When Prejudice Hits Home: Hate Crime and the Market for Mortgage Credit[*]

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ABSTRACT

Hate-motivated crimes have risen to unprecedented levels, yet their far-reaching economic consequences remain understudied. Utilizing comprehensive data on US mortgage applications and county-level hate crime statistics, we document significant effects on housing decisions. An increase in anti-minority racial hate crimes reduces mortgage applications, with both minority and White applicants exhibiting strong demand-side responses. We find that residents migrate away from hate crime–affected counties rather than delaying home purchases or entering the rental market. These patterns speak to an erosion of social cohesion in impacted neighborhoods. Supporting this, survey evidence shows elevated psychological distress levels and reduced visible consumption in affected counties, as well as a diminished presence of civic organizations. Our findings illuminate the far-reaching consequences of hate crimes on housing choice with consequences for the economic development of entire neighborhoods.

Keywords: Hate Crime, Racial Animus, Mortgage Demand, Housing Choice

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"*We have three people who are dead because they are Black," State Senator Tracie Davis, a Jacksonville Democrat, said at a vigil on Sunday morning. "Shopping. In our community. Gunned down. Because they were Black.*" — New York Times, 2023

I. Introduction

Acts of violence directed at people because of their race, color, or ethnicity have seen unprecedented increases in recent times. The 2023 FBI report highlights a significant surge in the reporting of hate-related (or bias-motivated) crimes, reaching the highest level since the initiation of the FBI's data collection efforts in the early 1990s. Such hate crimes have the potential to cause lasting economic harm (Cook, 2014) and displacement to lower-quality neighborhoods (Chetty et al., 2020; Christensen & Timmins, 2022). Understanding the full scope of economic consequences is therefore crucial. Emerging research suggests that hate crimes hinder the assimilation of immigrant communities and even diminish workplace productivity of fund managers (Gould & Klor, 2016; Agarwal et al., 2023). However, the broader impact of hate crimes on households' economic decisions, and potential spillover effects on nonminority groups, remains an important open issue that warrants further investigation.

In this paper, we set out to study the effects of racial hate crime on local economic investment and social cohesion by examining its impact on individuals' housing decisions, particularly in the way it is reflected in the demand for mortgage credit. Neighborhoods can experience decline due to racial hate crimes, since these incidents lead to communal segregation and certain areas being labeled unsafe or appearing undesirable for potential homebuyers. Further, incidences of racial hate crime can hinder neighborhood development, discouraging mortgage applications by certain groups of applicants, leading to a further widening of the racial wealth gap (Choi, 2020; Ray et al., 2021). Investigating the effect of racial hate crimes on homeownership is important because homeownership constitutes a fundamental cornerstone of the American Dream and serves as a principal vehicle for intergenerational wealth accumulation and economic mobility. Attaining higher homeownership rates therefore remains a central goal in the government's policy for housing and urban development. Homeownership also promotes the construction of a more cohesive social fabric, since homeowners tend to nurture unity and cohesion, creating stronger community ties and greater participation in civic activities.

In our empirical investigation of the link between racial hate crimes and mortgage demand, we utilize the near-universe of US mortgage loan applications retrieved from the Home Mortgage Disclosure Act (HMDA) database. Since each observation in the database is a loan application record that includes geographic, lender, and loan take-up information, we are able to observe the households' final mortgage decisions and exploit the information to disentangle demand-side from supply-side decisions. HMDA further records information on the race and ethnicity of the applicant(s), which enables us to observe variations in the number of mortgage applications made by different racial groups over time. County-level incident–based hate crime data is retrieved from the FBI Uniform Crime Reporting (UCR) program.

In identifying the effects empirically, key threats to identification are that county-level characteristics and other local conditions can be correlated with both mortgage demand and hate crimes, and that reverse causality may be present through the possibility that minority mortgage applications may lead to backlash in the form of hate crimes. We overcome these hurdles by conceptualizing county-level hate crime as the local exposure to aggregate national hate crime through its share of the minority population. The estimation is in the spirit of a shift-share design, where the predetermined minority shares and the nationwide hate crime rates are not likely to reflect local effects at the county level. Further, our investigation requires us to disentangle demand-side from supply-side effects. To shut down supply-side influences, we evaluate mortgage applications provided by lenders within a county in a given year and saturate our regression specifications with lender-year fixed effects. Additionally, we include county fixed effects and county-level control variables to account for time-invariant and time-varying county-level economic factors.

The results illuminate a substantial negative impact of racial hate crime on mortgage credit demand. We find that areas affected by racial hate crimes experience a 2.4% decline in mortgage applications and lenders originate 1.5% fewer mortgages for a one standard deviation increase in racial hate crimes (circa 673 additional incidents nationally). As a back-of-the-envelope calculation for the year 2020, this implies a drop of 498,886 mortgage applications and 132,670 mortgage originations on aggregate. Highlighting the distinct nature of hate crimes relative to nonbias crimes, we find that the economic magnitude of an additional hate crime is substantially larger than of a corresponding nonhate crime. This underscores the unique effect of hate crimes on housing decisions and rules out that a general aversion to crime is solely driving our results.

The adverse effect extends across various types of borrower, with both White applicants and minorities (Black, Asian and Hispanic applicants) similarly affected, highlighting the pervasive influence of these crimes on housing decisions. Further, minority applicants are seen to withdraw their applications from lenders in counties affected by hate crime incidences. Examining adjacent counties with shared borders, we find significant spillover effects on mortgage applications in neighboring counties, underlining the broader societal repercussions of racial hate crimes on housing market behavior beyond local boundaries.

Next, we investigate whether the hate-crime-induced reduction in mortgage demand correlates with the social erosion of a neighborhood: are individuals moving out of hate crime–affected areas, or are they staying and delaying home purchases (i.e., renting)? For this, we collect information on the number of residents migrating between counties from the individual income tax returns filed with the Internal Revenue Service (IRS), while rental market prices, proxying for the rental demand, are retrieved from Zillow. We show that residents leave counties affected by hate crime. Additionally, we see drops in rental prices in racial hate crime–affected counties, indicating that residents move out of such counties, instead of staying and delaying home purchases. Building on these migration patterns, we further examine whether outflows from hate crime–affected counties impact the housing markets and mortgage outcomes in the destination counties, as well as any pressure on the rental market in destination counties. Interestingly, we observe that an influx of people from hate crime–affected counties increases rental prices in destination counties, while suppressing mortgage applications and originations. These findings emphasize the real effects arising from racial hate crimes, which extend beyond local housing markets due to their impact on migration between counties and neighborhood choices.

To understand the societal effects more deeply, we utilize survey information and census data to document significant repercussions arising from racial hate crimes on neighborhoods. First, by analyzing psychological distress levels and expenditure behavior, we that hate crimes decrease psychological well-being and reduce visible consumption, such as clothing, jewelry, and outdoor recreation expenses. Second, we find the share of religious, civic and social organizations drops in response to hate crimes in a the local area. These results indicate that neighborhoods affected by racial hate crimes show heightened levels of fear and lower social capital, which can influence housing decisions and contribute to the observed patterns in mortgage demand.

This paper contributes to several strands of economic literature on racial bias and hate crimes, spanning their diverse of causes and far-reaching consequences. On the side of causes, studies have identified various factors, including backlash from terror attacks or immigrant-attributed crime in a local community (Gould & Klor, 2016; Riaz et al., 2024), regional economic shocks during the recent COVID-19 pandemic (Dipoppa et al., 2023), the role of social media in fostering xenophobia (Müller & Schwarz, 2021, 2023; Grosjean et al., 2023), inflammatory political campaigns (Grosjean et al., 2023) and the impact of entertainment media in perpetuating racial stereotypes (Ang, 2023). Regarding consequences, prior research documents significant societal and economic impacts, such as immigrant communities turning to traditional values and assimilating less successfully (Gould & Klor, 2016), as well as decreased productivity among fund managers (Agarwal et al., 2023). Building upon this literature, our paper elucidates how hate crimes influence mortgage credit decisions across both minority and nonminority households. We demonstrate profound effects on their choices regarding housing and neighborhoods, thereby adding a crucial dimension to understanding the broader economic implications of hate crime.

Moreover, our research intersects with studies on housing and neighborhood choice. Previous literature has highlighted the influence of noninstitutional determinants on homeownership decisions and decisions to hold a mortgage. For instance, factors include air pollution, violent crime, neighborhood racial composition, historical anti-Jewish sentiment, among others (Bayer et al., 2009; Bishop & Murphy, 2011; Bayer et al., 2016; D'Acunto et al., 2019). Our work extends these findings by pinpointing hate crime as a critical factor affecting households' location and housing decisions. Furthermore, we engage with the expanding body of research on racial bias within the mortgage market (Ambrose et al., 2021; Bhutta & Hizmo, 2021; Bartlett et al., 2022), which primarily focuses on supply-side discrimination by lenders against minority borrowers. In contrast, our study offers novel insights from the demand side, revealing that both White and minority borrowers self-select out of mortgage opportunities in neighborhoods affected by hate crimes and racial bias. This contribution not only deepens our understanding of the multifaceted consequences of hate crimes but also bridges significant gaps in the literature on housing economics and racial discrimination in lending markets.

The paper proceeds as follows. Section II provides background information on hate crimes in the US and their distinct nature relative to nonbiased crimes. Section III documents our data and variable definitions. Section IV explains the identification approach and presents the results of our main analyses. Sections V and VI document migration patterns arising from hate crimes as well as potential channels through which the effects of hate crimes operate, respectively. Section VII concludes.

II. The distinct nature of hate crime

Hate crimes, also known as bias-motivated crimes, are distinguished by the perpetrator's prejudice against specific perceived attributes such as "race, color, religion, national origin, sexual orientation, gender, gender identity, or disability" (US Dep. Justice, 2023). The majority of hate crimes are perpetrated on the basis of the victim's race (FBI, 2023). While bearing some similarities to other forms of offensive behavior, hate crimes differ fundamentally in their deep-seated origins in prejudice, identity, and societal attitudes (Rose & Mechanic, 2002; Lockwood & Cuevas, 2022), as well as in their far-reaching societal implications.

To classify reported crime incidents as hate crimes, the FBI employs a meticulous two-tier decision-making process. First, the responding law enforcement officer indicates whether the offender was bias-motivated, tagging the incident as a suspected bias crime. Subsequently, a second-level judgment officer reviews the facts and makes the final determination of a hate crime occurrence. Most US States have enacted hate crime laws stipulating increased penalties or sentence enhancements for bias-motivated crimes, due to their profound consequences.

While any crime can adversely impact the individual victim, hate crimes possess a unique capacity to ripple through communities. Victims often grapple with emotional distress, manifesting as anxiety, depression, anger, fear, and even post-traumatic stress disorder (Herek et al., 1999; McDevitt et al., 2001). Social repercussions include isolation, stigma, and diminished trust in communities (Perry, 2001; Iganski, 2001). At the neighborhood level, hate crimes can erode trust, amplify social tension (Green et al., 1998), undermine social cohesion (Lyons, 2007), and diminish community solidarity (Paterson et al., 2019). Thus, they not only inflict harm on the immediate victim but can also incite retaliation, escalate communal tension, and reverberate adverse effects both within and beyond the immediate locality. Such crimes, therefore, have the potential to destabilize neighborhoods and disrupt societal harmony.

The distinct nature of hate crimes is recognized within the US legal framework. Both federal and state laws (in the majority of states) have instituted heightened penalties or sentence enhancements for crimes demonstrably motivated by bias (US Dep. Justice, 2023). A notable piece of legislation in this regard is the Matthew Shepard and James Byrd Jr. Hate Crimes Prevention Act of 2009, which expanded the jurisdiction for prosecuting racial and religious hate crimes and introduced protections against other forms of bias-motivated violence. While these legal measures acknowledge the gravity of hate crimes, scholarly efforts have also been devoted to understanding their underlying drivers.

Theories on hate crimes recognize their complexity and multidimensional nature, spanning disciplines from psychology, sociology and economics. Integrated threat theory (Stephan et al., 2000) posits that hate crimes emerge from perceived threats from out-group members. This is complemented by social identity theory (Tajfel et al., 1979), which underscores the human inclination toward in-group favoritism and out-group discrimination as potent precursors to hate crimes. Additionally, the ethnic competition theory (Scheepers et al., 2002) emphasizes the role of aggression arising from economic competition between distinct groups. Lastly, relative deprivation theory (Walker & Smith, 2002) suggests that individuals perceiving themselves as unfairly disadvantaged may be inclined to commit hate crimes against those they deem more privileged.

Empirical studies offer concrete insights into the causes and consequences of hate crime. Regarding causes, backlash to terror attacks, entertainment media, and social media have been identified as contributing factors. Gould and Klor (2016) show that the 9/11 terrorist attacks led to anti-Muslim backlash, resulting in hate crimes against Muslim communities. In a similar vein, Riaz et al. (2024) document that hate crimes against refugees rise sharply in the immediate aftermath of an immigrant-attributed crime event in a local community. In turn, immigrant communities assimilate less well and turn to more traditional values. With the increase in racist attacks on the Asian community during the COVID-19 pandemic, Agarwal et al. (2023) document a reduction in female fund managers' productivity for those perceived as of East Asian origin. Müller and Schwarz (2021, 2023) find that social media can propagate and amplify xenophobia, leading to spikes in hate crimes against minorities. Using data on historical screenings of entertainment media depicting racial stereotypes, Ang (2023) documents significant effects on lynchings, race riots and modern day hate crimes.

Despite the distinct nature of hate crimes and their detrimental effects, the impact of hate crimes on consequential personal financial decisions, such as mortgage credit choices, remains an open area of investigation. This paper aims to bridge this gap by examining how the threat of hate crimes shapes households' housing market behavior and neighborhood selection across both minority and nonminority groups, contributing to the growing literature on the economic consequences of hate crime.

III. Data and variables

We provide a description of the multiple datasets and variables utilized in the paper. Table I presents the summary statistics on the variables of our sample, which covers the period from 2007 to 2020.

A. Mortgage data

We retrieve from the Home Mortgage Disclosure Act (HMDA) database comprehensive information on the near-universe of US mortgage applications, including lender identification, loan amount, purpose of the loan, status, location, as well as borrowers' personal information. In order to account for atypical loan and lender patterns, following Dagher and Kazimov (2015), we exclude loans below 25,000 and above a million dollars and exclude inactive lenders that originated fewer than fifty mortgage loans in any given year.

For a given application, we are able to observe the race and ethnicity of the applicant(s). Following Bhutta et al. (2017), if a (co-)applicant reports two races and one is White, that (co-)applicant is categorized under the minority race. Otherwise, (co-)applicants are categorized under the first race and ethnicity reported. Based on the applicant's and co-applicant's race and ethnicity, we categorize each application into one of the six mutually exclusive and exhaustive groups (Unknown, Black, Asian, Hispanic, White, Other), following the methodology of Gerardi et al. (2021). In order to observe the mortgage demand by each group for a country-lender combination, we then aggregate the data to the county-lender level and construct variables for each minority group, resulting in 4,067,019 observations for our main dataset.

B. *Hate crime data*

The hate crime data comes from the FBI Uniform Crime Reporting (UCR) program. The dataset provides incident-level information, including whether the offenders are motivated by their bias against the victim's perceived race, gender, gender identity, religion, disability, sexual orientation, or ethnicity. Law enforcement agencies report hate crime incidents to the UCR program through the Summary Reporting System (SRS) or National Incident-Based Reporting System (NIBRS). We thus draw on the combined information on incidents reported in the two sources to capture all reported county-level hate crime occurrences.

Hate crimes are classified into racial hate crimes, sex- and gender-based hate crimes, and religious hate crimes, with racial hate crimes predominating. Our primary analysis centers on racial hate crimes, given the focus of the research, while we examine the other two types as placebo tests. We aggregate the hate crime data to the county level. To prevent measurement issues, we exclude counties that have historically never reported hate crimes in Arkansas, South Carolina, and Wyoming, which do not have state-level hate crime laws.

To illustrate the evolution of hate crime incidences over time, Figure I plots the three main types of hate crime reported (i.e., racial, sex- and gender-based, and religious hate crimes), scaled by 1000 total crimes, from 1994 to 2020. Compared with racial hate crimes, the other two types play a smaller part. However, all hate crimes share a similar trend across time. A small peak is observed in 2001 due to the surge in hate crimes after the 9/11 terrorist attack. It can also be seen that reporting of hate crimes started to decline gradually during the Obama administration. This trend reversed following the election of Trump, during whose term reported hate crime numbers surged and hit a new historical high.

C. Survey data

To explore the neighborhood- and individual-level effects of hate crime, we utilize survey information from the Panel Study of Income Dynamics (PSID) restricted files and the Consumer Expenditure Survey (CEX).

The PSID surveys are conducted once every two years, with a nationally representative sample of households. The survey provides comprehensive information on household income, wealth, education, and household demographics. We use the PSID geospatial restricted files to retrieve each PSID respondent's location, which is used to match with county-level hate crime data. We use the information on respondents' psychological distress to study the potential heightened feeling of vulnerability and fear in affected neighborhoods. The detailed variable definitions can be found in the Appendix. Since the month of survey is disclosed in the data, we construct a monthly dataset for a more granular assessment of the effects. As shown in the summary statistics, nearly 15% of respondents are psychologically distressed to various degrees.

The CEX program is administrated by the US Bureau of Labor Statistics to provide data on expenditures, income, and demographic characteristics of consumers in the US. To further understand the role of fear in relation to hate crime and mortgage applications, we focus on the consumers' visible spending on clothing and jewelry, and outdoor recreation, since the literature has shown that spending on these goods and services is negatively related to fear caused by crimes (Mejía & Restrepo, 2016). The exact items used to construct the variables are reported in the Appendix. The CEX has been introducing state-level data and currently there are five states available – namely, California, Florida, New York, Texas, and New Jersey – covering population areas amounting to 36% of the US population. The data is measured at the quarterly frequency. In the summary statistics, we observe that households spend negligible amounts on clothing and jewelry (outdoor recreation) at the 10th percentile or as much as 520 (780) dollars at the 90th percentile, during the past quarter.

D. Migration data

To investigate the effect of hate crime on the migration of people, we further bring into play the county-to-county migration data from the Internal Revenue Service (IRS). The dataset provides the annual population migration between any two counties based on the year-to-year address changes reported on individual income tax returns filed with the IRS, which covers the majority of adults receiving an income from employment. We calculate the aggregate outflow and net outflow of people from a county each year. For each county, we also use its outflows to all its emigrants' destinations as weights to calculate the weighted average destination county characteristics to examine what factors attract people.

The migration variables are at the county–year level, with more than 30,000 observations. Most counties have a net outflow of people, since a few metropolises attract people from everywhere. An average county has an outflow of more than 5,000 people in a year.

E. Other geographic data

We gather additional geographic data from various sources. We collect the general crime data from the above-mentioned SRS to control for the overall crime rate in different regions.

These data are at the state level.[1] In addition, we obtain (minority) population data from the Census Bureau; unemployment data from Local Area Unemployment Statistics published by the Bureau of Labor Statistics; GDP, per capita personal income from the Bureau of Economic Analysis; poverty percentage data from the Small Area Income and Poverty Estimates Program; housing price and rent data from Zillow; population migration data from the Internal Revenue Service; and establishments data from County Business Patterns published by the Census Bureau. The summary statistics of the geographic variables show that our sample covers counties with a wide range of sizes, levels of economic development, housing costs, and crime.

IV. Racial hate crime and mortgage credit

A. *The effect of racial hate crime on the demand for mortgage credit*

In this paper, we investigate the impact of racial hate crimes on the demand for mortgage credit in US counties. Estimating this effect is challenging due to several identification issues. First, measurement error in county-level hate crime data, arising from heterogeneous reporting practices across jurisdictions, may attenuate coefficient estimates. Second, unobserved local confounders such as economic conditions, demographic shifts or social tensions could influence both hate crimes and mortgage demand, leading to omitted variable bias. Third, reverse causality is a concern, as increased mortgage demand from minorities could potentially inflame racial animosity and spur more hate crimes, biasing estimates upward.

To overcome these challenges, we employ a shift-share research design (Bartik, 1991; Adao et al., 2019). This approach identifies the effect of racial hate crimes by leveraging cross-county variation in exposure to the nationwide trend in such crimes. Specifically, we

[1] NIBRS also gathers general crime data that can be aggregated to the county level. However, most US law enforcement agencies did not submit data to NIBRS before 2020. Therefore, during our sample period, NIBRS covers less than one third of the population. So, we use the SRS crime rate since it is nationally representative. However, we utilize the NIBRS data to conduct additional subsample analysis.

construct a measure of the racial hate crime exposure of county c in year t as follows:

$$Racial\ Hate\ Crime_{c,t} = \left(\sum_{k=1,\, k \neq c}^{K} Anti\text{-}Minority\ Hate\ Crime_{k,t} \right) \times \frac{Minority\ Population_{c,t}}{Total\ Population_{c,t}}, \tag{1}$$

where $Anti\text{-}Minority\ Hate\ Crime_{k,t}$ represents local anti-minority hate crimes (in 1000s) in county k ($k \neq c$) and year t. In essence, this shift-share variable captures each county's exposure to the aggregate national hate crime trend through the lenses of its minority population[2].

The shift-share design addresses the aforementioned identification challenges. First, by using the leave-out construction in Equation (1), we ensure that fluctuations in hate crimes at the national level are uncorrelated with unobserved county-specific conditions or measurement errors, mitigating bias from these sources. Second, the interaction with county minority population shares serves as an exogenous source of cross-county variation in hate crime exposure, as the nationwide hate crime trend is plausibly orthogonal to local confounders, in particular after excluding the county's own crimes. Finally, the use of national hate crime variation alleviates concerns about reverse causality, as shocks to local mortgage demand are unlikely to drive hate crimes in other parts of the country. Together, these properties of the shift-share variable strengthen the causal interpretation of our estimates[3].

We embed our shift-share design in fixed effects regression model to assess the impact of racial hate crime on the demand for mortgage credit by, importantly, controlling for supply-side influences through the inclusion of lender-year fixed effects.

[2]We also consider two alternative ways of constructing the shift-share measure for racial hate crime. More specifically, we utilize ethnicity information to separately take into account hate crimes against specific groups. The results are provided in Online Appendix Tables A1 and A2.

[3]Shift-share designs have been a popular identification strategy applied to estimate local causal effects while accounting for potentially confounding factors (see, Adao et al., 2019, and references therein) and also overcomes the challenge of lack of data, where data is either not captured or publicly available in certain sample of counties.

Specifically, our regression model takes the following form:

$$M_{c,l,t} = \alpha_c + \lambda_{l,t} + \gamma Racial\ Hate\ Crime_{c,t-1} + X'_{c,t-1}\theta + \varepsilon_{c,l,t}, \tag{2}$$

where $M_{c,l,t}$ represents the dependent variable for mortgage credit demand in county c for lender l at time t. We study several mortgage outcomes, including number of mortgage applications, withdrawal rates, denial rates, and mortgage originations. The primary explanatory variable of interest is the lagged value of the racial hate crime, denoted by $Racial\ Hate\ Crime_{c,t-1}$. Lagging our hate crime variable by one period helps to account for the potential delayed effects of racial hate crime exposure on mortgage demand. $X_{c,l,t-1}$ represents a vector of control variables specific to county c and time $t-1$. These controls enable us to adjust for other factors that might simultaneously influence the demand for mortgage credit and include county-level population, GDP growth, personal income, unemployment rate, poverty rate, home prices, minority share and the state-wide crime rate. Inclusion of the minority share as a control variable ensures that variation in Equation (1) originates from changes in racial hate crimes only. Definitions of all the variables can be found in the Appendix. Further, α_c and $\lambda_{l,t}$ represent county fixed effects and lender-year fixed effects, respectively. The county fixed effects control for unobserved time-invariant characteristics at the county level. [4] One of the keys to identification of the demand-side effects relies on saturating the model with the lender-year fixed effects. This enables for the disentangling of the demand-side effects from the lender-specific time-varying factors, such as any lending policy changes or local conditions influencing lenders' behaviors. Standard errors are clustered at the county level.

In sum, the key identifying assumption is that, conditional on county and lender-year

[4]For robustness (unreported in table), we assess whether the results are even partially driven by variation in the racial hate crime arising from changes in the county-level minority share. For this, we explicitly control for year-on-year changes in counties' minority share, which captures changes in the share of the local minority population, and find that the results remain unchanged, underlying that our results are driven by the national racial hate crime levels.

fixed effects, variation in a county's racial hate crime exposure stems from their vulnerability to the nationwide hate crime trend rather than county-specific confounders. In other words, the shift-share variable isolates changes in local hate crime exposure that are driven by aggregate fluctuations, which are plausibly exogenous to individual counties.

The results of our baseline estimation are presented in Table II, where we report the coefficient estimates for the primary variables of interest across different specifications. Each column represents a different regression, where the dependent variable is either the volume of mortgage applications or mortgage originations by various types of borrowers, including minority borrower (Black, Asian, and Hispanic) and White borrowers. The estimated coefficient on racial hate crime is negative and statistically significant across both White and the minority borrower groups. In terms of the economic significance, the coefficient for total mortgage applications in Column 1, and its derived average marginal effects, implies that a one standard deviation increase in racial hate crimes (circa 673 additional incidents nationally, in 1000s) decreases mortgage applications to a given lender in a given county by $(0.673 \times 3.180\% =)$ 2.14%. As a back-of-the envelope calculation for the year 2020, the estimation results imply a drop in 498,886 mortgage applications. Further, the magnitude of this negative relationship is notably similar for mortgage applications by minority borrowers and for White borrowers, underlining the consistent impact of racial hate crimes across demographic groups.

To assess the robustness of our findings and potential influence of omitted unobserved factors, we conduct an Oster (2019) test, key results of which are presented at the bottom of Table II. This test estimates the potential bias introduced by omitted variables, under the assumption that unobservable factors are as influential as the observable ones, from which a range of plausible coefficient values for our key explanatory variable can be inferred. The test results for mortgage applications consistently indicate that the plausible ranges of coefficient values, accounting for potential omitted variable bias, encompass the estimated coefficients from our main analysis. For instance, for all borrowers in the mortgage applications model, the range spans from -0.514 to -0.121, reinforcing the reliability of our results. This suggests a persistent negative and statistically significant negative effect from exposure to racial hate crimes on mortgage applications, even when unobserved factors are considered. The estimate of δ for $\beta = 0$ confirms that omitted variable effects need to be large and 4.6 times the effect of the observable covariates to nullify the main effects. Thus, the Oster (2019) test provides convincing evidence that our main findings, of a significant negative relationship between exposure to racial hate crimes and mortgage applications, are robust and not driven by omitted unobservable factors.

To quantify the comparative effects of hate crimes relative to nonbias crimes, we conduct a subsample analysis where the local county-level crime and hate crime data are available from the NIBRS. To ensure comparability, we use local racial hate crime incidents (i.e., at the county level, in logs), instead of relying on the shift-share construction. The estimation results are reported in Table (III). In Column 1, we observe that the racial hate crime estimate is negative and significant similar to our baseline results. In Column 2 we include the number of county-level other crimes (in logs) instead of the state-level crime variable. The results indicate that the effect of racial hate crime remains stable and not subsumed by the effects of other types of crime. Although the coefficient of racial hate crime is smaller than that of other crimes, the marginal effect is much larger due to the fact that racial hate crime is much less common than other crimes on average. Based on the estimation in Column 2, one additional incident of racial hate crime would reduce the mortgage application by 0.5% for a lender in a county, whereas one additional other crime would reduce the application by only 0.001%. These findings show that the economic magnitude of an additional hate crime is substantially larger than of a corresponding nonhate crime, underscoring the unique effect of hate crimes on housing decisions and ruling out the possibility that our results are driven solely by a general aversion to crime.

Following the initial examination of mortgage applications, we further explore application withdrawals, denials and originations after being made to lenders within a county and its association with hate crimes. This investigation on withdrawals provides valuable insights into how potential borrowers may react to exposure to racial hate crimes in their decision to continue or withdraw a mortgage application process. For the purpose of this analysis, the dependent variable in our regression is the withdrawal rate (i.e., withdrawn applications over total applications made) for lenders within a county and in the same year as our explanatory variable of interest, racial hate crime. Further, by looking at the denial rate, we are able to isolate the effects coming from the supply side, as compared to demand side effects. And finally, mortgage originations enable us to examine the overall effect of racial hate crime on the local mortgage market.

The results of this analysis are presented in Table IV. We find that exposure to racial hate crimes tends to increase the likelihood of mortgage application withdrawals, and this association is statistically significant for minority applicants (except for Asian) and White applicants as shown in Panel A. The differentially larger impact of racial hate crimes on minority communities potentially indicates of heightened caution or insecurity among prospective borrowers in the face of such societal unrest. The results in Panel B indicate that racial hate crime does not affect the denial rate for minority applicants, although the denial rate is higher for White applicants. When we consider the estimated effects on mortgage originations, Panel C and the implied average marginal effects show that a one standard deviation increase in racial hate crimes (0.673 thousand crimes) results in lenders originating $(0.673 \times 2.205\% =)1.48\%$ fewer mortgages in a given county. Again, as a back-of-the envelope calculation for the year 2020, the estimation results imply a drop in 132,670 mortgage originations on aggregate. Given the average underwriting profit in 2020, the drop in the origination translates to a reduction of 557 million dollars in profits for all mortgage lenders.[5]

Overall, the empirical results provide evidence of the significant impact of exposure to racial hate crimes on housing market dynamics. Importantly, they reveal that racial hate

[5] The average underwriting profit for 2020 is \$4,202 (see HERE) and, with the estimated drop of 132,670 mortgage originations, the loss in profit is estimated to be 4,202×132,670=557,479,340.

crimes not only deter prospective borrowers from initiating a mortgage application but also encourage those who have started the process to withdraw their applications, ultimately affecting mortgage originations on aggregate. The findings underscore the far-reaching and multilayered effects of racial hate crimes on housing market behavior and the overall economic wellbeing of both minority and White communities.

B. *County-level impacts and spillover effects of racial hate crime*

In this section, we shift our focus to an aggregate analysis at the county level, differing from our previous investigation, which considered county-lender-level analyses. The aim here is to provide a more comprehensive view of the county-level mortgage market impact due to racial hate crimes. While lender-specific analyses are instrumental in isolating the supply side effects through the inclusion of lender-year fixed effects, analyzing total mortgage applications at the county-year level allows us to extend our analysis to capture broader market dynamics and potential spillover effects within the geographical boundaries of a county.

Laying the foundation for our subsequent examination of cross-county spillover effects, the regression specification adopted here, as follows, serves to establish the baseline effects of racial hate crimes at the county level:

$$M_{c,t} = \alpha_c + \tau_t + \gamma Racial\ Hate\ Crime_{c,t-1} + X'_{c,t-1}\theta + \varepsilon_{c,t}. \tag{3}$$

In this equation, $M_{c,t}$ denotes the dependent variable for mortgage credit for county c at time t, namely, log of number of mortgage applications. The primary explanatory variable remains the lagged racial hate crime variable, denoted by $RacialHateCrime_{c,t-1}$. The vector $X_{c,t-1}$ captures county-specific characteristics, including population, GDP growth, personal income, unemployment rate, poverty rate, house prices, and state-wide crime rate at time $t-1$ for each county c. Detailed definitions of all variables are provided in the Appendix.

The terms α_c and τ_t represent county and year fixed effects, respectively, controlling for unobserved time-invariant characteristics at the county level and capturing common shocks impacting all counties in a specific year. We cluster standard errors at the county level.

The results of these county-level regressions are presented in Table V. We find that the estimated coefficients on racial hate crime are negative and statistically significant across both specifications, echoing our earlier findings. Economically, a one standard deviation increase in racial hate crimes (circa 673 additional incidents nationally) corresponds to a significant reduction in the number of mortgage applications (3.7%) in a given county. This suggests that the aggregate effects of racial hate crime at the county level, capturing both demand and supply channels, are substantial.

The control variables provide further insights into the factors that influence mortgage demand at the county level. Similar to our earlier findings, population size, personal income, and poverty rate positively influence mortgage demand, while unemployment rate, home prices, and crime rate negatively impact mortgage demand. Specifically, an increase in the population size in a county significantly increases the demand for mortgage credit, while higher unemployment and crime rates decrease the demand. Meanwhile, the poverty rate shows a positive relationship with mortgage demand, potentially indicating that in areas with higher poverty rates, residents may be more likely to seek mortgage loans as a way of securing housing. Finally, higher home prices are associated with reduced mortgage demand, likely reflecting affordability challenges.

We now turn to extending our analysis to study the spillover effects of racial hate crimes on adjacent counties' mortgage market dynamics. This analysis allows us to explore how the hate crimes in one county might influence the demand for mortgage credit not only in the local county but also in the neighboring counties. This broader perspective allows us to understand the far-reaching impacts of racial hate crimes, since their effects may not be confined to the immediate neighborhood where they occur.

To account for potential spillover effects, we extend our regression model in Equation (3) to include a term representing the racial hate crimes occurring in counties adjacent to the county under consideration. Specifically, this new term, $\sum_{k \in Adj_c} w_k(RacialHateCrime_{k,t-1})$, represents a population-weighted average of racial hate crime from all counties k that share a border with county c. Here, Adj_c is the set of counties adjacent to county c, and w_k is the population weight used to account for the size of county k. This adjustment allows us to capture the influence of racial hate crimes not only from the local county, but also from surrounding counties. All other specification details remain identical to our previous model. Hence, our extended regression model now takes the form:

$$\begin{aligned} M_{c,t} = \ & \alpha_c + \tau_t + \gamma Racial\ Hate\ Crime_{c,t-1} \\ & + \delta \sum_{k \in Adj_c} w_k Racial\ Hate\ Crime_{k,t-1} + X'_{c,t-1}\theta + \varepsilon_{c,t}. \end{aligned} \tag{4}$$

The results of this analysis are reported in Column 2 of Table V. We find that the coefficient on racial hate crime remains statistically significant, affirming the detrimental impact of racial hate crimes on local mortgage market activity. Importantly, we also observe that racial hate crime in adjacent counties exert a statistically significant negative effect on mortgage demand in the local county. The result suggests the presence of significant spillover effects, where the exposure to racial hate crimes in neighboring counties leads to reduced mortgage demand in the local county. County controls are included in all regressions, and their estimated coefficients generally align with our previous findings. The adjusted R^2 values remain high, suggesting that our model explains a substantial proportion of the variation in mortgage demand, even when considering spillover effects.

In conclusion, the results demonstrate that racial hate crimes exert a significant negative impact on mortgage demand in both the local county and its adjacent counties. This underscores the far-reaching impact of racial hate crimes on housing market dynamics, extending beyond immediate localities to influence broader regional trends.

C. *Instrumental variable approach: Minority out-group marriages*

In this section, we explore the effect of racial hate crimes on mortgage demand by using an alternative identification approach. Instead of employing a shift share design, we now retain local racial hate crimes (i.e., at the county level) as our key explanatory variable and instrument it with the number of minority out-group marriages (with Whites) at the county level.

We suspect a strong first-stage relationship between such minority out-group marriages and hate crimes. Out-group marriages act as a powerful reflection of a society's acceptance and integration across racial boundaries, which is in line with contact theory postulating that inter-group contact promotes more positive attitudes and friendships among different groups (Allport et al., 1954; Pettigrew & Tropp, 2008). While hate crimes represent the most extreme and visible expression of prejudice, they are closely tied to the broader spectrum of societal attitudes and beliefs. Out-group marriages can play a significant role in softening these prejudices and reducing racial tensions. As more people enter out-group marriages, it can signal a growing acceptance of diversity and a move towards a more inclusive society, which can ultimately be reflected in the reduction of hate crimes.

In line with this reasoning, we argue that the primary channel through which out-group marriages affect mortgage applications is the decrease in hate crimes and the safer environment for minorities that they reflect. While other factors may play a role in shaping the relationship between out-group marriages and mortgage applications, we posit that given our model is saturated with county-levels controls, as well as county and lender-year fixed effects, the reduction in hate crimes is the most direct and influential pathway. The decline in hate crimes creates an improved atmosphere that encourages more people, especially from minority groups, to pursue significant financial steps like home ownership with reduced fear of overt discrimination or violence. Therefore, our model setup demonstrates that the exclusion restriction is likely to be satisfied, with out-group marriages influencing mortgage applications mainly through their effect on hate crimes.

Accordingly, we extend our baseline model by incorporating the following first-stage regression:

$$\begin{aligned} Local\ Racial\ Hate\ Crime_{c,t} = \alpha_c + \lambda_{l,t} + \beta(Minority\ Out\text{-}Group\ Marriages_{c,t}) \\ + X'_{c,l,t}\zeta + \epsilon_{c,l,t}, \end{aligned} \tag{5}$$

where local racial hate crime (i.e., at the county level) is instrumented by the number of county-level minority out-group marriages. The second-stage regression then takes the following form:

$$\begin{aligned} Mortgage\ Applications_{c,l,t+1} = \alpha_c + \lambda_{l,t+1} + \gamma Local\ Racial\ Hate\ Crime_{c,t} \\ + X'_{c,t}\theta + \varepsilon_{c,l,t+1}, \end{aligned} \tag{6}$$

where the key explanatory variable in this regression is now local racial hate crimes, and the remainder of the specification is unchanged relative to our baseline model in Equation (3).

The estimation results from the instrumental variables approach are reported in Table VI. The first-stage regression clearly indicates that out-group marriages are inversely related to racial hate crimes, with a significant coefficient of -0.025, confirming the anticipated strong first-stage relationship, with a first-stage F-statistic of 251.73. This finding supports the notion that out-group marriages may serve as a barometer of societal acceptance, contributing to a decrease in hate crimes. In the second stage, we observe a robust negative association between hate crimes and mortgage applications across all groups, with the coefficients suggesting a particularly pronounced impact on minority applicants. Specifically, the coefficient for the overall minority group is -0.681, while the effects are slightly varied across different minority subgroups: -0.672 for both Black and Asian applicants, -0.445 for Hispanic applicants, and a notably stronger effect for White applicants at -0.913. These results suggest that a reduction in hate crimes, signaled through an increase in interracial marriages, leads to a more inclusive environment, thereby enhancing mortgage demand.

D. *Instrumental variable approach: Lynchings of Black people (1900 to 1930)*

In addition to the instrumental variable approach in the previous section, we provide an alternative instrumental variable strategy in which we instrument local racial hate crimes (i.e., at the county level) with the total county-level number of lynchings of Black individuals (in logs) from the years 1900 to 1930. Following Ang (2023), we use lynching data from two sources. The first is the Historical American Lynching Data Collection Project ("Project HAL") based on the archival work by Tolnay and Beck (1995) and the second is from Seguin and Rigby (2019). We focus our analysis on the 581 counties in which lynchings occurred, given their specific regional characteristics.

Black Americans were the primary target of lynching, understood as racially-motivated extrajudicial killings perpetrated through mob action. For such counties in which lynchings have occurred historically, prior research has found that hate crime laws are enforced less strictly (King et al., 2009). Given the lax contemporary law enforcement responses to hate crimes in counties with legacies of lynchings, we hypothesize an average negative first-stage relationship between lynchings and reported hate crimes in such counties. Furthermore, historical lynchings are unlikely to be related to current mortgage market conditions, so that lynching as an instrumental variable satisfies both the relevance and exogeneity criteria.

Since the number of lynchings from 1900 to 1930 is time invariant from the perspective of a county in our sample, we formulate the following cross-sectional first-stage regression:

$$\overline{Local\ Racial\ Hate\ Crime}_c^{\text{2007-2020}} = \beta_0 + \beta_1 Lynchings_c^{\text{1900-1930}} + X_c'\zeta + \epsilon_c, \qquad (7)$$

where local racial hate crimes (i.e., at the county level) averaged over the sample years 2007 to 2020, is instrumented using the historical record of lynching in the same county. The subsequent second-stage regression assesses the effect of these instrumented hate crimes on average mortgage application outcomes:

$$\overline{Mortgage\ Applications}_c^{\text{2007-2020}} = \gamma_0 + \gamma_1 \overline{Local\ Racial\ Hate\ Crime}_c^{\text{2007-2020}} + X_c'\theta + \varepsilon_c. \quad (8)$$

Table VII presents the estimation results from this approach. The first-stage analysis reveals that historical lynching is significantly associated with an increase in racial hate crimes, evidenced by a coefficient of -0.134, which underscores the leniency in police enforcement of hate crime laws in counties with high numbers of historical lynchings. The first-stage F-statistic of 19.731 indicates a strong instrumental variable. In the second-stage regression, we find that hate crimes, as instrumented by historical lynching, significantly depress mortgage demand among Black applicants as can be expected, with a coefficient of -2.704. Further, it is noteworthy that the economic magnitude for White applicants is also sizable and negative at -1.673, which speaks to a local treatment effect due to the specific geographic and economic circumstances of areas in which lynchings occurred between 1900 and 1930.

E. George Floyd murder incident

Racial bias and discrimination are pervasive issues within the U.S. police system (Fryer Jr, 2019; Goncalves & Mello, 2021; Grosjean et al., 2023). In May 2020, the killing of the unarmed, Black civilian George Floyd by a White police officer led to widespread protests and demonstrations against police brutality and systemic racism. While the police officers involved were not convicted of a hate crime, the murder is widely perceived as an issue of racial injustice and violence (Reny & Newman, 2021). In this section, we study the impact of the George Floyd murder (GFM) on housing choices in an event study approach, exploiting the random timing of the incident to shed further light on the relationship between racial hate on mortgage applications.

Given that residents in all US counties were exposed to the GFM news to a larger or lesser extent through social media and other news channels, this suggests that counties which were more exposed to the incident should experience a larger drop in demand for mortgages. We measure each county's exposure to the GFM in two ways: (i) by its geographic distance to Hennepin County, where the incident occurred, and (ii) by its social media connectedness to Hennepin County, using the Social Connectedness Index from Facebook. Garcia and Ortega (2024) find that the increased social media and public attention following Floyd's death affected the public perception of racial equity issues, resulting in a positive moderating effect on the loan amounts distributed to Black owners relative to other racial-ethnic groups. If similar effects were present in the mortgage credit market, it would bias our estimates towards zero.

Since the GFM incident occurred toward the end of our main sample period and coincided with the COVID-19 pandemic, we utilize the more granular monthly Home Mortgage Disclosure Act (HMDA) data from Neil Bhutta, which covers the top 500 U.S. counties in terms of mortgage origination.[6] We regress county-level mortgage applications on a post-event dummy variable (Post George Floyd Murder equal to 1 from May 2020 onward), the distance measure capturing the exposure to the GFM incident, and the interactions between the two. The results are shown in Table VIII. In Columns 1 and 3, we observe a general increase in mortgage applications after the GFM, in line with the pandemic mortgage boom documented by Newton and Vickery (2022). However, the negative coefficients on the interaction terms suggest that counties physically closer to, or highly connected via social networks, to Hennepin County, experienced more reduction in mortgage demand. This pattern remains robust when adding county and year-month fixed effects in Columns 2 and

[6] The HMDA data at the county-month level are available on Neil Bhutta's website, https://sites.google.com/site/neilbhutta/data.

4.

The localized dampening effects on housing market activity in counties more exposed to the GFM underscore the significant economic impacts of high-profile racial violence incidents and highlight their broader relationship to the effect of racial hate in housing choices and mortgage demand.

F. *Additional analyses and robustness checks*

We conduct a series of additional analysis and checks to establish the robustness of our results. First, we offer a placebo test to rule out that our results are driven by unobserved factors affecting both hate crimes and the demand for mortgage credit. To do so, we confirm the effect of racial hate crimes to those based on prejudice against religion, sexual orientation or gender. If it is indeed racial bias driving our results, we should find no corresponding effect of these other types of hate crime on mortgage demand. We report the estimation results in Tables A3, and we find no evidence of a significant effect arising from other types of hate crime on mortgage demand. The absence of effects for these types of hate crime strengthens our finding related to racial hate crimes, ruling out the possibility that our results are driven any unobserved factors relating to a general aversion to crime or more widespread social instability.

Second, we explore the heterogeneity of the effect of racial hate crimes on mortgage applications with respect to the share of the minority population in a given county. The results, reported in Table A4, indicate that the effects are driven by counties in which minority borrowers make up less than 40% of the population.

Third, we restrict our sample of mortgages to home purchase mortgages only and find comparable results. This underscores that the drop in mortgage demand is not just toward general borrowing, but specifically towards acquiring property in affected areas. The results also confirm that the observed effects are not driven by changes in borrowing behavior for reasons unrelated to property acquisition, such as refinancing or equity withdrawal. The estimation results for this analysis is reported in Table A5 of the Online Appendix.

V. Implications of racial hate crimes on neighborhood choices and housing demand

A. *Migration patterns and housing market demand*

Hate crimes are observed to reduce mortgage demand and it is correlated with erosion of neighborhoods. This leads us to investigate what happens to neighborhoods affected by hate crimes, raising questions such as, are individuals moving out of hate crime–affected areas, or are they staying and simply delaying home purchases (i.e., renting)? To explore this, we interrogate the migration patterns of inflow and outflow of residents at the county level and investigate the local rental market demand.

To study migration, we utilize data on county-level inflows and outflows of residents, obtained from individual income tax returns filed with the IRS. For the housing rental demand analysis, we retrieve rental prices data from Zillow, a leading provider of real estate and rental marketplace data. Our empirical model takes the following form:

$$Outcome_{c,t} = \alpha_c + \tau_t + \gamma Racial\ Hate\ Crime_{c,t-1} + X'_{c,t-1}\theta + \varepsilon_{c,t} \tag{9}$$

Here, $Outcome_{c,t}$ represents either the outflow, inflow, net outflow of residents, or the average rental price index at county c in year t. The key explanatory variable is racial hate crime estimated following Equation (1) for a given county in the year prior to the current period, denoted by $Racial\ Hate\ Crime_{c,t-1}$. The vector $X_{c,t-1}$ stands for county-specific control variables. As with our earlier models, α_c and τ_t represent county fixed effects and year fixed effects, respectively.

The regression results of this analysis are presented in Panel A of Table IX. Columns 1 to 3 of Panel B show the effects of racial hate crimes on the outflow, inflow, and net outflow of residents at the county level, respectively. We find that an increase in racial hate crimes leads to a significant increase in the outflow of residents, with no significant effect on the inflow. This results in a substantial net outflow from counties experiencing more hate crimes. These results provide evidence that racial hate crimes can significantly reshape migration patterns, driving residents away from affected areas. Column 4 of Panel A investigates the effect of racial hate crimes on average rental price index at the county level, serving as a proxy for rental housing demand. The coefficient on racial hate crime is negative and significant, suggesting that an increase in racial hate crimes leads to a decrease in rental prices. This likely reflects a decrease in housing demand from renters in the wake of increased hate crimes. The results suggest that individuals move away from areas that are affected by racial hate crimes.

Having established the relationship between racial hate crimes and local migration patterns, we now turn our attention to the effects of such migration flows on the housing markets in the destination counties. Specifically, we examine how the outflow of people from counties with high incidences of racial hate crimes affects the mortgage market and rental demand in the destination counties.

In our pairwise county analysis, we consider the inflow of residents from county j into county i. The regression specification is as follows:

$$\begin{aligned} Outcome_{i,t} = \;& \alpha_i + \tau_t + \gamma_1 Racial\,Hate\,Crime_{i,t-1} + \gamma_2 Racial\,Hate\,Crime_{j,t-1} \\ & + \gamma_3 Net\,Inflow_{j\to i,t} + \gamma_4 (Racial\,Hate\,Crime_{j,t-1} \times Net\,Inflow_{j\to i,t}) \\ & + X'_{i,t-1}\theta + \varepsilon_{i,t} \end{aligned} \tag{10}$$

where $Outcome_{i,t}$ is either the log of the number of mortgage applications, the log of the number of originated mortgages, or the log of the average rental price index in county i in year t. The main independent variables of interest are the estimate of racial hate crimes in both county i (the destination county) and county j (the origin county), represented by $Racial\ Hate\ Crime_{i,t-1}$ and $Racial\ Hate\ Crime_{j,t-1}$, respectively. The net inflow of residents from county j into county i is denoted by $Net\ Inflow_{j \to i,t}$. The interaction term, $Racial\ Hate\ Crime_{j,t-1} \times Net\ Inflow_{j \to i,t}$, captures the effect of net inflow from a county with high hate crimes on the outcome in the destination county. The vector $X_{i,t-1}$ includes the same county-specific control variables used in previous models. α_i is the the main county fixed effect, which controls for time-invariant county characteristics, and τ_t is the year fixed effect, capturing common shocks that might influence the housing market.

The results of these analyses are presented in Panel B of Table IX. Column 1 shows the effect of racial hate crimes in the destination county (county i) on the number of mortgage applications, while Column 2 presents the effects on mortgage originations. The coefficient of interest is the interaction between net inflow and racial hate crime of origin county (county j), which is found to be negative and statistically significant in both regressions. This suggests that an increase in migration from origin counties induced by racial hate crimes do not result in increased demand for mortgages in the destination counties.

Column 3 presents the results for the effect on rental market demand. Here, we find that an increase in racial hate crimes in the destination county leads to a significant decrease in rental prices, in line with our previous findings. However, Interestingly, the coefficient on the interaction term between racial hate crime in the origin county and net inflow is significant and positive. This suggests that, as individuals move away from counties marked by hate crimes and settle in the destination counties, they tend to rent (than buy homes) and this consequently puts pressure on the rental demand in destination counties.

In summary, our findings suggest that racial hate crimes have significant implications for migration patterns and housing demand at the county level due to the movements of residents away from areas affected by hate crime. Further, significant spillover effects of racial hate crimes, which extend beyond the local housing market and can influence mortgage markets and rental markets in other counties. These results underscore the far-reaching implications of racial hate crimes on housing markets across county lines.

VI. Possible explanations for the link between racial hate crimes and mortgage credit demand

A. *Negative effects at the individual-level*

Homeownership is meant to provide a sense of safety for individuals. However, racial hate crimes can induce greater burdens of psychological distress within affected communities, also impacting the economic decision-making on individuals. In this section, we explore the negative effects of racial hate crime by considering psychological distress patterns and consumption behavior patterns of individuals surveyed within affected neighborhoods. Hate crimes can instill a sense of vulnerability and fear, which will in turn influence the housing decisions made by individuals.

For the empirical exploration, we utilize two datasets. First, we use individual-level survey information on psychological distress, available from the PSID. According to the psychological distress measurement literature, survey respondents who score above 12 on the K-6 Non-Specific Psychological Distress Scale are considered psychologically distressed (Kessler et al., 2002). We link this respondent-level data to racial hate crime incidences reported in the 12 months before the survey interview month. Second, for understanding consumption behavior patterns, we turn to the quarterly Consumer Expenditure Survey (CEX) and evaluate changes in expenditures on items often associated with conspicuous consumption: clothing and jewelry, and outdoor recreation. We expect the consumption of visible goods to be reduced by households in hate crime affected locations (Mejía & Restrepo, 2016). For this test, we evaluate racial hate crimes that have occurred in the quarter prior to the reference quarter for which expenditures are measured. The rationale is that if racial hate crimes instill fear in individuals, we should observe some effects on the behavior of conspicuous consumption.

To evaluate the individual-level effects of racial hate crimes, we estimate the following regression equation:

$$Behavior_{i,t} = \alpha_s + \gamma Racial\ Hate\ Crime_{i,t-1} + X'_{i,t-1}\theta + \varepsilon_{i,t} \tag{11}$$

where the dependent variable $Behavior_{i,t}$ represents either the measure of psychological distress or a measure of conspicuous consumption for individual i at time t. The primary explanatory variable is the past number of racial hate crime incidents, as discussed above. The vector $X_{i,t-1}$ contains individual-specific control variables such as race, age, education, family size, marital status, family income and family wealth. We also control for unobserved time-invariant characteristics at the state level by including state fixed effects, denoted by α_s.

The results of these analyses are presented in Table X. The estimates in Panel A indicate a positive and statistically significant association between racial hate crimes and psychological distress. This suggests that hate crimes instill fear in residents, contributing to increased levels of psychological distress. Panel B shows the impact of racial hate crimes on various types of consumption. The coefficients on racial hate crime are negative and statistically significant for clothing and jewelry, and outdoor recreation expenditures, indicating that instances of racial hate crimes lead to a decrease in these types of conspicuous consumption.

The results highlight the indirect effects of racial hate crimes on individuals' psychological well-being and consumption behavior, extending our understanding of the impacts of such crimes beyond their immediate victims. These findings lend support to the notion that the fear and vulnerability instilled by hate crimes may indeed lead to decreased demand for conspicuous consumption, which in turn may influence individuals' housing decisions and thus the observed patterns in mortgage demand.

In summary, the regression results reported in Table X suggest that racial hate crimes not only erode neighborhood cohesion and desirability, but also instil fear in residents, leading to increased psychological distress and altered consumption patterns. These effects likely contribute to the observed decrease in mortgage demand in areas with higher instances of racial hate crimes.

B. *Decline in local civic society*

A stronger civic society, with presence of religious, civic and social organizations in communities, will attract higher homeownership rates. Such organizations foster a sense of community and security, which can make a locality more attractive to potential homeowners. However, racial animus and incidences of racial hate crimes harm neighborhood cohesion, with potential declines in the civic service uptake and participation by individuals, as well as the ability of the local civil society to contribute positively to their communities.

We thus explore the impact racial hate crimes have on the share of religious, civic, and social organizations within a county. This information is gathered from the County Business Patterns database, where the number of religious, civic, and social organizations in a county in a given year are identified with the broadly defined NAICS industry code 813, as well as the narrow definition with the NAICS industry codes 8131 and 8134. To quantify the effect, we incorporate the share of these institutions in our regression framework as follows:

$$Institution\,Share_{c,t} = \alpha_c + \tau_t + \gamma Racial\,Hate\,Crime_{c,t-1} + X'_{c,t-1}\theta + \varepsilon_{c,t}, \qquad (12)$$

where the dependent variable $Institution Share_{c,t}$ is the number of religious, civic, and social organizations as a share of the total number of establishments in county c at time t. The key variable of interest is racial hate crime observed in the year prior to the current period, denoted by $Racial\ Hate\ Crime_{c,t-1}$. The vector $X_{c,t-1}$ represents county-specific control variables such as population, GDP growth, personal income, unemployment rate, poverty rate, home price, and crime rate at time $t-1$. As with our earlier models, α_c and τ_t represent county fixed effects and year fixed effects, respectively.

The results of this analysis are presented in Table XI. The coefficient estimate on racial hate crime is negative and statistically significant in all model specifications, indicating that an increase in racial hate crimes is associated with a decrease in the share of religious, civic, and social organizations in affected areas. The results suggest that an increase in racial hate crimes in a county have a detrimental impact on the prevalence of community institutions that might otherwise enhance neighborhood desirability for potential homeowners. Although a causal nature of the relationship cannot be established, the negative relationship between racial hate crimes and the share of these organizations might be due to various factors. For example, increased racial hate crimes might create an environment of fear and hostility, making it more challenging for these organizations to function effectively or attract members.

In summary, these findings suggest that racial hate crimes can affect the makeup of community institutions, potentially deteriorating the desirability of neighborhoods affected by racial hate crimes, thereby contributing to the observed negative relationship between racial hate crimes and mortgage demand. The disruption of community institutions provides a further pathway through which racial hate crimes can impact the demand for homeownership.

VII. Conclusion

This paper sheds new light on the real effects of hate crime and the market for mortgage credit. We find that US mortgage lenders in counties impacted by hate crimes experience an 2.4% decline in mortgage applications and originate 1.5% fewer mortgages. When examining the economic significance of racial hate crimes in comparison to other types of (nonhate) crime, it becomes evident that the marginal impact of racial hate crimes on mortgage applications significantly surpasses that of non-bias-motivated crimes.

The detrimental effect transcends racial boundaries, with both minorities (Black, Asian and Hispanic applicants) and White applicants witnessing a comparable decline. We also document significant spillover effects of hate crime on neighboring counties' mortgage markets, emphasizing the far-reaching consequences of hate crimes beyond their immediate geographic scope. Given the above, we investigate the granular effects of hate crimes on county-level migration pattern and explore whether individuals are leaving areas affected by hate crimes, or staying but delaying home purchases. Data from individual income tax returns filed with the IRS, along with rental market prices sourced from Zillow, reveal a significant outflow of residents from the affected counties. We also observe a decrease in rental prices within these counties, pointing to the trend that residents prefer to move out rather than stay and opt for renting. As a secondary consequence of this migration pattern on housing markets in destination counties, we find an increase in rental prices in counties that receive migrants from hate crime-affected areas, along with also inducing a negative effect on the mortgage market in destination counties. The evidence speaks to the erosion of social cohesion, the role of external fear, and societal cost arising from hate crimes.

Overall, our study reveals substantial real effects of racial hate crimes on the market for mortgage credit, informing housing and urban development policies. The effects are not isolated, but complexly intertwined with social cohesion, economic stability, and migratory patterns. As such, our paper contributes to the growing literature on the real-world repercussions of hate crimes, by providing a multidimensional view of how prejudice affects one of the most fundamental aspects of economic life – homeownership.

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Figure I
Hate crime

This figure demonstrates the evolvement of the three main hate crimes as a proportion of 1000 all total crimes over the period from 1994 to 2020.

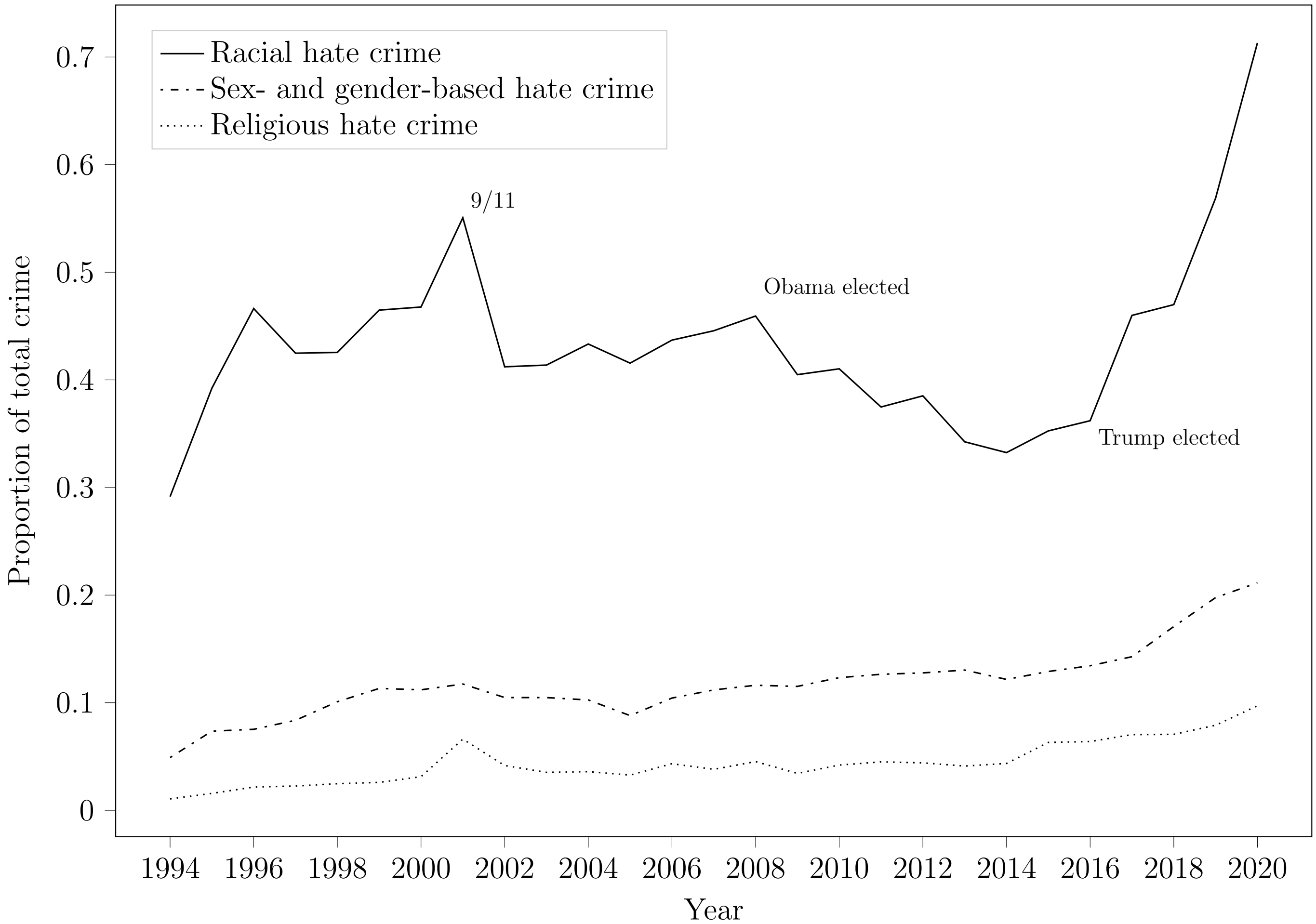

Table I
Summary statistics

The table reports the descriptive statistics of main variables. The sample period covers the years 2007 to 2020. The mortgage credit variables and geographic variables are at the lender-county-year level. The organization and migration variables are at the county-year level. The household variables are at the household-survey (month) level. Variable definitions are reported in Appendix A.

Variable	Mean	Std. dev.	10th	90th
Mortgage credit variables				
Mortgage applications	1.91	1.39	0.69	4.04
Minorities	1.06	1.29	0.00	3.00
White	1.53	1.34	0.00	3.56
Withdrawal rate	0.14	0.25	0.00	0.50
Minorities	0.14	0.27	0.00	0.50
White	0.14	0.26	0.00	0.50
Denial rate	0.18	0.29	0.00	0.63
Minorities	0.20	0.32	0.00	0.80
White	0.18	0.30	0.00	0.67
Mortgage originations	1.35	1.34	0.00	3.37
Minorities	0.63	1.03	0.00	2.08
White	1.14	1.26	0.00	3.04
Geographic variables				
Racial hate crime	0.65	0.57	0.13	1.44
Population	11.48	1.47	9.67	13.52
GDP growth rate	0.03	0.06	-0.02	0.09
Personal income	43.43	13.21	31.11	58.47
Unemployment rate	5.84	2.60	3.20	9.50
Poverty percentage	14.39	5.45	7.90	21.40
Home price	11.93	0.55	11.24	12.64
Crime rate	3.00	0.70	2.09	3.92
Minority share	0.26	0.19	0.06	0.55
Household variables				
Psychological distress	0.15	0.35	0.00	1.00
Clothing and jewelry	3.46	2.53	0.00	6.26
Outdoor recreation	4.25	2.66	0.00	6.67
Organization and Migration variables				
Share of religious, civic, and social organizations (broad)	1.06	0.54	0.54	1.66
Share of religious, civic, and social organizations (narrow)	0.84	0.48	0.35	1.42
Migraton flows				
Outflow	9.70	31.62	0.18	21.70
Inflow	4.61	12.08	0.15	11.00
Net outflow	5.09	24.13	-0.53	9.73

Table II

Racial hate crime and mortgage demand by ethnicity

This table reports regression estimates at the lender-year level. The dependent variable is the log of the number of mortgage applications a lender receives in a county in a year. Racial hate crime is defined as in Equation (1). Column 1 report estimates for all applications, Column 2 for applications received from all minority groups, Columns 3-5 for applications from the sub-minority groups, Black, Asian and Hispanic, respectively, and Column 6 for White applicants. All specifications include lender-year and county fixed effects. Key estimates from the Oster (2019) test on the relationship between racial hate crime and mortgage applications is presented at the bottom of the table. Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

		Minorities				
	All	All	Black	Asian	Hispanic	White
	(1)	(2)	(3)	(4)	(5)	(6)
Racial hate crime	–0.121***	–0.145***	–0.082***	–0.036***	–0.101***	–0.085***
	(0.008)	(0.007)	(0.006)	(0.005)	(0.007)	(0.008)
Population	1.002***	0.941***	0.457***	0.476***	0.507***	0.849***
	(0.045)	(0.041)	(0.028)	(0.028)	(0.028)	(0.045)
GDP growth	0.035***	0.030***	0.019***	0.007*	0.027***	0.032***
	(0.008)	(0.008)	(0.005)	(0.004)	(0.006)	(0.008)
Personal income	–0.000	0.001**	0.001***	0.002***	0.001***	–0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment rate	–0.018***	–0.013***	–0.005***	–0.003***	–0.007***	–0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Home price	0.008	0.036***	0.034***	–0.032***	–0.014*	–0.031**
	(0.013)	(0.012)	(0.009)	(0.008)	(0.008)	(0.013)
Crime rate	–0.052***	–0.029***	–0.017***	0.001	–0.021***	–0.046***
	(0.009)	(0.007)	(0.005)	(0.004)	(0.006)	(0.008)
Minority share	0.012***	0.028***	0.022***	0.015***	0.018***	–0.006***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Lender-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.393	0.460	0.345	0.331	0.319	0.360
$\beta^* \mid \delta = 1$	–0.514	–0.611	–0.355	–0.142	–0.437	–0.319
$\delta \mid \beta = 0$	–4.569	–2.363	–3.333	–1.312	–3.575	78.011
Observations	4,066,328	4,066,328	4,066,328	4,066,328	4,066,328	4,066,328

Table III

Comparing the economic effects of local racial hate crime versus other crime

This table compares the effects of local racial hate crime and other (nonhate) crimes on mortgage applications using a sub-sample with county-level crime data available. The dependent variable is the log of the number of mortgage applications a lender receives in a county in a year. Local racial hate crime is measured by the log of number of racial hate crime incidents. Other crime is the log of the number of nonhate crime incidents. All specifications include lender-year and county fixed effects. Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Local racial hate crime	–0.006**	–0.006**
	(0.003)	(0.003)
Other crime		–0.035***
		(0.005)
Controls	Yes	Yes
Lender-year FE	Yes	Yes
County FE	Yes	Yes
Adjusted R^2	0.391	0.391
Observations	1,390,253	1,390,253
Calculating the economic effects of local racial hate crime		
Sample average of racial hate crime (in levels)		1.165
Marginal effect of 1% increase in local hate crime		–0.006
Marginal effect from one additional local hate crime		–0.5149
Calculating the economic effects of other crime		
Sample average of other crime (in levels)		2692.727
Marginal effect of a 1% increase in other crime		–0.035
Marginal effect from one additional other crime		–0.0013

Table IV

Effects of racial hate crime and on withdrawal rates, denial rates and originations

This table reports estimates of the effect of racial hate crime on various mortgage demand outcomes at the lender-year level. Panel A reports the withdrawal rate, which is the number of withdrawn applications over total applications, Panel B reports the denial rate, which is the number of denied applications over total applications, and Panel C reports the total number of mortgage originations (in logs). Column 1 report estimates for all applications, Column 2 for applications received from all minority groups, Columns 3–5 for applications from the sub-minority groups, Black, Asian and Hispanic, respectively, and Column 6 for White applicants. Racial hate crime is defined as in Equation (1). All specifications include lender-year and county fixed effects. Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

		Minorities				
	All	All	Black	Asian	Hispanic	White
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Withdrawal rates						
Racial hate crime	0.004***	0.006***	0.006***	0.003	0.003*	0.002**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.205	0.227	0.153	0.150	0.143	0.180
Observations	4,066,328	2,473,156	921,387	685,349	919,252	3,465,864
Panel B: Denial rates						
Racial hate crime	0.007***	0.002	–0.002	0.002	0.001	0.006***
	(0.001)	(0.002)	(0.004)	(0.004)	(0.003)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.313	0.342	0.315	0.241	0.262	0.291
Observations	3,859,007	2,323,433	858,256	635,730	857,894	3,278,854
Panel C: Originations						
Racial hate crime	–0.106***	–0.101***	–0.055***	–0.032***	–0.075***	–0.083***
	(0.008)	(0.007)	(0.005)	(0.004)	(0.006)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.346	0.353	0.278	0.286	0.269	0.328
Observations	4,066,328	4,066,328	4,066,328	4,066,328	4,066,328	4,066,328

Table V
Racial hate crime and mortgage applications at the county-level

This table reports estimates of the overall effect of racial hate crime on mortgage applications at the county level and its spillover effects on neighboring counties. The dependent variable is the log of the number of mortgage applications in a county in a year. Racial hate crime is defined as in Equation (1). All continuous variables are z-score standardized, and specifications include county and year fixed effects. Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Racial hate crime	–0.112***	–0.088***
	(0.009)	(0.014)
Racial hate crime of neighboring counties		–0.043**
		(0.019)
Population	1.556***	1.551***
	(0.084)	(0.084)
GDP growth	0.001	0.001
	(0.001)	(0.001)
Personal income	0.011*	0.012*
	(0.006)	(0.006)
Unemployment rate	–0.041***	–0.040***
	(0.003)	(0.003)
Poverty rate	0.011***	0.011***
	(0.004)	(0.004)
Home price	–0.009	–0.008
	(0.009)	(0.009)
Crime rate	–0.057***	–0.057***
	(0.007)	(0.007)
Minority share	0.132***	0.120***
	(0.039)	(0.039)
County FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.984	0.984
Observations	31,333	31,305

Table VI
Instrumental variable approach: Minority out-group marriages

This table reports the regression results on the effect of racial hate crime on mortgage applications using instrumental variables approach. The instrumental variable is the number of minority out-group marriages (with Whites) in a county in a year, with the second-stage dependent variable as number of mortgage applications a lender receives in a year (in logs). Column 1 reports the first stage results, where the dependent variable is the number of racial hate crimes (in logs), while Column 2–7 report the second stage results. Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	First stage:	Second stage: Mortgage applications					
	Local racial		Minorities				
	hate crime	All	All	Black	Asian	Hispanic	White
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Minority out-group marriages	–0.025***						
	(0.002)						
Local racial hate crime		–0.845***	–0.681***	–0.672***	–0.672***	–0.445***	–0.913***
		(0.161)	(0.106)	(0.102)	(0.110)	(0.152)	(0.149)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-statistic	251.730						
Observations	1,249,662	1,249,662	1,249,662	1,249,662	1,249,662	1,249,662	1,249,662

Table VII
Instrumental variable approach: Lynchings (1900-1930)

This table reports the regression results on the effect of racial hate crime on mortgage applications using instrumental variables approach. The instrumental variable is number of lynchings between 1900 and 1930 in a county (in logs), and the dependent variable in the second stage is the average mortgage applications a lender receives between 2007 and 2020. Only counties with recorded lynchings enter the analysis. Column 1 reports the first stage results, where the dependent variable is the number of racial hate crimes (in logs), while Column 2–7 report the second stage results. Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	First stage: Local racial hate crime	Second stage: Mortgage applications					
			Minorities				
		All	All	Black	Asian	Hispanic	White
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lynchings	–0.134***						
	(0.030)						
Local racial hate crime		–0.134	–0.315*	–2.704***	–0.104	0.608	–0.233
		(0.159)	(0.176)	(0.696)	(0.331)	(0.419)	(0.168)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-statistic	19.731						
Observations	581	581	581	581	581	581	581

Table VIII
George Floyd murder incident

This table reports estimates of the overall effect of George Floyd murder incident on mortgage applications at the county level. The sample period is from October 2019 to December 2020. The dependent variable is the log of the number of mortgage applications in a county in a month. Post George Floyd Murder is a dummy variable equal to 1 for months May 2020 onward. Geographic distance is defined as –log(miles to Hennepin County). Social connectedness is the Facebook Social Connectedness Index of each county to Hennepin County. Columns 2 and 4 include county and year-month fixed effects. Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Post George Floyd Murder	0.117**		0.486***	
	(0.059)		(0.065)	
Geographic distance	–0.232***			
	(0.052)			
Post George Floyd Murder × Geographic distance	–0.030***	–0.023***		
	(0.009)	(0.006)		
Social connectedness			0.035	
			(0.036)	
Post George Floyd Murder × Social connectedness			–0.022***	–0.009**
			(0.008)	(0.004)
County FE	No	Yes	No	Yes
Year-month FE	No	Yes	No	Yes
Adjusted R^2	0.072	0.991	0.034	0.991
Observations	6,970	6,970	6,970	6,970

Table IX
Migration pattern and housing rents

This table reports the effects of racial hate crime on county-level migration pattern and housing rents. The dependent variables in Panel A are outflow, inflow and net outflow of people (in thousands) and the average rental price index (in logs). Panel B show regressions for county i, county j pairs, with the dependent variables number of mortgage applications, number of mortgage originations, and the average rental price index, all in logs, for county i in a year. Net inflow$_{j \to i}$ is the migration numbers (in thousands) from county j to county i. Racial hate crime is defined as in Equation (1). All specifications include county and year fixed effects. Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Migration pattern				
	Outflow	Inflow	Net outflow	Rents
	(1)	(2)	(3)	(4)
Racial hate crime	29.120***	–0.293	29.413***	–7.460***
	(3.387)	(0.196)	(3.469)	(2.014)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.680	0.973	0.425	0.964
Observations	30,535	30,535	30,535	3,036

Panel B: Migration and mortgage			
	Mortgage applications$_i$	Mortgage originations$_i$	Rents$_i$
	(1)	(2)	(3)
Racial hate crime$_i$	–0.264***	–0.297***	–7.128***
	(0.052)	(0.062)	(1.187)
Net inflow$_{j \to i}$	0.012***	0.015***	–0.034
	(0.003)	(0.004)	(0.032)
Racial hate crime$_j$ ×Net inflow$_{j \to i}$	–0.003**	–0.003**	0.027*
	(0.001)	(0.001)	(0.016)
Controls$_i$	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.985	0.980	0.989
Observations	998,572	998,572	247,227

Table X
Racial hate crime and individual-level effects

This table reports the effect of racial hate crimes on individual residents. The dependent variable in Panel A is a dummy variable equal to 1 if the respondent is psychologically distressed, while in Panel B is the expenditure on clothing and jewelry, and expenditure on outdoor recreation. In Panel A, local racial hate crime is the number of racial hate crimes (in logs) recorded during the 12 months before the PSID interview month, and analogously in Panel B local racial hate crime is the number of racial hate crimes (in logs) recorded during the quarter before the reference quarter in the CEX expenditure survey. Standard errors are clustered at the individual level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Psychological distress

	Black	Asian	Hispanic	White
	(1)	(2)	(3)	(4)
Local racial hate crime	0.042***	0.069*	0.070***	0.027***
	(0.005)	(0.031)	(0.012)	(0.005)
Age	–0.000	0.004	–0.001*	–0.001***
	(0.000)	(0.003)	(0.001)	(0.000)
Education	0.001***	0.003***	0.002*	0.001***
	(0.000)	(0.001)	(0.001)	(0.000)
Family size	0.009***	–0.013	0.014***	0.006***
	(0.002)	(0.017)	(0.005)	(0.002)
Employed	–0.029***	–0.013	–0.029*	–0.031***
	(0.008)	(0.066)	(0.016)	(0.008)
Family income	–0.556***	–0.237	–0.187**	–0.127***
	(0.081)	(0.423)	(0.083)	(0.048)
Family wealth	0.006	–0.017	0.068*	0.001
	(0.007)	(0.016)	(0.038)	(0.002)
County FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.012	0.128	0.009	0.002
Observations	12,352	457	2,762	16,213

Panel B: Visible spending

	Clothing and Jewelry				Outdoor recreation			
	Black	Asian	Hispanic	White	Black	Asian	Hispanic	White
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local racial hate crime	–0.172	–0.364**	–0.321***	–0.382***	0.209	–0.541***	–0.372***	–0.305***
	(0.123)	(0.158)	(0.086)	(0.059)	(0.138)	(0.181)	(0.096)	(0.057)
Age	–0.012***	–0.027***	–0.024***	–0.023***	0.020***	0.023***	0.013***	0.017***
	(0.003)	(0.003)	(0.002)	(0.001)	(0.003)	(0.004)	(0.002)	(0.001)
Education	0.163***	0.048*	0.063***	0.264***	0.267***	0.419***	0.257***	0.246***
	(0.025)	(0.028)	(0.013)	(0.013)	(0.035)	(0.032)	(0.015)	(0.013)
Family size	0.288***	0.206***	0.245***	0.259***	0.165***	0.222***	0.230***	0.148***
	(0.036)	(0.044)	(0.021)	(0.019)	(0.041)	(0.048)	(0.022)	(0.021)
Maritial status	0.025	0.365***	-0.015	0.277***	0.874***	0.392***	0.463***	0.581***
	(0.108)	(0.137)	(0.064)	(0.047)	(0.116)	(0.150)	(0.072)	(0.047)
Income	0.001	–0.021**	0.004***	0.000	0.011	0.024**	0.005***	0.002***
	(0.028)	(0.010)	(0.001)	(0.001)	(0.014)	(0.010)	(0.000)	(0.000)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.097	0.104	0.101	0.133	0.108	0.139	0.089	0.087
Observations	2,772	2,227	6,971	15,681	2,772	2,227	6,971	15,681

Table XI
Local civic society

This table reports the effect of racial hate crime on local civic society, measured by the share of religious, civic and social organizations at the county-level. The dependent variable in Column 1 is the number of religious, civic and social organizations broadly defined with the NAICS industry code 813, scaled by the total number of establishments in a county in a year, while analogously the dependent variable in Column 2 uses the narrow definition with the NAICS industry codes 8131 and 8134. Racial hate crime is defined as in Equation (1). Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Broad	Narrow
	(1)	(2)
Racial hate crime	–0.026**	–0.020**
	(0.011)	(0.009)
Population	–0.817***	–0.634***
	(0.093)	(0.071)
GDP growth	–0.003	–0.023*
	(0.018)	(0.013)
Personal income	–0.007***	–0.006***
	(0.001)	(0.001)
Unemployment rate	0.000	0.001
	(0.002)	(0.002)
Poverty rate	0.002**	0.001
	(0.001)	(0.001)
Home price	0.040	0.033
	(0.030)	(0.026)
Crime rate	–0.010	–0.024***
	(0.010)	(0.008)
Minority share	–0.015***	–0.015***
	(0.003)	(0.002)
County FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.906	0.924
Observations	31,370	31,370

A. Definitions of key variables

Variable	Definition	Source
Mortgage credit variables		
Mortgage applications	The number of mortgage applications a lender in a county receives (in logs)	HMDA
Minorities	The number of mortgage applications from minorities a lender in a county receives (in logs)	HMDA
White	The number of mortgage applications from white people a lender in a county receives (in logs)	HMDA
Denial rate	The denied applications over all not withdrawn applications received by a lender in a county	HMDA
Minorities	The denied applications over all not withdrawn applications from minorities received by a lender in a county	HMDA
White	The denied applications over all not withdrawn applications from white people received by a lender in a county	HMDA
Withdrawal rate	The withdrawn applications over all applications received by a lender in a county	HMDA
Minorities	The withdrawn applications from minorities over all applications from minorities received by a lender in a county	HMDA
White	The withdrawn applications from white people over all applications from white people received by a lender in a county	HMDA
Mortgage originations	The number of mortgage applications that are granted by a lender in a county (in logs)	HMDA
Minorities	The number of mortgage applications that are granted by a lender to minorities in a county (in logs)	HMDA
White	The number of mortgage applications that are granted by a lender to white people in a county (in logs)	HMDA
Geographic variables		
Racial hate crime	As defined in Equation (1)	FBI
Population	Population in a county (in logs)	US Census Bureau
GDP growth rate	The year on year GDP growth rate in a county	Bureau of Economic Analysis
Personal income	The average personal income of a county	Bureau of Economic Analysis

(Continued)

Variable	Definition	Source
Unemployment rate	The unemployment rate in a county	US Bureau of Labour
Poverty percentage	The percentage of people in a county living in poverty	Small Area Income and Poverty Estimates Program
Crime rate	Violent crime and property crime per 100 people	FBI
Minority share	Minority population divided by total population (in percentage)	US Census Bureau
Share of religious, civic and social organizations (broad)	Number of broadly defined religious, civic and social organizations divided by total number of organizations	County Business Patterns
Share of religious, civic and social organizations (narrow)	Number of narrowly defined religious, civic and social organizations divided by total number of organizations	County Business Patterns
Household variables		
Psychological distress	Dummy variable equal to 1 if respondent's psychological distress scale is larger than 12 and 0 otherwise	PSID
Clothing and jewelry	Log of the amount spent on the two items (the exact item code can be found in appendix)	CEX
Outdoor recreation	Log of the amount spent on outdoor activities and equipments	CEX
Migration variables		
Outflow	Number of people moving out of a county (in thousands)	IRS
Inflow	Number of people moving to a county (in thousands)	IRS
Net outflow	Net number of people moving out of a county (in thousands)	IRS

When Prejudice Hits Home:

Hate Crime and the Market for Mortgage Credit*

Online Appendix

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Table A1
Alternative shift share construction for racial hate crime – I

This table reports the coefficient estimates of the baseline regressions using an alternative shift-share construction for racial hate crime. Racial hate crime is defined as

$$Racial\ Hate\ Crime_{c,t} = \left(\sum_{k=1,\, k\neq c}^{K} Anti\text{-}minority\ Racial\ Hate\ Crime_{k,t} \right) \times \frac{Minority\ Population_{c,t}}{Total\ Population_{c,t}} + \left(\sum_{k=1,\, k\neq c}^{K} Anti\text{-}White\ Racial\ Hate\ Crime_{k,t} \right) \times \frac{White\ Population_{c,t}}{Total\ Population_{c,t}},$$

The dependent variable is the log of the number of mortgage applications a lender receives in a county in a year. Column 1 report estimates for all applications, Column 2 for applications received from all minority groups, Columns 3-5 for applications from the sub-minority groups, Black, Asian and Hispanic, respectively, and Column 6 for White applicants. All specifications include lender-year and county fixed effects. Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

		Minorities				
	All	All	Black	Asian	Hispanic	White
	(1)	(2)	(3)	(4)	(5)	(6)
Racial hate crime	–0.134***	–0.160***	–0.090***	–0.035***	–0.108***	–0.080***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.008)	(0.008)
Population	1.000***	0.939***	0.456***	0.477***	0.507***	0.852***
	(0.045)	(0.041)	(0.028)	(0.028)	(0.028)	(0.045)
GDP growth	0.034***	0.030***	0.018***	0.007	0.027***	0.032***
	(0.008)	(0.008)	(0.005)	(0.004)	(0.006)	(0.008)
Personal income	–0.000	0.001**	0.001***	0.002***	0.001***	–0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment rate	–0.018***	–0.013***	–0.005***	–0.003***	–0.007***	–0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Poverty rate	0.000	0.000	0.000	0.000	0.000	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Home price	0.006	0.034***	0.033***	–0.032***	–0.016**	–0.033**
	(0.013)	(0.012)	(0.009)	(0.008)	(0.008)	(0.013)
Crime rate	–0.051***	–0.029***	–0.017***	0.001	–0.020***	–0.046***
	(0.009)	(0.007)	(0.005)	(0.004)	(0.006)	(0.008)
Minority share	0.012***	0.027***	0.022***	0.014***	0.018***	–0.007***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Lender-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.393	0.460	0.345	0.331	0.319	0.360
Observations	4,066,328	4,066,328	4,066,328	4,066,328	4,066,328	4,066,328

Table A2

Alternative shift share construction for racial hate crime – II

This table reports the coefficient estimates of the baseline regressions using an alternative shift-share construction for racial hate crime. Racial hate crime is defined as

$$Racial\ Hate\ Crime_{c,t} = \sum_{g} \left(\sum_{k=1,\, k \neq c}^{K} Local\ Racial\ Hate\ Crime_{g,k,t} \right) \times \frac{Population_{g,c,t}}{Total\ Population_{c,t}}$$

where g = Black, Asian, Hispanic and White. The dependent variable is the log of the number of mortgage applications a lender receives in a county in a year. Column 1 report estimates for all applications, Column 2 for applications received from all minority groups, Columns 3-5 for applications from the sub-minority groups, Black, Asian and Hispanic, respectively, and Column 6 for White applicants. All specifications include lender-year and county fixed effects. Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

		Minorities				
	All	All	Black	Asian	Hispanic	White
	(1)	(2)	(3)	(4)	(5)	(6)
Racial hate crime	–0.343***	–0.401***	–0.242***	–0.105***	–0.183***	–0.056**
	(0.027)	(0.026)	(0.021)	(0.017)	(0.023)	(0.027)
Population	1.021***	0.964***	0.469***	0.482***	0.527***	0.870***
	(0.045)	(0.041)	(0.028)	(0.028)	(0.028)	(0.046)
GDP growth	0.033***	0.028***	0.017***	0.007	0.026***	0.031***
	(0.008)	(0.008)	(0.005)	(0.004)	(0.006)	(0.008)
Personal income	–0.000	0.001**	0.001**	0.002***	0.001***	–0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment rate	–0.017***	–0.012***	–0.005***	–0.003***	–0.006***	–0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Poverty rate	0.001	0.001*	0.001**	0.000	0.001**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Home price	0.001	0.027**	0.029***	-0.034***	–0.020***	–0.036***
	(0.013)	(0.012)	(0.008)	(0.008)	(0.008)	(0.013)
Crime rate	–0.047***	–0.025***	–0.014***	0.003	–0.019***	–0.047***
	(0.008)	(0.007)	(0.005)	(0.004)	(0.006)	(0.008)
Minority share	0.007***	0.022***	0.019***	0.013***	0.014***	-0.010***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Lender-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.393	0.460	0.345	0.331	0.319	0.360
Observations	4,066,328	4,066,328	4,066,328	4,066,328	4,066,328	4,066,328

Table A3
Placebo analysis - other types of hate crime

This table report estimates of the effect of other types of hate crime, which are unrelated to race, on mortgage demand at the lender-year level. The dependent variable is the log of the number of mortgage applications a lender receives in a county in a year. Sex and gender-based hate crime, and religious hate crime are the number of hate crime reported under the respective categories (in logs) in a county in a year. All specifications include county and year fixed effects. Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Sex and gender-based hate crime incidents	Religious hate crime incidents
	(1)	(2)
Hate crime	0.001	–0.003
	(0.002)	(0.003)
Population	1.035***	1.036***
	(0.046)	(0.046)
GDP growth	0.034***	0.033***
	(0.008)	(0.008)
Personal income	–0.000	–0.000
	(0.000)	(0.000)
Unemployment rate	–0.017***	–0.017***
	(0.001)	(0.001)
Poverty rate	0.001**	0.001**
	(0.000)	(0.000)
Home price	0.001	0.001
	(0.013)	(0.013)
Crime rate	–0.053***	–0.053***
	(0.009)	(0.009)
Minority share	0.007***	0.006***
	(0.002)	(0.002)
Lender-year FE	Yes	Yes
County FE	Yes	Yes
Adjusted R^2	0.393	0.393
Observations	4,066,328	4,066,328

Table A4
Heterogeneity in county-level share of minority population

This table reports the estimates of the effect of racial hate crime on the number of mortgage applications (in logs) for counties with a population share of minorities larger than 60%, between 40% and 60%, and those smaller than 40%. Applications from all applicants, minority applicants and White applicants are separately analyzed in the various columns. Racial hate crime is defined as in Equation (1). All specifications include lender-year and county fixed effects. Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Minority share > 60%			Mixed (40% - 60%)			Minority share < 40%		
	All	Minorities	White	All	Minorities	White	All	Nonwhite	White
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Racial hate crime	–0.021	–0.041	0.042	–0.044	–0.082	–0.010	–0.176***	–0.158***	–0.148***
	(0.062)	(0.061)	(0.056)	(0.062)	(0.065)	(0.059)	(0.015)	(0.013)	(0.014)
Lender-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.501	0.503	0.462	0.462	0.473	0.422	0.391	0.453	0.362
Observations	277,201	277,201	277,201	615,060	615,060	615,060	3,158,063	3,158,063	3,158,063

Table A5
Home purchase mortgages

This table reports the coefficient estimates of the baseline regressions restricting the sample to home purchase mortgages only. The dependent variable is the log of the number of mortgage applications a lender receives in a county in a year. Racial hate crime is defined as in Equation (1) in the paper. Column 1 report estimates for all applications, Column 2 for applications received from all minority groups, Columns 3-5 for applications from the sub-minority groups, Black, Asian and Hispanic, respectively, and Column 6 for White applicants. All specifications include lender-year and county fixed effects. Standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

		Minorities				
	All	All	Black	Asian	Hispanic	White
	(1)	(2)	(3)	(4)	(5)	(6)
Racial hate crime	–0.062***	–0.093***	–0.038***	–0.053***	–0.059***	–0.034***
	(0.009)	(0.009)	(0.004)	(0.005)	(0.006)	(0.008)
Population	0.633***	0.715***	0.279***	0.346***	0.335***	0.433***
	(0.043)	(0.042)	(0.023)	(0.022)	(0.023)	(0.040)
GDP growth	0.061***	0.050***	0.009**	0.016***	0.032***	0.043***
	(0.009)	(0.008)	(0.004)	(0.004)	(0.005)	(0.007)
Personal income	–0.003***	–0.001	0.000**	0.001**	0.000	–0.002***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Unemployment rate	–0.012***	–0.008***	–0.003***	–0.001**	–0.003***	–0.009***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Poverty rate	–0.001*	–0.000	0.000	–0.000*	0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Home price	–0.210***	–0.133***	–0.051***	–0.051***	–0.064***	–0.180***
	(0.017)	(0.014)	(0.008)	(0.006)	(0.007)	(0.014)
Crime rate	–0.061***	–0.033***	–0.020***	–0.004	–0.018***	–0.050***
	(0.007)	(0.006)	(0.003)	(0.003)	(0.004)	(0.007)
Minority share	0.002	0.020***	0.016***	0.011***	0.014***	–0.012***
	(0.002)	(0.002)	(0.001)	(0.010)	(0.001)	(0.001)
Lender-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.380	0.400	0.264	0.265	0.254	0.335
Observations	4,066,328	4,066,328	4,066,328	4,066,328	4,066,328	4,066,328