0511	0.0348	-0.0219	0.249	0.0786	0.2240	0.0852
	(0.0779)	(0.218)	(0.229)	(0.609)	(0.128)	(0.639)	(0.1440)	(0.0811)
Log Population Density	-0.0014	-0.0008	0.0034	-0.0068	-0.0044	-0.0020	0.0072*	-0.0023
	(0.0015)	(0.0057)	(0.0047)	(0.0109)	(0.0024)	(0.0139)	(0.0033)	(0.0017)
Bachelor's Degree Gap	-0.0002	-0.0009	0.0004	-0.0009	-0.0005	-0.0046	-0.0001	-0.0002
	(0.0003)	(0.0008)	(0.0007)	(0.0016)	(0.0003)	(0.0030)	(0.0004)	(0.0003)
Unemployment Gap	0.0005	-0.0080*	-0.0019	-0.0093	0.0001	-0.0118	-0.0006	0.0006
	(0.0011)	(0.0040)	(0.0039)	(0.0075)	(0.0014)	(0.0101)	(0.0026)	(0.0011)
Self-Employment Gap	0.0011	-0.0026	-0.0023	-0.0004	0.0006	-0.0050	0.0009	0.0005
	(0.0011)	(0.0046)	(0.0034)	(0.0056)	(0.0015)	(0.0153)	(0.0016)	(0.0012)
Percent Subprime Credit	0.0005	-0.0030	0.0003	-0.0050	0.0007	-0.0008	0.0001	0.0008*
	(0.0003)	(0.0016)	(0.0010)	(0.0029)	(0.0005)	(0.0035)	(0.0007)	(0.0004)
Percent Subprime Credit*Black	-0.0011	0.0017	0.0009	0.0096	-0.0045	-0.0006	-0.0043	-0.0017
	(0.0019)	(0.0056)	(0.0058)	(0.0170)	(0.0030)	(0.0151)	(0.0037)	(0.0020)
Wealth Gap	-0.0002	-6.48E-06	-0.0003	0.0005	-0.0002	-0.0015	0.0002	-0.0002
	(0.0002)	(0.0006)	(0.0004)	(0.0010)	(0.0002)	(0.0014)	(0.0003)	(0.0002)
Delinquency Gap	0.0003	0.0035	-0.0003	-0.0003	-0.0016	-0.0055	0.0006	-0.0001
	(0.0008)	(0.0028)	(0.0023)	(0.0060)	(0.0010)	(0.0063)	(0.0017)	(0.0008)
Owned Free/Clear Gap	0.0006*	-0.0001	0.0007	0.0010	0.0001	-0.0019	2.42E-06	0.0006*
	(0.0003)	(0.0009)	(0.0008)	(0.0015)	(0.0003)	(0.0024)	(0.0004)	(0.0003)
Housing Costs Exceed 35% Gap	-0.0006*	0.0004	-0.0019*	-0.0004	-0.0006	0.0006	-0.0003	-0.0007*
	(0.0003)	(0.0010)	(0.0008)	(0.0016)	(0.0004)	(0.0027)	(0.0004)	(0.0003)
Home Affordability Index	0.0001	0.0002	-0.0001	-0.0001	3.19E-05	-0.0002	0.0001	4.14E-05
	(3.06e-05)	(0.0001)	(0.0001)	(0.0003)	(4.54e-05)	(0.0003)	(0.0001)	(3.16e-05)
R-Squared	0.28	0.20	0.18	0.09	0.23	0.14	0.16	0.27
Counties	189	187	187	186	188	179	185	189

[a] Bootstrap standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

[b] The table reports the coefficients from a regression of the black-white gap in originated loans above the rate spread in each county on an index of the average prejudice of whites in those counties. The dependent variable is the coefficient on the black indicator variable from separate linear probability models that control for the income and gender of the applicant, the gender of the co-applicant if applicable, the amount of the loan, the purpose of the loan, the type of the property, information on occupancy and lien status, and census tract, lender, and year fixed effects; additionally, each linear probability model controls for the ratio of the loan amount to the median housing value of homes owned by members of the individual's racial group in the county of interest. The weights for each county are explained in the text.

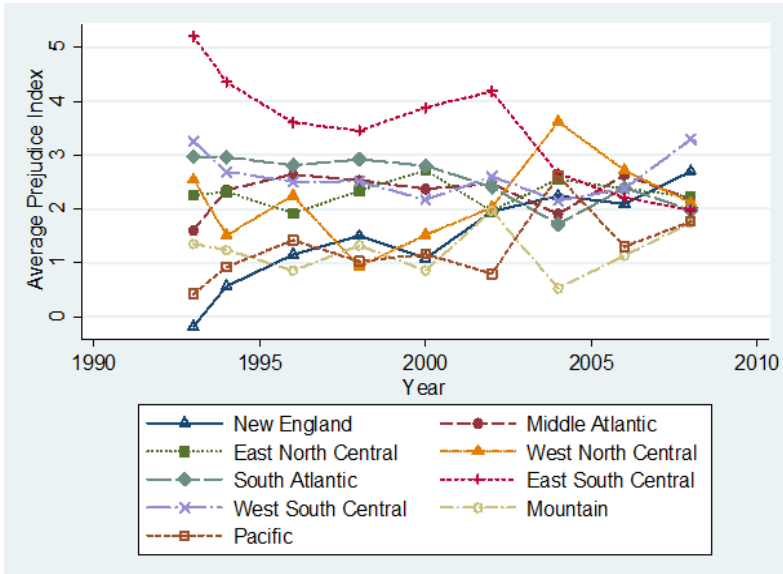
[c] Each regression shown also includes indicator variables representing whether the county is a central metropolitan county, outlying metropolitan county, or micropolitan county, with rural county being the omitted category.

Fig. A1 How Answers to GSS Prejudice Questions Change over Time



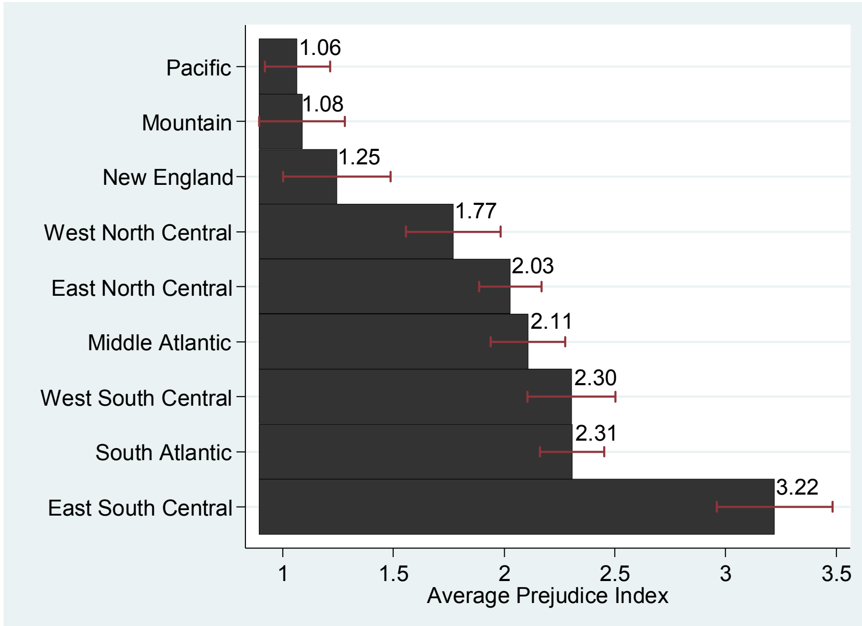
[a]Figure A1 shows how standardized responses to each GSS prejudice question have changed over time.
[b]Responses are standardized by the mean and standard deviation of the first year that each question is asked.

Fig. A2 How the Average Prejudice Index has changed over Time across Census Divisions



[a]Figure A2 shows how the average prejudice index has changed in each census division over time.

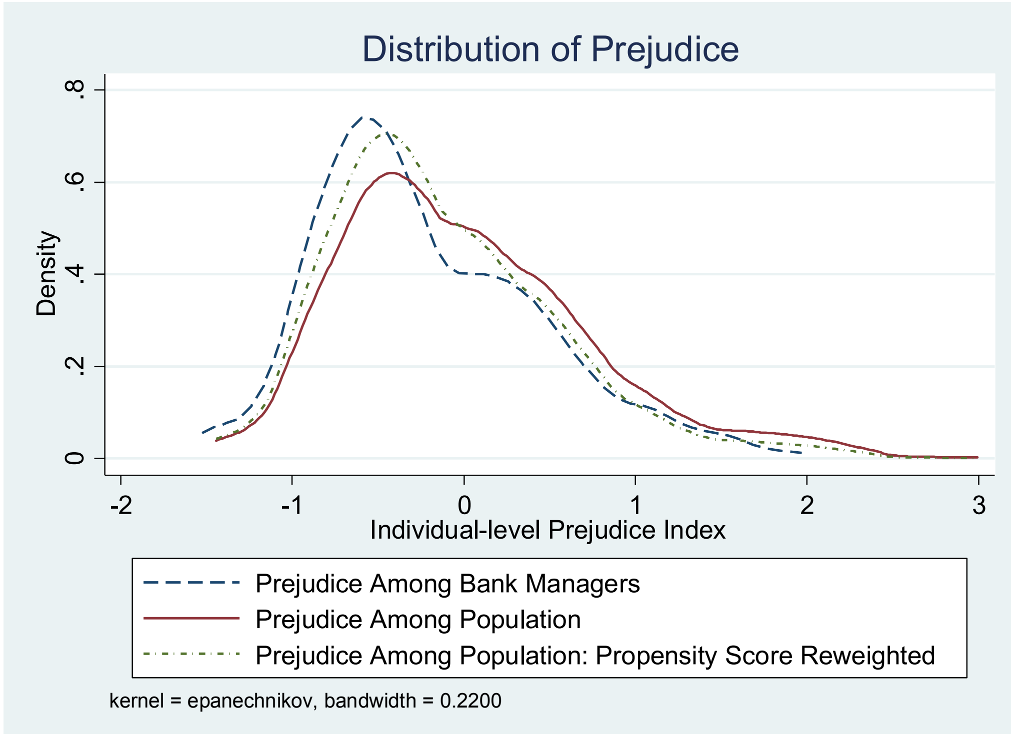
Fig. A3 The Average Prejudice Index across Census Divisions



aFigure A3 shows the average prejudice index across each census division in the United States.

bThe error band on each bar represents the 95% confidence interval on the estimate of average prejudice in that census division.

Fig. A4 Distribution of Prejudice among Managers in the Banking, Savings, and Loan Industry and Among the Entire White Population



aThe red solid line shows the distribution of the individual-level prejudice index, as measured by the GSS, from 1993-2008.
bThe blue dashed line shows the distribution of the individual-level prejudice index among the 171 individuals identified as working in managerial occupations in banking, savings, and loan organizations.
cUsing the propensity score to weight all individuals by the probability that they work in a managerial occupations in a banking, savings, or loan organization based on age, years of education, gender, and all 4^{th}-degree polynomials and interaction terms gives the distribution of prejudice shown by the dashed dotted gray line.