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

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March 5, 2025

ABSTRACT

Racial-hate-motivated crimes have risen to unprecedented levels, yet their far-reaching economic consequences remain understudied. Using detailed U.S. mortgage market data paired with county-level racial hate crime incidents, we reveal strong neighborhood effects arising from racial hate crimes. Aggregate mortgage demand drops significantly in hate crime-affected counties. Communities impacted by racial hate crimes exhibit heightened safety concerns and a marked erosion of social cohesion. We find that residents migrate away from hate crime–affected counties, as opposed to the alternative housing choice of staying and delaying home purchases. We also observe a fall in labor productivity and an overall drop in macroeconomic conditions. Our findings illuminate the far-reaching consequences of hate crimes for neighborhoods.

Keywords: Hate Crime, Racial Animus, Mortgage Demand, Housing Choice
JEL Codes: D12, R21, R23, J15

*We acknowledge helpful comments received from John Gathergood, Pedro Gete, Michael Haliassos, Duc Duy (Louis) Nguyen, Denis Sosyura, and participants at EFiC Conference in Banking and Corporate Finance, Financial Intermediation Network of European Studies (FINEST) workshop, Sheffield Household Finance Workshop, St Andrews Finance Workshop, IE University seminar and ICMA Centre Reading seminar.

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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. These 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 study, we analyze the economic costs of racial hate crimes, particularly through their effects on the demand for mortgage credit. Homeownership constitutes a fundamental cornerstone of the American Dream and serves as a principal vehicle for intergenerational wealth accumulation and economic mobility (Ray et al., 2021). At the same time, homeownership 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 the civic society. However, with the rise in racial hate crimes, which embody prejudice toward out-groups, affected neighborhoods can experience heightened perceptions of insecurity and social fragmentation. As a result, these areas may become less desirable for homeownership, leading to shifts in migration patterns and broader adverse effects on local economic conditions.

Our empirical investigation leverages the near-universe of U.S. mortgage loan applications retrieved from the Home Mortgage Disclosure Act (HMDA) database to examine mortgage demand. Each observation in the database represents a loan application that includes geographic, lender, and loan take-up information, allowing us to track households' final mortgage decisions and distinguish between demand-side and supply-side factors. Additionally, HMDA records the race and ethnicity of the applicant(s), enabling us to observe variations in mortgage application patterns across different racial groups over time. Data on county-level hate crime incidences are retrieved from the FBI Uniform Crime Reporting (UCR) program.

When identifying the effects empirically, a key identification challenge is that county-level characteristics and other local conditions can be correlated with both mortgage demand and hate crimes. Additionally, reverse causality may arise if minority mortgage applications trigger backlash in the form of hate crimes. We address these issues by conceptualizing county-level hate crime as local exposure to aggregate national hate crime through the county demographic composition. The estimation is in the spirit of a shift-share design, where racial composition is predetermined and nationwide hate crime is unlikely to capture local effects. Furthermore, our investigation requires disentangling demand-side from supply-side effects. To control for supply-side influences, we evaluate mortgage applications submitted to 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 both time-invariant and time-varying county-level economic factors.

The results reveal a substantial negative impact of racial hate crime on mortgage credit demand. We find that in areas affected by racial hate crimes, mortgage applications decline by 2.51%, while lenders originate 2.33% fewer mortgages for a one standard deviation increase in racial hate crime. Hate crimes differ meaningfully from that of nonbias crimes. We run a comparative analysis between bias and nonbias crimes to document the distinct impact of racial hate crimes on the mortgage market. We note that non-hate crimes are often financially motivated. For example, larceny accounts for nearly 30% of incidents and primarily reflects opportunistic theft. In contrast, hate crimes follow a different pattern. The three most prevalent hate crime categories are property destruction (25.78%), intimidation (22.66%), and simple assault (20.35%). These offenses tend to combine property damage with personal victimization, reinforcing their intent to instill fear. This distinction explains why hate crimes influence housing decisions in ways that general crime does not, ruling out the possibility that a general aversion to crime cannot explain the results.

The adverse effect is evident across different borrower groups, with both White applicants and minority applicants (Black, Asian and Hispanic applicants) similarly affected, underscoring the pervasive influence of these crimes on housing decisions. Additionally, minority applicants are more likely to withdraw their applications from lenders in counties affected by hate crime incidences.

Next, we investigate whether the reduction in mortgage demand due to hate crimes is linked to neighborhood decline. Specifically, we investigate whether individuals move out of hate crime–affected areas or remain and postpone home purchases by renting instead. To explore this, we analyze county-to-county migration data from individual income tax returns filed with the Internal Revenue Service (IRS) and use Zillow rental market data as a proxy for rental demand. Our findings indicate that residents leave counties affected by hate crime. In addition, rental prices in these counties decrease, suggesting that instead of staying and renting, individuals are choosing to relocate. Building on these migration patterns, we further assess whether outflows from hate crime–affected counties influence the housing markets and mortgage activity in destination. We find that an influx of residents from these areas leads to higher rental prices in destination counties, but suppress mortgage applications and originations. These findings highlight the broader consequences of racial hate crimes, which not only disrupt local housing markets but also reshape migration patterns and neighborhood composition across counties.

To understand the how racial hate crimes contribute to an erosion of community trust and social cohesion, we utilize information from consumer surveys and census data. First, analyzing psychological distress levels and expenditure behavior, we find that hate crimes decrease psychological well-being and reduce visible consumption, such as clothing, jewelry, and outdoor recreation expenses. Our findings suggest that racial hate crimes not only erode psychological well-being but also amplify safety concerns. Second, we find the share of 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 will influence housing decisions and contribute to the observed patterns in mortgage demand.

Our article contributes to several strands of recent literature on racial bias and hate crimes, spanning their diverse causes and far-reaching consequences. As for 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). Recent research shows that increased public concerns about immigration translate into discriminatory consumer behavior (Law & Zuo, 2022). 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). Based on this literature, our study 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.

In addition, our research intersects with studies on housing and neighborhood choice. Previous literature has highlighted the influence of noninstitutional determinants on homeownership decisions. 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 this important literature by documenting how racial hate crimes create localized disruptions, leading to reduced housing demand. 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; Dustmann & Fasani, 2016). 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. These crimes 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. As for 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. To account for atypical loan and lender patterns, following Dagher and Kazimov (2015), we exclude loans below $25,000 and above $1 million and exclude inactive lenders that originated fewer than fifty mortgage loans in any given year. Our sample of mortgages comprises the majority of the US mortgage market (e.g., home purchases, home improvements, refinancing), covering 5,413 lenders.

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 six mutually exclusive and exhaustive groups (Unknown, Black, Asian, Hispanic, White, Other), following the methodology of Gerardi et al. (2021). The White group produces the largest number of mortgage applications with 6.28 million on average per year and an average loan amount applied for of $212,634. This is followed by the groups Hispanic (799,437 applications; $212,853), Black (646,087 applications; $192,007), and Asian (607,762 applications; $310,010).

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 come 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 consider a hate crime to be a racial hate crime if its bias motivation is racially or ethnically based. Accordingly, we observe the following types of hate crimes in our data: anti-Black or African American, anti-Jewish, anti-White, anti-Hispanic or Latino, anti-Asian, anti-American Indian or Alaska Native, anti-Arab, anti-Native Hawaiian or other Pacific Islander, anti-other race/ethnicity/ancestry, and anti-multiple races. The frequencies of various bias motivations are reported in Table A1 of the online Appendix. We aggregate hate crime data to the county level. To avoid 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 to racial hate crimes, the other two types play a smaller role. However, all hate crimes share a similar trend over 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 reported hate crimes started to decline gradually during the Obama administration. This trend reversed following the election of Trump, during whose term the reported number of hate crimes 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 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 administered 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 introduced state-level data for five states – namely, California, Florida, New York, Texas, and New Jersey – covering population areas amounting to 36% of the US population. The data are 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) at the 90th percentile, during the past quarter.

D. Migration data

To investigate the effect of hate crime on the migration of people, we utilize 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 the establishment-level sales and employee data from National Establishment Time Series (NETS) Database. 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 empirical model

The primary objective of the paper is to assess the impact of racial hate crimes on the demand for mortgage credit. To estimate this effect, we have to overcome several identification challenges. The first challenge is to disentangle unobserved local confounders such as economic conditions, demographic shifts or social tensions that could influence both hate crimes and mortgage demand. Secondly, there could be measurement issues in county-level hate crime data arising from varying levels of reporting practices across jurisdictions. Thirdly, reverse causality could be a concern, as increased mortgage demand from minorities could

[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.

potentially inflame racial animosity and spur more hate crimes, biasing estimates upward.

In light of the above, the use of a shift-share specification for racial hate crime is naturally appealing, as it circumvents the aforementioned problems (Adao et al., 2019). We identify the effect of racial hate crimes by leveraging cross-county variation in exposure to the nationwide trend in such crimes. Specifically, we model the exposure of racial hate crime in the county c in year t as follows:

$$Racial\ Hate\ Crime_{c,t} = \sum_{g} \sum_{k,\, k \neq c} Racial\ Hate\ Crime_{g,k,t} \times \frac{Population_{g,c,t}}{\sum_{g} Population_{g,c,t}} \qquad (1)$$

where $Racial\ Hate\ Crime_{g,k,t}$ is the count of hate crime incidences against racial group g in county k and year t. From our incident-level hate crime data, we observe anti-Black, anti-Jewish, anti-White, anti-Hispanic, anti-Asian, anti-American Indian or Alaska Native, anti-Arab, anti-Native Hawaiian, and other racial hate crimes. In our estimation, we group together hate crimes against all types of minorities and also take into account anti-White hate crimes. The county-level racial population estimates that form the basis for our minority and White shares come from the Census Bureau. In essence, our hate crime variable captures each county's exposure to the aggregate national hate crime trend through the lenses of its racial composition[2].

Our shift-share approach relies on some identifying assumptions, as discussed in Borusyak et al. (2025). First, we assume that nationwide hate crime trends are as good as randomly assigned conditional on our controls and fixed effects. Given that in our empirical specifications we account for county and lender-year fixed effects, variation in national hate crime levels is unlikely to be correlated with unobserved determinants of local mortgage demand. Secondly, again conditional on our controls and fixed effects, the identification relies on hate

[2]Hate crime incidences against minority groups are aggregated together in our estimation since the Census Bureau provides disaggregated information of the population numbers only for the major minority groups. We also consider an alternative way of constructing the shift-share measure for racial hate crime by utilizing the race and ethnicity information to separately take into account hate crimes against the Black, Asian and Hispanics groups. The results are provided in the online Appendix, see Table A2.

crime shocks being independent across different geographic areas and not clustered within certain locations. We observe that there are no location-specific clustering dominating the nationwide hate crime trend. Combined with the fact that the validity of the approach increases with the number of counties supplying shifts (i.e., hate crime shocks) (Adao et al., 2019), the empirical setup provides the foundation for valid statistical inference.

Our baseline fixed effects regression model uses the lender–county–year information to assess the impact of racial hate crime on the demand for mortgage credit. We include in the model county-level controls, county fixed effects as well as saturating the model with supply-side influences through the inclusion of lender-year fixed effects. Specifically, our regression model takes the following form:

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

where $M_{l,c,t}$ represents the mortgage credit demand for lender l in county c in year t. We study several mortgage outcomes, including the number of mortgage applications, withdrawal rates, denial rates, and mortgage originations. The primary explanatory variable of interest is the lagged values of racial hate crime, denoted by $Racial\ Hate\ Crime_{c,t-1}$. Lagging hate crime by one period helps account for the potential delayed effects of racial hate crime exposure on mortgage demand. $X_{c,t-1}$ represents a vector of control variables specific to county c in year $t-1$. 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.[3] 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.

Overall, the key identifying assumption is that, conditional on county and lender-year 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.

B. *Baseline results*

Table II presents the baseline results measuring the impact of racial hate crime on mortgage demand. The Column (1) reports results of the baseline specification outlined in equation (2) controlling for county and lender-year fixed effects. As the results show, racial hate crimes have a substantial and statistically significant negative impact on mortgage applications. The estimated coefficient on racial hate crime implies that a one standard deviation increase in racial hate crime decreases mortgage applications received by a given lender in a county by 2.51%. To illustrate the economic impact, this translates to a drop in 606,566 mortgage applications nationwide for the year 2020, considering the level of applications in that year[4].

Columns (2)-(4) explore how the results evolve with varying levels of fixed effects in Table

[3]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.

[4]In 2020, lenders received an aggregate of 24.17 million mortgage applications for a credit volume of 6.33 trillion USD.

II. While Column (1) includes both county fixed effects and lender-year fixed effects for the most saturated specification, Columns (2) through (4) progressively relax the fixed effects structure, incorporating different combinations of lender, year, and county fixed effects to assess the sensitivity of our findings. When we relax the lender-year fixed effects, the effect of racial hate crime increases. For example, in Column (2) the effect of racial hate crime increases by 3 percentage points when we control for lender fixed effects and year fixed effects. Overall, the results consistently show a negative impact of racial hate crimes on mortgage applications across all specifications.

C. *The mortgage demand effects for various race and ethnicity groups*

We now examine the effects of racial hate crimes on different racial groups in Table III. The extent to which these effects differ by race group is an empirical question. Minority groups may be particularly affected due to heightened fear and insecurity stemming from their minority status and being the most likely targets of racial hate crimes. White borrowers, representing the majority in many counties, may experience different dynamics given structural advantages such as economic resilience and a lower perceived vulnerability to targeted violence. However, both groups may respond to broader societal and economic implications of hate crimes, including increased fear, neighborhood instability, and eroding social cohesion. These considerations suggest that while differences are plausible, the overall housing market effects could exhibit common patterns across groups.

The results indicate that the estimated coefficient on racial hate crime is negative and statistically significant for both White and minority borrower groups. The magnitude of the effect is notably similar across groups, reflecting the widespread impact of racial hate crimes on housing market behavior. This finding underscores that even majority populations are not insulated from the wider consequences of hate crimes, while minority groups, despite their distinct vulnerabilities, show comparable responses in terms of reduced mortgage demand.

These results highlight the broad-reaching effects of racial hate crimes on mortgage demand.

D. *Comparing the effects of hate crime to overall crime*

To assess the comparative effects of racial hate crimes relative to other types of crimes, we conduct subsample analysis of counties, where both county-level crime and hate crime data are available. We retrieve these from the NIBRS. Instead of relying on the shift-share construction, this analysis uses the actual number of racial hate crime incidents (in logs), which allows us to examine the disaggregated effects across various types of offenses. The estimation results are presented in Table IV.

Model I in Table IV estimates the effect of total crime, while Model II incorporates racial hate crime as a separate category in the regression. Both models include county controls, county fixed effects, and lender-year fixed effects. Separate regressions are run for the different offense types and reported in the rows of the table. Across offense types, the results show that racial hate crimes are associated with significant reductions in mortgage applications compared to overall crime. For example, the estimated coefficients for destruction, damage or vandalism of property offenses are small and statistically insignificant in both models (Columns (1) and (3)), whereas the coefficient for racial hate crime is larger in magnitude and statistically significant (Column (5)). Similarly, intimidation offenses show no significant relationship in Model I but exhibit a significant negative effect when analyzed as racial hate crimes in Model II. While certain crimes, such as robbery or burglary, also show significant negative effects when considered across all crimes, racial hate crimes subsume the overall effect in Model II. Further, racial hate crimes involving weapon law violations are associated with a more substantial negative effect on mortgage applications compared to overall crimes in the same category. These findings suggest that the impact of racial hate crimes on housing decisions is more pronounced than that of other crime types. In terms of economic significance, these results indicate that racial hate crimes are more strongly associated with reduced mortgage applications than overall crimes in the same category, even after accounting for variations across offense types.

These differential effects across offense types align with patterns in the frequency and nature of hate crimes versus other crimes, shown in online Appendix A3. While larceny/theft offenses dominate non-hate crimes (significant also in Table IV), accounting for nearly 30% of incidents and typically representing opportunistic, financially motivated behavior, the most frequent hate crimes follow a distinctly different pattern. The three most prevalent hate crime categories - property destruction (25.78%), intimidation (22.66%), and simple assault (20.35%) - exhibit similar frequencies and suggest a systematic targeting approach combining property damage with personal victimization.

This clustering of property and personal attacks in hate crimes is particularly revealing when contrasted with non-hate crimes, where property and personal offenses show clearer separation. Non-hate crimes display a broader distribution after larceny (29.94%), with property damage, assault, and drug offenses each comprising 11-13% of incidents, followed by burglary and fraud offenses in the 5-8% range. This pattern reinforces that non-hate crimes are often motivated by financial gain rather than targeting specific groups.

The regression results in Table IV mirror these fundamental differences in criminal intent. The significant negative coefficients for racial hate crimes involving property destruction and intimidation, compared to their insignificant effects when considered as general crimes, align with how hate crimes employ property damage as an end goal rather than a means for financial gain. This distinction is particularly important given that property destruction in hate crimes often carries symbolic meaning intended to inspire fear within targeted communities, potentially explaining its stronger influence on mortgage applications compared to financially motivated property crimes.

Overall, these patterns suggest that racial hate crimes, beyond their direct effects, may influence housing market behavior by shaping perceptions of community stability and safety.

These findings also provide evidence against the possibility that the observed effects are driven solely by general crime aversion.

E. *Results for mortgage withdrawals, denials and originations*

Following the initial examination of mortgage applications, we further explore application withdrawals, denials, and originations after being made to lenders within a county and their 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 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. 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 V. In Panel A, we find that exposure to racial hate crimes tends to increase the likelihood of mortgage application withdrawals, and this association is statistically significant for Black and White applicants and insignificant for Asian and Hispanic applicants. 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. This could reflect a shift in the composition of applicants, with lower-quality White applicants potentially being more inclined to apply following hate crimes. Such behavior may arise if these applicants perceive reduced competition or anticipate leniency in lending standards in areas experiencing heightened social tensions, even if such perceptions are unfounded. 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 results in lenders originating 2.33% 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 324,306 mortgage originations on aggregate[5]. Given the average underwriting profit in 2020 of $4,202 (Mortgage Bankers Association, 2021), the drop in originations translates to a reduction of $1.36 billion in profits for all mortgage lenders.

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 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.

F. *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

[5] In 2020, lenders originated an aggregate of 13.92 million mortgage loans for a credit volume of $3,76 trillion.

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:

$$\begin{aligned} Local\ Racial\ Hate\ Crime_{c,t} &= \alpha_c + \lambda_{l,t} + \beta(Minority\ Out\text{-}Group\ Marriages_{c,t}) \\ &\quad + X'_{c,l,t}\zeta + \epsilon_{c,l,t}, \end{aligned} \tag{3}$$

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:

$$\begin{aligned} Mortgage\ Applications_{c,l,t+1} &= \alpha_c + \lambda_{l,t+1} + \gamma Local\ Racial\ Hate\ Crime_{c,t} \\ &\quad + X'_{c,t}\theta + \varepsilon_{c,l,t+1}, \end{aligned} \tag{4}$$

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 (**??**).

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.

G. 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:

$$\overline{Local\ Racial\ Hate\ Crime}_c^{\text{2007-2020}} = \beta_0 + \beta_1 Lynchings_c^{\text{1900-1930}} + X_c'\zeta + \epsilon_c, \tag{5}$$

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:

$$\overline{Mortgage\ Applications}_c^{\text{2007-2020}} = \gamma_0 + \gamma_1 \overline{Local\ Racial\ Hate\ Crime}_c^{\text{2007-2020}} + X_c'\theta + \varepsilon_c. \tag{6}$$

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.

H. 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 (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.

I. Additional analyses and robustness checks

We conduct a series of additional analysis and checks to establish the robustness of our results. First, we assess the sensitivity of our baseline results using three alternative ways of measuring racial hate crimes. The first is a more granular shift-share construction, where we use the subsample of hate crimes incidences against races identifiable in the census data, namely, Black, Asian, Hispanic and White, and use their respective county-level proportion of total population to construct the shift-share (the exact formula is provided in Table A2 in

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

the online Appendix). This alternative construction provides a robustness check to potential aggregation errors, with the drawback of using only the subsample of racial hate crimes with identifiable races. The second alternative way of measuring racial hate crime is simply using the county-level number of racial hate crime incidences (in logs). The third alternative way is the number of victims of racial hate crime incidences in a county (in logs), which is obviously correlated with the number of racial hate crimes, but it also takes into account the heterogeneity in severity of different incidences. The regression results for the three alternative racial hate crime specifications are reported in the online Appendix (Table A2). We find that the effects we are uncover remain robust to alternative ways of capturing racial hate crimes.

Second, 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 the online Appendix (Table A4), 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.

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 reduce mortgage demand and are 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:

$$Outcome_{c,t} = \alpha_c + \tau_t + \gamma Racial\ Hate\ Crime_{c,t-1} + X'_{c,t-1}\theta + \varepsilon_{c,t} \tag{7}$$

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 A 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:

$$\begin{aligned} Outcome_{i,t} = \; & \alpha_i + \tau_t + \gamma_1 Racial\,Hate\,Crime_{i,t-1} + \gamma_2 Racial\,Hate\,Crime_{j,t-1} \\ & + \gamma_3 Net\,Inflow_{j\rightarrow i,t} + \gamma_4 (Racial\,Hate\,Crime_{j,t-1} \times Net\,Inflow_{j\rightarrow i,t}) \\ & + X'_{i,t-1}\theta + \varepsilon_{i,t} \end{aligned} \tag{8}$$

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 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 does not result in an 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. Notably, 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 (rather 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. We also find 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.

B. *Economic effects on labor markets and economic growth*

In the previous section, we document significant migration outflows from counties affected by racial hate crimes. This motivates us to further investigate their broader economic impact on key county-level labor market and growth indicators, including labor productivity, GDP growth, and unemployment rates. Labor productivity is measured as establishment-level sales divided by number of employees, using data from the National Establishment Time Series (NETS) and aggregated at the county level. GDP growth and unemployment rates are sourced from the Bureau of Economic Analysis. Using these county-level indicators, we estimate the relationship between reported racial hate crimes and economic outcomes while controlling for a comprehensive set of county characteristics, lagged values of the economic indicators, and employing county and year fixed-effects regression models.

The results are presented in Table X. Column (1) demonstrates that racial hate crimes are associated with a statistically significant decrease in labor productivity. This negative effect persists even after accounting for the lagged productivity and other controls, suggesting that racial hate crimes disrupt local labor markets potentially through increased workplace tension, lowering worker morale and dampening broader economic activity. Similarly, Column (2) reveals that GDP growth slows in affected counties, indicating economic declines potentially due to reduced investment and curtailed consumer spending. The adverse effects extend to unemployment, as reported in Column (3), likely as businesses become reluctant to expand in an environment of economic uncertainty. The analysis highlights the profound economic cost of racial hate crimes beyond their immediate social and moral consequences.

VI. Possible explanations: role of external fear and the erosion of civic communities

The substantial decline in mortgage demand and neighborhood stability following racial hate crimes raises important questions about the underlying mechanisms driving these effects. While direct victimization impacts a relatively small portion of the population, the broader economic consequences we document suggest that racial hate crimes generate spillover effects that reverberate throughout communities. Two potentially interconnected channels emerge as particularly relevant: the role of external fear that extends beyond immediate victims to affect the broader population's sense of security, and the erosion of social cohesion that can fundamentally alter the fabric of community life. Understanding these mechanisms is crucial not only for explaining our empirical findings but also for developing effective policy responses to mitigate the economic costs of hate crimes. This section examines how these two channels might operate and presents evidence supporting their role in driving our results.

A. Role of external fear: Results from individual-level surveys

Homeownership typically provides individuals with a sense of safety and security. However, racial hate crimes may undermine this through their effects on external fear, as manifested in psychological well-being and economic behavior of residents in affected communities. We therefore examine how hate crimes relate to patterns of psychological distress and consumption behavior among surveyed individuals in affected neighborhoods. These patterns can provide insight into how hate crimes may influence housing decisions through their impact on residents' sense of security and fear. 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 households to reduce their consumption of visible goods in locations affected by hate crimes (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:

$$Behavior_{i,t} = \alpha_s + \gamma Racial\ Hate\ Crime_{i,t-1} + X'_{i,t-1}\theta + \varepsilon_{i,t} \tag{9}$$

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 XI. 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 XI suggest that racial hate crimes not only erode neighborhood cohesion and desirability, but also instill 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. *Erosion of civic communities*

A strong civic community, characterized by active religious, civic, and social organizations, provides the foundation for neighborhood stability and cohesion. This social infrastructure makes localities more attractive to potential homeowners. However, racial animus and hate crimes can severely damage neighborhood cohesion by reducing the uptake of civic services and engagement among residents, while also diminishing the capacity of local civil society organizations to contribute positively to their communities.

We examine the relationship between racial hate crimes and the presence of religious, civic, and social organizations within counties. To measure organizational presence, we use data from the County Business Patterns database, which allows us to construct two measures. Our broad measure captures all religious, civic, and social organizations classified under NAICS industry code 813, while our narrow measure focuses specifically on civic and social organizations (NAICS codes 8131 and 8134). For each county-year observation, we calculate these organizations' share relative to the total number of establishments. To assess this relationship empirically, we estimate the following regression specification:

$$Institution\ Share_{c,t} = \alpha_c + \tau_t + \gamma Racial\ Hate\ Crime_{c,t-1} + X'_{c,t-1}\theta + \varepsilon_{c,t}, \qquad (10)$$

where the dependent variable $InstitutionShare_{c,t}$ 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 XII. 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 has 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 documents the economic consequences of racial hate crimes in U.S. mortgage markets. Our analysis reveals that counties affected by hate crimes experience a 2.51% decline in mortgage applications and a 2.33% reduction in mortgage originations. The impact of racial hate crimes significantly exceeds that of non-bias-motivated crimes, reflecting their distinct nature. While general crime is predominantly characterized by financially motivated offenses such as larceny (29.94% of incidents), hate crimes follow a different pattern, combining property destruction (25.78%), intimidation (22.66%), and simple assault (20.35%) in ways that suggest intentional targeting rather than opportunistic behavior.

We find that the adverse effects on mortgage demand are widespread, affecting both minority and White applicants similarly. Using detailed migration data from IRS tax returns and housing market information from Zillow, we document significant population outflows from hate crime-affected counties, accompanied by declining rental prices. These patterns show that residents choose to relocate rather than remain as renters. The deterioration of affected communities manifests through multiple channels: increased psychological distress, reduced visible consumption, declining labor productivity, and erosion of civic organizations. These findings point to a broader degradation of social cohesion and economic vitality in areas experiencing racial hate crimes.

Our findings contribute to the literature on racial bias and hate crimes by illuminating their substantial economic costs through the lens of mortgage markets. The results demonstrate that hate crimes' impact extends beyond immediate victims, creating broader spillover effects that reshape community composition and economic activity. This evidence suggests that the societal costs of hate crimes are more far-reaching than previously documented, affecting fundamental aspects of economic life including housing choices, migration patterns, and community stability.

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Figure I
Hate crime

This figure illustrates the evolution of three primary hate crime categories as a proportion of total crimes per 1,000 incidents over the period from 1994 to 2020. The categories displayed are racial hate crimes, sex- and gender-based hate crimes, and religious hate crimes. The data is sourced from the FBI Uniform Crime Reporting (UCR) program.

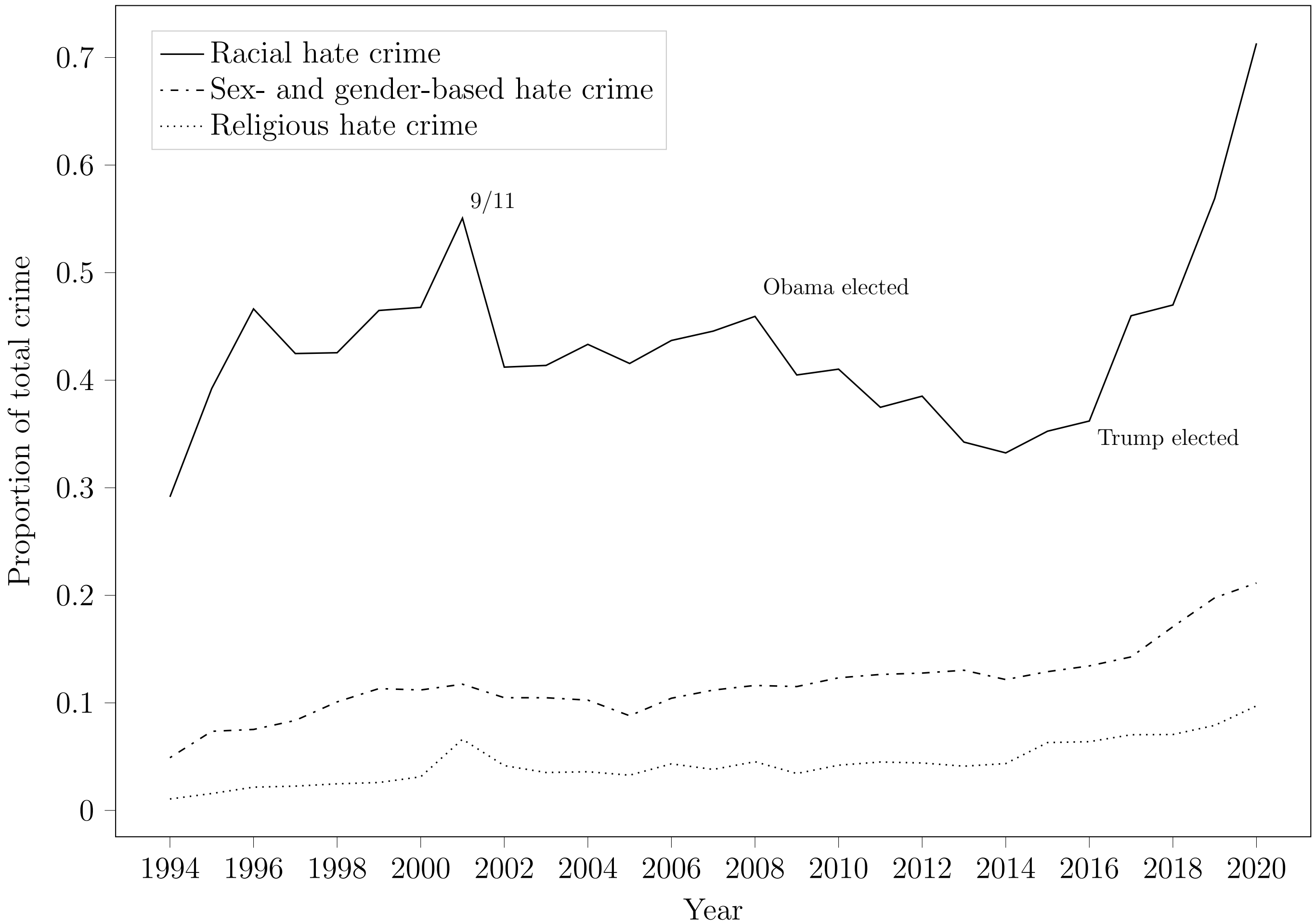

Table I
Summary statistics

This table presents descriptive statistics for the primary variables used in the analysis, covering the sample period from 2007 to 2020. Mortgage credit variables are at the lender-county-year level, while geographic and migration variables are at the county-year level and matched to lenders in a given county. Household variables are based on household survey data and are measured at the household-survey level (monthly frequency). Detailed definitions of all variables are provided 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	0.76	0.20	0.56	1.02
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
Share of religious, civic, and social organizations	1.06	0.54	0.54	1.66
Share of civic and social organizations	0.84	0.48	0.35	1.42
Labor productivity	87.06	9.98	75.85	99.14
Migration variables				
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
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

Table II
Racial hate crime and mortgage applications

This table reports the estimated effects of racial hate crime on mortgage applications. The dependent variable is the log of the number of mortgage applications received by a lender in a county-year. The key explanatory variable is racial hate crime, defined in Equation (1). Control variables include county-level characteristics detailed in Appendix A. Fixed effects (FE) specifications are listed at the bottom of the table. Standard errors are clustered at the county level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Racial hate crime	–0.134***	–0.164***	–0.154***	–0.182***
	(0.008)	(0.009)	(0.008)	(0.011)
Population	1.000***	1.094***	0.856***	0.403***
	(0.045)	(0.046)	(0.045)	(0.004)
GDP growth	0.034***	0.037***	0.024***	0.114***
	(0.008)	(0.008)	(0.008)	(0.016)
Personal income	–0.000	–0.000	0.002***	–0.003***
	(0.000)	(0.000)	(0.000)	(0.001)
Unemployment rate	–0.018***	–0.019***	–0.012***	0.008***
	(0.001)	(0.001)	(0.001)	(0.002)
Poverty rate	0.000	–0.000	0.001**	–0.017***
	(0.000)	(0.000)	(0.000)	(0.001)
Home price	0.006	–0.003	–0.038***	0.200***
	(0.013)	(0.013)	(0.013)	(0.009)
Crime rate	–0.051***	–0.031***	–0.029***	–0.004
	(0.009)	(0.008)	(0.008)	(0.007)
Minority share	0.012***	0.014***	0.016***	0.007***
	(0.002)	(0.002)	(0.002)	(0.000)
County FE	Yes	Yes	Yes	No
Lender-year FE	Yes	No	No	No
Lender FE	No	Yes	No	Yes
Year FE	No	Yes	Yes	Yes
Adjusted R^2	0.401	0.361	0.106	0.351
Observations	4,066,328	4,067,013	4,067,019	4,067,013

Table III

Racial hate crime and mortgage applications by race and ethnicity

This table presents regression estimates of the impact of racial hate crimes on mortgage demand. The dependent variable is the log of the number of mortgage applications a lender receives in a county-year. The key explanatory variable is racial hate crime, defined in Equation (1). Column (1) reports results for all minority group applications, Columns (2)–(4) for Black, Asian, and Hispanic subgroups, respectively, and Column (5) for White applicants. Control variables include county-level characteristics and all specifications incorporate lender-year and county fixed effects. Variable definitions are detailed in Appendix A. Standard errors are clustered at the county level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

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

Table IV
Comparing the effects of local racial hate crime versus other crime

This table compares the effects of local racial hate crimes and total crime on mortgage applications. The dependent variable is the log of the number of mortgage applications received by a lender in a county-year. Model I includes total crime (log of all incidents) as the key explanatory variable, while Model II incorporates both racial hate crimes (log of incidents) and total crime to facilitate a direct comparison. The total incident-based crime and hate crimes data come from the NIBRS. Separate regressions are run for each specification. Control variables include county-level characteristics such as population, GDP growth, personal income, unemployment rate, poverty rate, home prices, and minority ratio. Variable definitions are detailed in Appendix A. Both models include lender-year and county fixed effects, with standard errors clustered at the county level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model I		Model II			
	Crime		Crime		Racial hate crime	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)
Offense types:						
Destruction/damage/vandalism of property	–0.001	(0.002)	–0.001	(0.002)	–0.007***	(0.003)
Intimidation	–0.001	(0.002)	–0.000	(0.002)	–0.006**	(0.003)
Simple assault	–0.002	(0.002)	–0.002	(0.002)	–0.001	(0.003)
Aggravated assault	–0.001	(0.002)	–0.001	(0.002)	0.001	(0.004)
Larceny/theft offenses	–0.003*	(0.002)	–0.003*	(0.002)	–0.004	(0.004)
Drug/narcotic offenses	–0.002	(0.002)	–0.002	(0.002)	–0.008	(0.005)
Burglary/breaking and entering	–0.003*	(0.002)	–0.003	(0.002)	–0.009*	(0.005)
Robbery	–0.004**	(0.002)	–0.004**	(0.002)	0.000	(0.007)
Fraud offenses	–0.001	(0.002)	–0.001	(0.002)	0.006	(0.006)
Weapon law violations	–0.001	(0.002)	–0.001	(0.002)	–0.013**	(0.007)
Sex offenses	–0.003	(0.002)	–0.003	(0.002)	–0.008	(0.009)
Motor vehicle theft	–0.002	(0.002)	–0.002	(0.002)	–0.004	(0.007)
Arson	–0.001	(0.002)	–0.001	(0.002)	–0.009	(0.011)
Counterfeiting/forgery	–0.003*	(0.002)	–0.003*	(0.002)	0.017	(0.010)

Table V

Racial hate crime and its effects on mortgage withdrawals, denials and originations

This table presents regression estimates of the effects of racial hate crime on mortgage application outcomes at the lender-year level. Panel A examines withdrawal rates (withdrawn applications as a share of total applications), Panel B reports denial rates (denied applications as a share of non-withdrawn applications), and Panel C analyzes mortgage originations (log of total originations). Column (1) includes all applications, Column (2) focuses on minority groups, Columns (3)–(5) separately evaluate Black, Asian, and Hispanic subgroups, and Column (6) focuses on White applicants. Racial hate crime is defined in Equation (1). Variable definitions are detailed in Appendix A. All models include lender-year and county fixed effects, with standard errors 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***	0.004	0.003	0.002*
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-year 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 rate						
Racial hate crime	0.006***	0.001	–0.002	0.003	0.002	0.006***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-year 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: Origination						
Racial hate crime	–0.110***	–0.103***	–0.061***	–0.030***	–0.079***	–0.075***
	(0.009)	(0.008)	(0.005)	(0.004)	(0.007)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.346	0.356	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 VI
Instrumental variable approach: Minority out-group marriages

This table presents regression estimates of the effect of racial hate crime on mortgage applications using an instrumental variable approach. The instrument for local racial hate crime is the number of minority out-group marriages (with Whites) in a county-year. The dependent variable in the second stage is the log of the number of mortgage applications a lender receives in a year. Column (1) reports the first-stage results, where the dependent variable is the log of racial hate crimes, while Columns (2)–(7) present the second-stage results. An additional control for county-level new marriages is included in all specifications. Variable definitions are detailed in Appendix A. Standard errors are clustered at the county level. ***, **, and * denote 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)
Minority out-group marriages	–0.021***						
	(0.002)						
Local racial hate crime		–0.835***	–0.879***	–0.746***	–0.550***	–0.551***	–0.260
		(0.200)	(0.185)	(0.134)	(0.124)	(0.134)	(0.187)
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	161.872						
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 presents regression estimates of the effect of racial hate crime on mortgage applications using an instrumental variable approach. The instrument is the log of the number of lynchings recorded in a county between 1900 and 1930. The dependent variable in the second stage is the average log of mortgage applications a lender receives annually between 2007 and 2020. Only counties with recorded lynchings are included in the analysis. Column (1) reports the first-stage results, where the dependent variable is the log of racial hate crimes, while Columns (2)–(7) present the second-stage results, focusing on total applications and applications by ethnic groups. Standard errors are clustered at the county level. ***, **, and * denote 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 (0.159)	–0.315* (0.176)	–2.704*** (0.696)	–0.104 (0.331)	0.608 (0.419)	–0.233 (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 the George Floyd murder 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 patterns 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 shows 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 flows (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	35.059***	–0.367*	35.426***	–7.728***
	(4.034)	(0.208)	(4.120)	(2.057)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.693	0.973	0.449	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$_i$	–0.298***	–0.316***	–7.396***	
	(0.054)	(0.064)	(1.236)	
Net inflow$_{j\to i}$	0.015***	0.017***	–0.083	
	(0.004)	(0.005)	(0.050)	
Racial hate crime$_j$ $\times$Net inflow$_{j\to i}$	–0.003**	–0.004**	0.043*	
	(0.001)	(0.002)	(0.022)	
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

The economic effects of racial hate crime on labor markets and growth

This table presents regression estimates of the effects of racial hate crime on labor productivity, GDP growth, and unemployment rates using county-level data. The dependent variable in Column (1) is labor productivity, in Column (2) is the GDP growth rate, and in Column (3) is the unemployment rate. The key explanatory variable is racial hate crime, defined as in Equation (1). Control variables include county-level characteristics and the lagged values of the dependent variables. Variable definitions are detailed in Appendix A. All specifications include county and year fixed effects, with standard errors clustered at the county level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Labor productivity	GDP growth	Unemployment
	(1)	(2)	(2)
Racial hate crime	–0.774***	–0.011**	0.565***
	(0.199)	(0.005)	(0.074)
Population	–9.865***	0.068***	1.531***
	(1.141)	(0.026)	(0.240)
GDP growth ($t-1$)	–0.074	0.026	–0.908***
	(0.217)	(0.027)	(0.075)
Personal income	–0.031***	–0.005***	0.029***
	(0.011)	(0.001)	(0.003)
Unemployment rate ($t-1$)	0.057***	–0.002***	0.694***
	(0.018)	(0.001)	(0.006)
Poverty rate	0.010	0.002***	–0.025***
	(0.011)	(0.000)	(0.004)
Home price	0.543**	0.001	0.334***
	(0.273)	(0.007)	(0.075)
Crime rate	–0.076	0.004	0.310***
	(0.090)	(0.004)	(0.032)
Minority share	–0.104***	–0.003***	0.059***
	(0.025)	(0.001)	(0.009)
Labor productivity ($t-1$)	0.796***	–0.001***	–0.000
	(0.040)	(0.000)	(0.002)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.875	0.081	0.925
Observations	31,370	31,370	31,370

Table XI
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. Variable definitions are detailed in Appendix A. 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	0.111***	0.056*	0.122***	0.108***
	(0.003)	(0.029)	(0.007)	(0.002)
Age	0.000	0.005	0.000	–0.000
	(0.000)	(0.003)	(0.001)	(0.000)
Education	0.001***	0.002***	0.001*	0.001***
	(0.000)	(0.001)	(0.001)	(0.000)
Family size	0.002	–0.017	0.008	–0.001
	(0.002)	(0.017)	(0.005)	(0.002)
Employed	–0.036***	–0.011	–0.022	–0.031***
	(0.008)	(0.066)	(0.016)	(0.008)
Family income	–0.439***	–0.220	–0.162**	–0.089**
	(0.076)	(0.428)	(0.069)	(0.040)
Family wealth	0.003	–0.009	0.052	–0.001
	(0.005)	(0.019)	(0.034)	(0.002)
County FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.036	0.184	0.016	–0.003
Observations	12,048	455	2,612	15,894

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	–0.448*	–1.360***	–0.646***	–0.781***	0.190	–0.681***	–0.840***	–0.864***
	(0.256)	(0.221)	(0.148)	(0.096)	(0.267)	(0.264)	(0.161)	(0.097)
Age	–0.012***	–0.026***	–0.024***	–0.022***	0.020***	0.024***	0.013***	0.018***
	(0.003)	(0.003)	(0.002)	(0.001)	(0.003)	(0.004)	(0.002)	(0.001)
Education	0.134***	0.008	0.048***	0.238***	0.235***	0.363***	0.238***	0.217***
	(0.026)	(0.028)	(0.013)	(0.013)	(0.034)	(0.031)	(0.015)	(0.013)
Family size	0.259***	0.185***	0.229***	0.234***	0.131***	0.194***	0.211***	0.120***
	(0.036)	(0.044)	(0.021)	(0.019)	(0.041)	(0.047)	(0.022)	(0.020)
Marital status	–0.086	0.268**	-0.049	0.212***	0.758***	0.2777*	0.422***	0.507***
	(0.107)	(0.134)	(0.064)	(0.047)	(0.119)	(0.148)	(0.072)	(0.047)
Total expenditure	0.064***	0.049***	0.039***	0.036***	0.071***	0.069***	0.047***	0.040***
	(0.009)	(0.006)	(0.005)	(0.003)	(0.014)	(0.007)	(0.006)	(0.002)
Income	0.007	–0.031***	0.004***	0.000	0.017	0.009	0.006***	0.001***
	(0.029)	(0.009)	(0.001)	(0.001)	(0.013)	(0.009)	(0.000)	(0.000)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.094	0.112	0.100	0.133	0.104	0.134	0.089	0.089
Observations	2,772	2,227	6,971	15,681	2,772	2,227	6,971	15,681

Table XII
Racial hate crime and the effect on 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 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) considers the number of civic and social organizations only (with the NAICS industry codes 8132-8134). Racial hate crime is defined as in Equation (1). Variable definitions are detailed in Appendix A. 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	–0.025**	–0.026*
	(0.012)	(0.009)
Population	–0.816***	–0.131***
	(0.093)	(0.044)
GDP growth	–0.003	0.004
	(0.018)	(0.011)
Personal income	–0.007***	–0.001
	(0.001)	(0.001)
Unemployment rate	0.000	0.000
	(0.002)	(0.001)
Poverty rate	0.002**	0.001***
	(0.001)	(0.000)
Home price	0.040	–0.022*
	(0.030)	(0.011)
Crime rate	–0.010	–0.017***
	(0.010)	(0.004)
Minority share	–1.538***	–0.013
	(0.347)	(0.219)
County FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.915	0.805
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
Withdrawal rate	The withdrawn applications divided by all applications received by a lender in a county	HMDA
Minorities	The withdrawn applications from minorities divided by all applications from minorities received by a lender in a county	HMDA
White	The withdrawn applications from white people divided by all applications from white people received by a lender in a county	HMDA
Denial rate	The denied applications divided by all not withdrawn applications received by a lender in a county	HMDA
Minorities	The denied applications divided by all not withdrawn applications from minorities received by a lender in a county	HMDA
White	The denied applications divided by all not withdrawn 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

(Continued)

Variable	Definition	Source
Personal income	The average personal income of a county	Bureau of Economic Analysis
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	Number of broadly defined religious, civic and social organizations divided by total number of organizations	County Business Patterns
Share of civic and social organizations	Number of narrowly defined religious, civic and social organizations divided by total number of organizations	County Business Patterns
Labor Productivity	Sales divided by number of employees (county-level average)	NETS
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
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

When Prejudice Hits Home:

Hate Crime and the Market for Mortgage Credit

Online Appendix

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5 March 2025

Table A1
Bias motivation frequencies for hate crimes

This table presents the count, percentage and cumulative percentage for the various types of bias-motivated hate crimes. Data are sourced from the FBI Uniform Crime Reporting (UCR) program.

Bias motivation	Obs.	Freq. (%)	Cuml. (%)
Anti-Black or African American	31,468	44.65	44.65
Anti-Jewish	11,886	16.87	61.52
Anti-White	9,708	13.77	75.29
Anti-Hispanic or Latino	6,450	9.15	84.44
Anti-Other race/ethnicity/ancestry	4,391	6.23	90.67
Anti-Asian	2,231	3.17	93.84
Anti-Multiple races	2,178	3.09	96.93
Anti-American Indian or Alaska Native	1,562	2.22	99.14
Anti-Arab	515	0.73	99.88
Anti-Native Hawaiian or Other Pacific Islander	88	0.12	100

Table A2
Alternative measures for racial hate crime

This table reports the regression estimates of the baseline regressions using alternative measures for racial hate crime. In Column (1), 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. Columns (2) and (3) use county-level racial hate crimes incidences and victims, respectively. Across specifications, the dependent variable is the log of the number of mortgage applications a lender receives in a county in a year. 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)	(3)
Racial hate crimes (alternative shift-share)	–0.343***		
	(0.027)		
Racial hate crime (incidences)		–0.007***	
		(0.002)	
Racial hate crime (victims)			–0.006***
			(0.002)
Population	1.021***	1.037***	1.083***
	(0.045)	(0.046)	(0.046)
GDP growth	0.033***	0.033***	0.032***
	(0.008)	(0.008)	(0.008)
Personal income	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Unemployment rate	-0.017***	-0.017***	-0.016***
	(0.001)	(0.001)	(0.001)
Poverty rate	0.001	0.001**	0.001***
	(0.000)	(0.000)	(0.000)
Home price	0.001	0.002	-0.000
	(0.013)	(0.013)	(0.013)
Crime rate	-0.047***	-0.054***	-0.055***
	(0.008)	(0.009)	(0.009)
Minority share	0.734***	0.639***	0.110
	(0.168)	(0.172)	(0.215)
Lender-year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.393	0.393	0.392
Observations	4,066,328	4,066,328	4,066,328

Table A3

Offense type frequencies for hate crimes and non-hate crimes

This table presents counts, percentages and cumulative percentages for offense types for hate crimes (Panel a) and non-hate crimes (Panel b), ranked in descending order by their occurrence. Data on hate crime and non-hate crime are drawn from the National Incident-Based Reporting System (NIBRS).

(a) Hate crime				(b) Non-hate crime			
Offense type	Obs.	Freq. (%)	Cuml. (%)	Offense type	Obs.	Freq. (%)	Cuml. (%)
Destruction/damage/vandalism of property	12,523	25.78	25.78	Larceny/theft offenses	25,573,237	29.94	29.94
Intimidation	11,011	22.66	48.44	Destruction/damage/vandalism of property	11,499,922	13.47	43.41
Simple assault	9,886	20.35	68.79	Simple assault	10,488,622	12.28	55.69
Aggravated assault	4,408	9.07	77.86	Drug/narcotic offenses	10,072,005	11.79	67.49
Larceny/theft offenses	4,033	8.30	86.16	Burglary/breaking & entering	7,189,224	8.42	75.90
Drug/narcotic offenses	1,650	3.40	89.56	Fraud offenses	4,761,447	5.58	81.48
Burglary/breaking & entering	1,586	3.26	92.82	Intimidation	3,253,798	3.81	85.29
Robbery	798	1.64	94.47	Motor vehicle theft	3,097,461	3.63	88.92
Fraud offenses	641	1.32	95.79	Aggravated assault	2,788,068	3.26	92.18
Weapon law violations	433	0.89	96.68	Weapon law violations	1,291,283	1.51	93.69
Sex offenses	393	0.81	97.49	Counterfeiting/forgery	1,251,011	1.46	95.16
Motor vehicle theft	354	0.73	98.22	Sex offenses	1,226,014	1.44	96.59
Arson	228	0.47	98.68	Robbery	1,107,146	1.30	97.89
Counterfeiting/forgery	185	0.38	99.07	Stolen property offenses	594,447	0.70	98.59
Kidnapping/abduction	119	0.24	99.31	Embezzlement	294,964	0.35	98.93
Stolen property offenses	109	0.22	99.53	Kidnapping/abduction	233,226	0.27	99.20
Pornography/obscene material	56	0.12	99.65	Arson	219,635	0.26	99.46
Homicide offenses	55	0.11	99.76	Prostitution offenses	148,904	0.17	99.64
Embezzlement	45	0.09	99.86	Pornography/obscene material	147,144	0.17	99.81
Extortion/blackmail	40	0.08	99.94	Homicide offenses	68,376	0.08	99.89
Prostitution offenses	16	0.03	99.97	Extortion/blackmail	39,514	0.05	99.93
Animal cruelty	8	0.02	99.99	Animal cruelty	31,474	0.04	99.97
Bribery	3	0.01	99.99	Gambling offenses	15,277	0.02	99.99
Gambling offenses	2	0.00	100.00	Bribery	5,563	0.01	100.00
Human trafficking	1	0.00	100.00	Human trafficking	3,743	0.00	100.00
				Federal liquor offenses	4	0.00	100.00
				Illegal entry	1	0.00	100.00

Table A4
Placebo analysis - other types of hate crime

This table reports 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 A5
Home purchase mortgages

This table presents regression estimates from the baseline model, restricting the analysis to home purchase mortgages. The dependent variable is the log of the number of mortgage applications received by a lender in a county-year. Racial hate crime is defined as in Equation (1) of the paper. Column (1) reports results for all applications, Column (2) for minority group applications, Columns (3)–(5) for Black, Asian, and Hispanic applicants, respectively, and Column (6) for White applicants. All regressions include lender-year and county fixed effects. Standard errors are clustered at the county level. ***, **, and * denote 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	–0.067***	–0.108***	–0.049***	–0.060***	–0.068***	–0.027***
	(0.010)	(0.009)	(0.005)	(0.006)	(0.007)	(0.009)
Population	0.633***	0.712***	0.277***	0.345***	0.333***	0.436***
	(0.044)	(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	–0.211***	–0.134***	–0.051***	–0.051***	–0.064***	–0.181***
	(0.017)	(0.014)	(0.008)	(0.006)	(0.007)	(0.014)
Crime rate	–0.061***	–0.032***	–0.019***	–0.004	–0.018***	–0.050***
	(0.007)	(0.006)	(0.003)	(0.003)	(0.004)	(0.007)
Minority share	0.001	0.020***	0.016***	0.010***	0.014***	–0.013***
	(0.002)	(0.002)	(0.001)	(0.001)	(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