Perceptions and Credit Access*

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Abstract

We find that dominant beliefs about the causes of socioeconomic disparities between Black and White individuals affect access to credit for the Black community. Mortgage denials are lower for Black applicants when a greater proportion of White respondents in a county attribute socioeconomic disparities to external factors such as a lack of educational opportunities rather than inherent deficiencies in Black individuals. Using public protests as a catalyst for changes in perceptions, we find that mortgage access improves for Black applicants following such protests. This improvement is associated with the extent of news media coverage, highlighting the role of the media in shaping perceptions. However, the changes are temporary and revert over time. We also investigate the effects of the widespread protests following the death of George Floyd, which received nationwide media coverage, and find the impacts of these protests are short-lived.

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1. Introduction

If the majority views socioeconomic disparities as stemming from a lack of opportunities rather than from personal attributes, would this perception lead to measurable outcomes for the minority community? While recent research documents that disparities between Black and White individuals persist along a range of socioeconomic indicators,[1] much less work examines how *beliefs* about the causes of these disparities affect outcomes for the Black community. Understanding the role of beliefs is important because it influences decisions that can have long-lasting implications.

We examine this question in the context of credit access, which conveys significant social and economic benefits. For example, Stein & Yannelis (2020) find that access to financial services led to higher education levels, employment, income, and real estate wealth for African Americans in the nineteenth century. Célerier & Matray (2019) use the setting of U.S. bank deregulation and find that financial inclusion leads to greater savings, investment in durable assets, access to debt, and a lower probability of facing financial strain. Several studies in developing markets show that financial inclusion and access to credit have positive outcomes for individuals, households, and businesses (e.g., Banerjee et al., 2013, 2015; Karlan & Morduch, 2010; Tomy & Wittenberg-Moerman, 2024). In our study, we focus on mortgage loans because they have the additional benefits of intergenerational wealth accumulation, greater educational achievement, and a lower likelihood of incarceration.[2]

We begin our analyses by examining the relationship between beliefs about socioeconomic disparities and mortgage access. We contend that dominant perceptions about the causes of disparities can influence lenders' behavior and consequently impact mortgage access for minorities for several reasons. First, dominant perceptions about the reasons for socioeconomic disparities might make lenders aware of disparities in lending decisions. For example, credit

[1] See, for example, Bayer & Charles (2018); Chetty et al. (2020); Chernenko & Scharfstein (2024); Collins & Wanamaker (2022); Currie et al. (2023); Margo (2016); Sowell (2019).

[2] See, for example, Aaronson (2000); Blau & Graham (1990); Collins & Margo (2001); Di et al. (2007); Green et al. (1997); Newman & Holupka (2016); Shapiro (2006); Wainer & Zabel (2020).

scores disadvantage minorities because minorities are less likely to have a credit history and more likely to face income shocks (Acolin et al., 2016; Bostic, 1997; Gyourko et al., 1999). Thus, lenders might use alternative metrics to evaluate minority applications. Second, if the general public recognizes the role of systemic discrimination, financial institutions may face growing public scrutiny to address disparities and implement processes and systems that reduce bias in lending decisions (An et al., 2024).[3] Third, such recognition could provide minority communities with better employment prospects, enabling them to build stronger credit scores and gain access to credit. Finally, societal shifts in perceptions might direct regulators' attention to disparities in lending, motivating them to better enforce regulations that prohibit discrimination in credit markets.[4]

We use the National Opinion Research Center's General Social Survey (NORC GSS) to examine how beliefs about the causes of socioeconomic gaps between Black and White individuals relate to mortgage denials. We find that a greater attribution of disparities by survey respondents to external factors such as educational opportunities, rather than to a lack of motivation or inborn ability, is associated with lower denials of mortgage loan applications from Black individuals. We do not find a similar result for mortgage loan applications from White individuals. These findings suggest a relationship between perceptions and mortgage access for the Black community, which we explore in greater depth next.

A key empirical challenge in identifying the impact of dominant perceptions on credit access is the issue of reverse causality. Factors other than changes in perceptions could

[3]For example, following the 2020 Black Lives Matter (BLM) protests in Chicago, activists called on JP Morgan Chase to make billions of dollars in reparations to black neighborhoods in Chicago or face the consequences, including sit-ins at bank locations and calls to stop deposits at the bank. Activists cited a study that of the $7.5 billion home loans the bank made in 2012–2018, only 1. 9% went to black neighborhoods, whereas 79. 6% went to majority white areas. See, "Activists Want Reparations From Chase Bank For Chicago's Black Neighborhoods," *NPR WBEZ Chicago*, June 16, 2020. The BLM movement, which started in 2013, advocates for the rights and justice of Black and African American individuals, highlighting issues of systemic racism and police brutality.

[4]Federal fair lending laws prohibit discrimination in lending. These include the Equal Credit Opportunity Act (ECOA), the Fair Housing Act (FHAct), and the Community Reinvestment Act (CRA). The ECOA prohibits discrimination in credit transactions. The FHAct prohibits discrimination in residential real-estate-related transactions. The CRA serves to encourage credit availability in low- and moderate-income areas.

improve credit access for the Black community. These improvements may lead to social and economic gains, which could shift attitudes toward race. Thus, to identify the effect of perceptions on credit access, we need a shock to perceptions. We leverage public protests triggered by the deaths of Black or African American individuals during interactions with police as such a shock that shifts attitudes towards race. Research finds protests and social movements such as BLM changes public perceptions about race (Dunivin et al., 2022; Sawyer & Gampa, 2018).

An additional empirical challenge is that unobservable factors that drive protests could also drive changes in lending. We utilize an instrumental variables approach to address this challenge. Specifically, we instrument protest intensity (measured as the protest crowd size) with inclement weather based on the conjecture that people are less likely to attend protests in bad weather. Rainfall on the protest day is unlikely to directly influence lending to Black applicants, except through its impact on the protest, thereby meeting the exclusion restriction.

Our sample of protests covers ten U.S. states and extends from 2000 to 2020. To construct the dataset, we rely on cases of Black civilian deaths in the presence of police. For each incident of civilian death, we search the local news media for whether the incident resulted in a protest. We collect details related to the protest, including crowd size, duration, and incidents of arrests. We also gather information on media coverage, including whether the protest was featured in the national news, the number of news articles covering the event, and the duration of the protest's coverage in the news media.

We examine changes in perceptions following these protests using county-level information and a staggered difference-in-differences design (De Chaisemartin & d'Haultfoeuille, 2020). Our results indicate that after the protests, more survey respondents attribute socioeconomic disparities between Black and White individuals to external factors such as a lack of educational opportunities and discrimination, rather than to lack of motivation or inborn ability, although these changes in perceptions do not persist. Importantly, we find

that the magnitude of changes in perceptions are economically greater for protests that are covered in the news media for a period of 90 days or longer, relative to protests that are covered for a period of less than 90 days, highlighting the crucial role of the news media in forming public opinion.

For robustness, we develop three alternative measures of perceptions and find consistent results. First, we find that following the protests, more respondents believed that civil liberties should be restricted for individuals with racist views compared to before the protests. Second, more respondents favored policies that support affirmative action following the protests compared to before the protests. Finally, more respondents favored the social integration of races after protests than before.

We next study whether improvements in perceptions translate into greater mortgage access for Black individuals by using protests as a proxy for shock to perceptions. We find that mortgage denials decline for Black borrowers in the year following protests, but only for those protests that are covered by the news media for a prolonged period (90 days or longer). This is consistent with our findings that protests with more sustained news coverage are also more effective in changing perceptions. In terms of economic magnitude, following these protests, the likelihood of loan denials declines 5.3–7.2 percentage points for a one percent increase in protest crowd size. In contrast, when the protests are covered by the media for a shorter period of time (<90 days), the likelihood of denial *increases* 4.6–5 percentage points for a one percent increase in protest crowd size. Protests covered in the news media for a shorter duration could have a negative effect on credit access if the brief coverage fails to adequately convey the protests' underlying issues and goals, thereby reinforcing negative stereotypes and biases. On the other hand, prolonged media coverage might help shift public perceptions by offering more in-depth reporting on the underlying issues driving the protests. We also examine whether improved mortgage access after protests with longer media coverage persists beyond one year. We extend our sample to two- and three-year windows following these protests and find these improvements dissipate over time.

Several features of our research design and findings allow us to make a causal link between perceptions and credit access. First, we utilize protests as a proxy for changing perceptions mitigating concerns that unrelated changes in credit access could be driving changes in perceptions. Second, our finding that protests significantly influence perceptions in the short term, particularly immediately following the protest events, allows us to better tie the short-run changes in perceptions to credit access following the protests. Third, we show that prolonged media coverage of protests leads to more pronounced shifts in perceptions, and credit access also improves to a greater extent following protests with extended media coverage. Finally, we use an instrumental variable approach to estimate the causal impact of protests on credit access. The instrumental variable approach addresses concerns that unobserved factors that drive the protest events could also drive changes in lending. Overall, the mosaic of evidence we provide shows that changes in perceptions improve credit access for the Black community.

As an extension to our main analyses, we examine the protests following the death of George Floyd in May 2020. The George Floyd protests (hereafter, GF protests) received extensive and sustained media coverage and were widespread, encompassing at least 140 U.S. cities.[5] We find that perceptions about socioeconomic disparities remain largely unchanged following the GF protests. Using the alternative measures of perceptions, consistent with our earlier results, we observe that more survey respondents believe race issues dominate civil liberties in the immediate aftermath of the GF protests; however, these beliefs show a downward trend two years after the start of the protests. Support for affirmative action policies was stagnant, and there was a distinct decline in survey respondents' positive views toward social integration, with such views rebounding in 2022.

We also study monthly time-series variation in mortgage loan approval rates for Black individuals from January 2018 to April 2023. We find an increase in mortgage approvals following the GF protests from June 2020 to March 2021. However, approvals decline in

[5]See for example, "George Floyd Protests: A Timeline," *The New York Times*, November 05, 2021.

March 2021 and revert to the levels prevailing before the protests. We find no such changes in approvals for White applicants. Thus, although the GF protests changed perceptions and increased access to credit for Black applicants, such changes did not persist. Altogether, our findings suggest that the changes following the GF protests were not lasting. In additional analyses, we find that the increase in credit access lasted for at least two years after the GF protests, compared to only one year in our earlier sample of smaller protests that had less extensive media coverage than the GF protests, suggesting that media coverage played an important role. These findings suggest that the prominence of an issue may influence public attention, with interest diminishing once it is no longer in the media spotlight.

We contribute to the literature that explores the reasons for socioeconomic disparities. Extensive literature has explored the reasons for the persistence of these inequalities. These include labor market outcomes such as employment status or earnings (Bayer & Charles, 2018; Chetty et al., 2020); unequal access to opportunity (Sowell, 2019); wealth gaps driven by structural inequities (Collins & Wanamaker, 2022); intergenerational mobility (Bhattacharya & Mazumder, 2011; Chetty et al., 2020); and health outcomes (Alsan & Wanamaker, 2018; Eli et al., 2023), among others. We contribute to this extensive literature by exploring the role of perceptions about the causes of these socioeconomic disparities, which have not been studied much in the literature. In particular, we explore how perceptions influence mortgage loan denials. Unequal access to mortgage loans contributes to racial disparities (Asiedu et al., 2012; Stein & Yannelis, 2020). Furthermore, homeownership is instrumental in explaining the wealth gap between Black and White communities (Blau & Graham, 1990; Collins & Margo, 2001; Di et al., 2007; Newman & Holupka, 2016; Shapiro, 2006; Wainer & Zabel, 2020). We document that perceptions about the reasons for socioeconomic disparities influence credit access for the Black community.

2. Data and sample

2.1. Data on perceptions

We utilize GSS data to measure changes in public perceptions. The GSS captures societal trends and public opinion in the United States, covering various topics, including social behavior and attitudes toward various political and social issues. We specifically utilize the questions related to race to construct our measures of perceptions.

NORC conducted the GSS from 1972 to 2022, generally every two years. However, due to the COVID-19 pandemic, the 2020 survey was delayed and conducted in 2021.[6] We utilize survey data from 1996 to 2018 for our main tests. We accessed sensitive GSS data, which includes respondents' location information. However, at the time of our study, the sensitive data was only available up to 2018. We use GSS data spanning from 2004 to 2022 for tests involving the GF sample that do not require location data.

Drawing from extant literature (Hunt, 2007; Kluegel & Smith, 1982), our main variable measuring race perceptions is *Progress in beliefs about racial differences*. This variable captures whether White respondents attribute socioeconomic disparities between Black or African American and White individuals to systemic factors such as discrimination; or intrinsic factors such as a lack of motivation and ability. Specifically, we utilize responses to four questions which are framed as follows:

> *On average Blacks/African Americans have worse jobs, income, and housing than White people. Do you think these differences are...*
>
> A. *Because most Blacks/African Americans just don't have the motivation or willpower to pull themselves up out of poverty?*
> B. *Because most Blacks/African Americans don't have the chance for education that it takes to rise out of poverty?*
> C. *Because most Blacks/African Americans have less in-born ability to learn?*
> D. *Mainly due to discrimination?*

[6] For details related to the GSS data, please see Smith et al. (2019).

Note that these are four different questions because respondents could answer "Yes" to all questions, attributing socioeconomic disparities to systemic and intrinsic factors. We identify White respondents using the GSS variable "RACE."

The responses were coded as a one if the respondent answered "No" to questions A or C and 0 otherwise. Similarly, the responses were coded as a one if the respondent answered "Yes" to questions B or D and 0 otherwise. Our measure *Progress in beliefs about racial differences* takes a value of 1 if the responses to any of the four questions was coded as a one and 0 otherwise. Thus, the measure reflects respondents who attribute racial disparities to external factors along at least one of the four dimensions mentioned above.

The first row of Table 1, Panel A, presents the descriptive statistics for this measure. Over the years of GSS data included in our main analysis, 63.4% of respondents from the ten states in our sample attributed socioeconomic disparities to systemic factors.

We construct three additional measures of perceptions and provide detailed descriptions of the coding for these measures in Appendix A. Our first additional measure *Believe that race issues dominate civil liberties* is an indicator that represents respondents' attitudes towards protecting or restricting the freedoms of individuals whose beliefs are considered harmful or dangerous by others, specifically in the context of racial issues. The coding of responses to the survey questions reflects whether respondents support or oppose various civil liberties for individuals with racist views, for example, whether racists should be allowed to speak at a college or university. A value of one indicates a preference for restricting the freedoms of individuals who hold and express racist views, while a value of zero indicates support for protecting racist individuals' civil liberties.

Our second additional measure *Support policies that favor affirmative action* is an indicator that represents individuals' opinions on government actions and policies related to addressing racial discrimination and promoting equality for Black or African American individuals. A value of one reflects that respondents support various policies aimed at improving the conditions for Black and African American communities, whereas a value of zero indicates

that individuals oppose such policies.

Finally, our third additional measure *Favor social integration of races* is an indicator that represents individuals' attitudes towards personal and community-level interactions with Black or African American individuals. A value of one reflects that respondents support various forms of social integration, whereas a value of zero indicates that individuals oppose social integration. Table 1, Panel A, also presents the descriptive statistics for these additional measures. In our sample, 81% of White respondents believe that race issues dominate civil liberties, 43.7% support policies that favor affirmative action, and 45.5% favor the social integration of races.

2.2. Data on protests

In this section, we describe the steps we follow to create a database of protests from 2000–2020. We begin by sourcing data from the website *fatalencounters.org*, which collects and publishes information on civilian deaths in the presence of police. The database states its objective to be "A step toward creating an impartial, comprehensive, and searchable national database of people killed during interactions with police." As of our data-retrieval date (September 1, 2020), this database contained 28,701 such incidents across all 50 states and the District of Columbia for 2000–2020.[7] The database provides demographic details such as the name, gender, age, and race of the civilian victim, as well as the location of the incident and cause of death. We restrict our sample to cases where the civilian involved is Black or African American, which comprise 21% of all fatal incidents. We further restrict our sample to the top ten states with incidents involving the African American or Black community, which account for 57.8% of all such incidents (or a total of 3,532 incidents). The states included in the sample are California, Florida, Georgia, Illinois, Louisiana, Missouri, New York, North Carolina, Ohio, and Texas. Using a database of fatal incidents to create our sample of protests (as opposed to searching for protests directly) limits the effect of

[7]Each civilian death is counted as a separate incident in the database.

unobservable factors driving the likelihood of a protest.

For each of the 3,532 incidents, we check whether the incident is covered in the NewsBank and Factiva news archives. We find that the majority of these incidents are covered in the news media.[8] We also search whether the incident is covered in the national news media, defined as the following publications: *The Washington Post*, *The Wall Street Journal*, *The New York Times*, *New York Post*, and *USA Today*. We further search whether the fatal incident led to a protest and collect related details, including crowd size, length of the protest, the number of news articles covering the protest, the dates of the first and last news articles that cover the protest within a period of one year, and whether any arrests were made at the protest.[9] Our sample of 3,532 fatal encounters for ten states reduces to 3,357 when we collapse multiple deaths that resulted as part of one incident to a single incident and remove observations with insufficient data related to the control variables. Our sample consists of 728 protests, for 592 of which we were able to collect crowd size data.

Table 1, Panel B, presents descriptive statistics related to the incidents and protests in our sample. The average age of a victim (*Age*) is 29 years, and 8.5% are female (*Female*). While all incidents are covered in the local news, only 9.1% are covered in the national news media (*National News (Incident)*). The majority of victims (72%) die by a gunshot wound (*Lethal Gunshot*); 7.4% by other forms of violence (*Lethal Violence*) including tasered, asphyxiated/restrained, beaten/bludgeoned with instruments, or chemical agent/pepper spray; and 15.6% die in incidents involving a vehicle (*Vehicle*). The omitted categories for the cause of death, which comprise the remaining 5% of incidents, include burned/smoke inhalation, drowning, drug overdose, falling from a height, medical emergency, stabbed, or other/undetermined. In 3.3% of the sample incidents, there were multiple victims (*Multiple*

[8]The *fatalencounters.org* database also includes incidents identified through FOIA requests to police departments which might not covered in the news media.

[9]To ensure data accuracy, we had at least two researchers collect the information related to a protest. Furthermore, our data collection involved two rounds: in the first round, data on protests was collected from news articles, whereas in the second round, all collected data were rechecked against the articles for accuracy of data entry.

Victims) associated with the same incident.

Table 1, Panel B, also shows the summary statistics related to protest events: 8.4% of incidents are associated with protests (*Protest*), the mean crowd size (*Protest Crowd Size*) at a protest is 64 persons, and 85% of all protests last longer than a day (*Protest > 1 Day*). While all protests are covered in the news media, the intensity of such coverage varies. On average, a protest event is covered in 27 news articles (*Protest News Coverage (#Articles)*) and the coverage lasts for 91 days *Protest News Coverage (Length)*.[10] We provide detailed descriptions of all variables in Appendix B.

We further provide a descriptive analysis of the probability of protests and their intensity by estimating variations of the following OLS model:

$$\begin{aligned} Y_{itcs} = \beta_0 &+ \beta_1 Age_i + \beta_2 Female_i + \beta_3 National\ News\ (Incident)_i + \beta_4 Lethal\ Gunshot_i \\ &+ \beta_5 Lethal\ Violence_i + \beta_6 Vehicle_i + \beta_7 Multiple\ Victims_i \\ &+ \beta_c X_{(t-1)c} + \delta_s + \gamma_t + \epsilon_{itcs}\ , \end{aligned} \tag{1}$$

where i, t, c, and s represent the fatal incident, year, county, and state, respectively. The dependent variable Y represents the following outcomes: an indicator that takes the value of one if the fatal incident results in a protest (*Protest*); measures of protest intensity, including crowd size (*Protest Crowd Size*), and whether the protest lasted for longer than a day (*Protest > 1 Day*).

We include various county-level controls (X) to account for county characteristics that could drive the probability and intensity of protests. X is a vector of predetermined county characteristics lagged by one year and includes the natural logarithm of population size, the population share of Black or African Americans, the natural logarithm of per capita income, the unemployment rate, and the Democratic party vote share for the most recent presidential

[10] The variables *Age*, *Protest Crowd Size*, *Protest News Coverage (#Articles)*, and *Protest News Coverage (Length)* are reported in natural logarithm in Table 1, Panel B.

election. δ_s represents state fixed effects, γ_t year fixed effects, and ϵ is the error term. We include state fixed effects (instead of county fixed effects) because few counties have multiple protests.

Table 2 presents the results from the estimation of Equation 1. The results in column (1) show that protests are more likely when the victim is younger: doubling the age of a victim reduces the probability of protest by 3.81 percentage points.[11] Coverage of the fatal incident in the national news media increases the probability of a protest by 35 percentage points. Also, relative to the omitted category, protests are 4–5.4 percentage points more likely when the cause of death is *Lethal Gunshot* or *Lethal Violence*, whereas they are 3.8 percentage points less likely when death is caused by a vehicle. Protests are less likely in larger counties and more likely in counties with higher per capita income.

The dependent variable in column (2) is the protest crowd size. Crowd sizes are larger for younger victims: doubling the age of the victim reduces the crowd size by 28.6%. Crowd sizes are 36.5% larger when the victims in the fatal incident include a female victim and 53.7% larger when the fatal incident is covered in the national news media.[12] County-level characteristics are also associated with the protest crowd size: counties with smaller populations and higher per capita income have larger protest crowds. Also, counties with a larger percentage of Black or African Americans have greater crowd sizes at protests.

In column (3), the dependent variable is an indicator if the protest event extends beyond a day. As the column shows, protests are 26.7 percentage points more likely to extend beyond a day if the fatal incident is covered in the national news media. Also, the higher the share of Black or African Americans in a county, the less likely that protests extend to beyond a day.

[11] These magnitudes are calculated as follows: $log(2) \times -0.055 = -0.0374$. This is illustrative of the approach we use in all subsequent analogous cases.

[12] These magnitudes are calculated as follows: $(e^{0.311} - 1) \times 100 = 36.5$. This is illustrative of the approach we use in all subsequent analogous cases.

2.3. Precipitation data

Information on precipitation comes from the Global Historical Climatology Network Daily, which is a database of daily climate summaries from the National Oceanic and Atmospheric Administration. The data contain a composite of climate records from approximately 56,000 weather stations in the U.S. over the period of 1970—2019. We construct the measure of inclement weather by aggregating the weather station data to the county level and extracting the mean daily rainfall.[13]

Table 1, Panel B, shows the summary statistics related to precipitation on the week of the incident and the day of the protest. In 34% of cases, rainfall was high during the week of the incident, defined as precipitation in the week of incident being greater than the week's average in that county over the past 30 years. Twenty-one percent of all protest events occurred on a day with high rainfall, defined as precipitation on the day of protest being greater than the week's average in that county over the past 30 years. The share of protests witnessing high rainfall is similar at 24% if we use an alternative definition of high rainfall, that is, precipitation on the day of protest being greater than 2mm.

2.4. County characteristics

We collect population data from the Census Bureau. The county-level per capita income is from the U.S. Bureau of Economic Analysis (BEA), and the unemployment rates are from the U.S. Bureau of Labor Statistics (BLS). We use the MIT Election Lab data to construct the variables of county-level political leaning. In particular, we use each presidential election result to describe the political climate for the four years following the election. Table 1, Panel C, summarizes the county-level characteristics for the states in our sample.

[13] In 6.3% of the cases for which the data are missing on the day of the protest, we use the neighboring county or state averages.

2.5. Mortgage data

We source mortgage data from the Home Mortgage Disclosure Act (HMDA) data, which provide transaction-level data on residential mortgage loan applications and denials. These data are available annually starting in 1997. For a subset of our analyses we rely on confidential HMDA (cHMDA) data available through the Federal Reserve Board. Starting from 2018, cHMDA data include information on borrower characteristics, such as their FICO scores.

3. Perceptions and credit access

We begin our analyses by examining if there is a relation between perceptions and mortgage denial rates for Black or African American individuals. Specifically, we estimate the following equation:

$$Denial\ Rate_{c,t+\tau} = \beta_0 + \beta_1 Race\ Perceptions_{c,t} + \beta_c \mathrm{X}_{t-1,c} + \delta_s + \gamma_t + \epsilon_{c,t}\ , \tag{2}$$

where *Denial Rate* is the mortgage denial rate for county c in year $t+\tau$ (τ goes from 1 to 5). *Race Perceptions* is our main measure *Progress in beliefs about racial differences* described in Section 2.1. The lagged county characteristics X include the natural logarithm of population size, the population share of Black or African Americans, the natural logarithm of per capita income, and the unemployment rate. The remaining variables are as described before. We utilize a fractional probit model to estimate Equation 2 because the dependent variable, *Denial Rate*, is a proportion bounded between 0 and 1. Additionally, we only utilize the *Race Perceptions* variable from the years when sensitive GSS data is available, namely 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, and 2018. Mortgage data for all years is used.

Table 3 presents marginal effects from the estimation of Equation 2. The table is divided into two sections: columns (1) to (5) analyze the denial rates for Black or African American

applicants, while columns (6) to (10) focus on the denial rates for White applicants. The estimates in columns (1) to (3) suggests that a one-unit improvement in perceptions (i.e., more attribution of socioeconomic disparities to systemic factors) is associated with a 1.1–1.3 percentage point decrease in the mortgage denial rate for Black applicants in the following one to three years. The results suggest that improved perceptions in a given year are associated with lower mortgage denial rates for Black applicants in the following years, though the effect diminishes over time. There is no significant impact of perceptions on denial rates for White applicants across any of the time horizons as seen from columns (6)–(10).

County-level economic factors show significant relationships with mortgage denial rates, and interestingly, these effects differ by race. For White applicants, income plays a stronger role in securing credit, while for Black applicants, factors such as the racial composition of the population of the county are associated with denial rates. Overall, the results in Table 3 indicate a relationship between perceptions and credit access. We explore this relationship further in the following sections.

4. Protests and changes in perceptions

Our empirical strategy leverages protests as a shock to perceptions. We first validate the use of protests as a proxy for shifts in attitudes toward race. Specifically, we use the perceptions measures outlined in Section 2.1 to assess how White respondents' views on race relations change following protest events. Since these demonstrations are largely localized, we focus on changes in perceptions at the county level.

We estimate the following staggered difference-in-differences model:

$$Race\ Perceptions_{jtc} = \beta_0 + \beta_1 Post_{tc} + \beta_c X_{(t-1)c} + \alpha_c + \gamma_t + \epsilon_{jtc}, \tag{3}$$

where j represents a respondent and *Race Perceptions* represents our measures of perceptions discussed in Section 2.1. *Post* is an indicator for the six years following the protest and α_c represents county fixed effects. The remaining variables are as defined before.

For estimating Equation 3, we restrict the GSS sample to the ten states covered in our sample of protests and use two years before the protest event as the benchmark years. Since the GSS is conducted biannually, we use responses from the previous survey year as a proxy for the missing years in our main analyses. This allows us to fill in gaps and merge the data with the protest dataset, as protests may occur in years when the GSS survey was not conducted. We further divide our sample based on the duration of media coverage, distinguishing between coverage lasting 90 days or more and coverage lasting less than 90 days. We estimate Equation 3 in the full sample and in each of the subsamples, utilizing the staggered differences-in-differences approach described in De Chaisemartin & d'Haultfoeuille (2020). Figure 2–Figure 5 and Table 4 present the results from this estimation.

Figure 2 shows changes in our main measure *Progress in beliefs about racial differences*. Panel A of the figure shows that following protests, more White respondents believe that socioeconomic disparities are due to external factors such as a lack of educational opportunities and discrimination rather than inherent deficiencies in Black individuals. However, such beliefs about racial differences dissipate in the third year after the protests. In Panel B, we divide our sample by the duration of media coverage. We find that changes in beliefs about racial differences are more pronounced when the protests are covered in the news media for a longer duration (i.e., $\geq$ 90 days). In both subsamples, the changes in perceptions begin to fade by the third year following the protest events. Table 4 provides the magnitudes of these changes. Following protests, compared to counties without protests, the probability of White respondents attributing socioeconomic disparities to external factors increases by 12.5 percentage points in counties with protests that receive longer media coverage. In contrast, for protests with shorter media coverage, the increase is 8.4 percentage points. Although these differences are economically large, as columns (4) and (5) show, the differences in magnitudes are not statistically significant at conventional levels.

We find similar patterns in Figure 3–Figure 5 for our additional measures of *Race Perceptions*. In all cases, the improvements in perceptions about race are generally short-lived and

dissipate over time. In addition, as Table 4 shows, the improvement in perceptions is more pronounced when the protests receive longer media coverage, although the differences are not statistically significant. Overall, our findings indicate that protests effectively improve perceptions about race, even if these improvements are temporary, thus validating protests as a measure of change in perceptions.

5. Protests and the access to credit

We utilize protests as a shock to examine if changes in perceptions can yield tangible benefits for the Black community. Specifically, we examine whether access to mortgage loans improves for the Black community following protests. We focus on home loans due to the critical role of homeownership in explaining the wealth gap between Black or African American and White communities (Blau & Graham, 1990; Collins & Margo, 2001; Di et al., 2007; Newman & Holupka, 2016; Shapiro, 2006; Wainer & Zabel, 2020). Homeownership is also associated with significant social and economic benefits. For instance, owning a home facilitates intergenerational wealth accumulation, and the stability it provides enhances educational achievement and reduces the likelihood of incarceration (Aaronson, 2000; Green et al., 1997).

The empirical challenge in estimating the effect of protests on changes in private lenders' actions is that unobserved factors that drive the protest could also drive changes in lending, making it difficult to attribute the increase in lending to minorities to protests. For example, changes in beliefs in a community could drive both the probability of a protest as well as private lenders' actions.[14] Also, the fatal incident that led to the protest could drive credit access rather than the protest itself.

To deal with these identification challenges, we use an instrumental variables approach to estimate the causal impact of protest events on changes in lenders' actions. Specifically,

[14]Although we find in Section 4 that beliefs about race-related issues changed following protests, there might have been shifts in beliefs prior to the protests. These broader shifts in beliefs could influence both the occurrence of protest demonstrations and credit access.

we use rainfall as an instrument for the likelihood and intensity of a protest based on the assumption that people are less likely to attend protests in rainy weather.[15] Furthermore, it is unlikely that rainy weather on the day of the protest would directly affect lenders' decisions to extend credit to Black or African American applicants (except through the protest event), suggesting that the exclusion restriction is likely met.

We first test the validity of our instrument by estimating variations of the following model, where we regress protests' crowd size on an indicator variable that captures whether there was significant rainfall in that county on the day of the protest. Specifically, we estimate the following equation:

$$\textit{Protest Crowd Size}_{tc} = \beta_0 + \beta_1 \textit{Precipitation}_{tc} + \beta_k X_k + \beta_c X_{(t-1)c} + \delta_s + \gamma_t + \epsilon_{tc} \ , \tag{4}$$

where *Protest Crowd Size* represents the crowd size at a protest event, measured as the natural logarithm of the number of participants at the event. The variable *Precipitation* is an indicator of excess precipitation on the day of the protest. In our main specification, the indicator for excess precipitation takes the value of one if precipitation on the day of the protest is greater than the average for that week in that county over the past 30 years and zero otherwise. Conditional on the expectation of high precipitation, precipitation on the day of the protest is a random event. Because precipitation on the day of the protest is expected to mute protest intensity, we expect β_1 to be negative. X_k is a vector of k control variables related to the fatal incident and includes *Age, Female, National News, Lethal Gunshot, Lethal Non-Gunshot, Vehicle* and *Multiple Victims*. The remaining variables are as defined before.

In column (1) of Table 5 we present the results from this estimation and find that crowd

[15] This assumption is supported by anecdotal evidence, see for example, "Rain Dampens The Crowd, But Peaceful Protesters Remain At The White House," *WAMU 88.5 American University Radio*, June 04, 2020. Collins & Margo (2007) also provide anecdotal evidence to suggest that people are less likely to engage in collective action when it rains.

size is 27% smaller on a day with high precipitation. In column (2), we use an alternative measure of high precipitation defined as an indicator if precipitation on the day of protest is greater than 2mm. The threshold of 2mm is similar to that in Madestam et al. (2013), who use 0.1 inch. Although not statistically significant at conventional levels, the coefficient estimate suggests that crowd size is 24% smaller on high precipitation days.

We also assess whether inclement weather is associated with the probability of a protest by re-estimating Equation 4 with the dependent variable as an indicator for whether the fatal incident resulted in a protest event. Because not all fatal incidents result in protests, in this estimation, we measure *Precipitation* as the average for the week of the fatal incident (measured from the day of the fatal incident to six days after). That is, the indicator variable for excess precipitation takes the value of one if the average precipitation in the week of the incident is greater than the average precipitation for the week in that county over the past 30 years and zero otherwise. We present results from this estimation in column (3) of Table 5 and find that rainfall in the week of the fatal incident is not associated with the probability of a protest. Overall, the results in Table 5 support the validity of high precipitation as an instrument for protest crowd size. The estimation of Equation 4 implements the first stage of the instrumental variables approach.

The second-stage equation estimates the effect of a protest on lending to the Black or African American community by using high precipitation as an instrument for the efficacy of protests. Specifically, we estimate variations of the following model:

$$Y_{bctl} = \beta_0 + \beta_1 \widehat{Protest\ Crowd\ Size}_{ct} + \beta_c X_{(t-1)c} + \beta_l X_l + \delta_s + \gamma_t + \epsilon_{bctl} \ , \tag{5}$$

where b, c, t and l represent the borrower, county, year, and loan-type, respectively. The dependent variable Y is an indicator for whether a mortgage loan application from a Black or African American applicant is denied. X_l represents loan-level controls including loan purpose and occupancy status of the property, and loan type. The remaining variables are

as described before.

We estimate Equation 5 using a two-stage least squares (2SLS) approach, where Equation 4 is the first-stage regression. The coefficient β_1 in Equation 5 can be causally interpreted as the effect of protests on the likelihood of loan denial because we expect high precipitation to affect loan denial only through protest crowd size. Furthermore, β_1 estimates the local average treatment effect (LATE) for individuals who are sensitive to rainfall on the day of the protest. The sample is limited to mortgage loan applications from the Black or African American borrowers in a county in the year following the protest event. Furthermore, we estimate Equation 5 separately for protests with longer and shorter media coverage, based on our findings in Table 4 that progressive race-related perceptions improve more with prolonged media coverage.

We present results from the estimation of Equation 5 in Table 6. Columns (1) and (2) show results for protests that are covered in the news media for a longer duration (≥ 90 days), whereas columns (3) and (4) include results for protests covered for a shorter duration (< 90 days). Also, columns (2) and (4) include loan-level controls (loan purpose and occupancy status of the property, and loan type) whereas columns (1) and (3) do not. The results indicate that denials of loan applications from Black or African American applicants decline only when the protest event is covered in the news media for a longer duration. Specifically, in these cases, the likelihood of loan denials declines by 5.3–7.2 percentage points in the one year following protest events, for a 1% increase in protest crowd size. In contrast, when the protest events are covered by the media for shorter time, the likelihood of denial *increases* by 4.6–5 percentage points for a 1% increase in protest crowd size. Table 6 also reports first-stage F-statistics which is greater than 10 in all cases, indicating that our instrument is not weak (Stock et al., 2002; Stock & Yogo, 2002). Brief media coverage of protests may negatively impact credit access, as it may fail to fully communicate the underlying issues and goals of the protests, potentially reinforcing harmful stereotypes and biases. In contrast, extended coverage can help shift public perceptions by providing more comprehensive reporting on

the root causes behind the protests. While our results show significant changes in denials conditional on applying for mortgage loans, in untabulated analyses, we find no significant changes in the number of applications.

Given our findings that credit access improves in the year following protests with longer media coverage, we next examine whether this improvement persists. This is particularly relevant in light of our findings in Figure 2–Figure 5, which show that race-related perceptions improve only briefly before dissipating. Therefore, in Table 7, we re-estimate Equation 5 by expanding our sample of mortgage applications from Black or African American applicants to include the two and three years following protests that received longer media coverage. In contrast to our findings in columns (1) and (2) of Table 6, we do not find significant declines in denials in the two and three years following the protests with longer media coverage. These results indicate that, similar to changes in perceptions, improvements in credit access also dissipate over time.

Our findings thus far indicate that longer media coverage of protests is critical for change in perceptions and increased credit access for Black borrowers, even though these improvements are short-lived. Building on these findings, we next examine the protests following the George Floyd incident, which received extensive media coverage.

6. The George Floyd protests

We next examine whether our findings extend to a different sample of protests: those following the tragic death of George Floyd. The GF protests received widespread national attention, drawing focus to the treatment of minorities, particularly the Black and African American community, not just by the police, but in general. The media coverage of GF protests far exceeded coverage of previous protests in our sample.[16]

In Figure 6 we plot the duration of media coverage in days (X-axis) by the count of

[16]The GF protests are not included in our main sample because the GF incident occurred in Minnesota, which is not part of the ten states in our primary sample.

protests (Y-axis). The size of the bubble is indicative of the number of news articles that cover the protests. Panel A of the figure excludes the GF incident and plots the protests in the ten states in our sample. In Panel B, we include the GF incident, represented by the blue circle. The panel shows that the GF incident surpassed all previous protests by a large margin in terms of media coverage duration, count of protest events, and the number of news articles. Also, in Figure 7, we plot the location of the protests and the crowd size. Panel A shows these variables for the ten states in our sample and excludes the GF protests. Panel B provides location and crowd size for the GF protests.[17]

Finally, Figure 8 shows the temporal trend in media coverage. News coverage was the highest during the GF incident and related protests in 2020, but also sustained in 2021 around the conviction of the police officer responsible and the first anniversary of George Floyd's death. These figures show that the GF protests were extensive and covered much of the country. Therefore, given our results discussed in Section 4 and Section 5, if protests are to have any significant effects on perceptions and credit access, we should expect to see such changes following the GF incident.

We next track changes in aggregate perceptions around the GF protests for the entire country using results from the GSS for the survey years. That is, unlike for our analyses in Section 4, for these aggregate trends, we do not fill in missing years with information from the previous year. Also, because the GF protests were widespread, covering almost the entirety of the United States, we do not assess these changes relative to a control sample as in our earlier tests in Section 4.

Figure 9 presents these trends for 2004–2022.[18] The solid black lines shows average mean responses, whereas the blue lines are fitted trendlines. Panel A shows trends for our measure *Progress in beliefs about racial differences*, which is an average of White respondents' beliefs

[17] We source data on crowd sizes for the GF protests from the *Crowd Counting Consortium (CCC)* which is a joint project of Harvard Kennedy School and the University of Connecticut. The CCC collects publicly available data on political crowds in the United States.

[18] We begin our sample from 2004 because the GSS data from 2000 and 2002 lack consistent survey weights.

that socioeconomic disparities are not due to inherent deficiencies in Black or African American individuals but rather due to external factors such as lack of educational opportunities and discrimination. The panel shows that such beliefs were largely stagnant following the GF protests, with much of the increase occurring after 2014, following the BLM movement.

Panel B shows a distinct increase in respondents' beliefs that race issues dominate civil liberties. Specifically, in the aftermath of the GF protests, more respondents' oppose various civil liberties for individuals with racist views. However, this variable shows a downward trend in the latest year (2022). Panel C shows trends in White respondents' support for policies that favor affirmative action. The panel shows a slight upward trend in the support for such policies following the GF protests, although the most significant increase in such support occurred following the BLM movement. Finally, Panel D shows trends in White respondents' attitudes towards personal and community-level interactions with Black individuals. The plot shows a sharp decline in favorability towards social integration following the GF protests. However, this favorability appears to have rebounded in 2022. Overall, changes in perceptions towards race relations are mixed in the years following the GF protests. However, we do not have a valid counterfactual for comparison, as these protests were widespread rather than located in specific regions, unlike in our previous sample.

Finally, we assess how credit access for Black applicants changes in the aftermath of the GF protests by estimating the following model:

$$Denial_{btcms} = \beta_0 + \sum_{m=1}^{N} \beta_m M_m + \beta_c X_{(t-1)c} + \beta_i X_b + \delta_s + \gamma_t + \epsilon_{btcms} \ , \tag{6}$$

where *Denial* is an indicator for whether a mortgage loan application by a Black or African American person is denied. M represents month (m) indicators for N months, $X_{(t-1)c}$ is a vector of lagged county controls, X_b is a vector of borrower and loan controls, δ_s is state fixed-effects and γ_t is year fixed effects. Finally, ϵ is the error term.

We present results from the estimation of Equation 6 in Figure 10. In the months

preceding the GF protests, the likelihood of denial for Black or African American applicants hovered around 9%, which is consistent with the prior studies (An et al., 2024; Black et al., 1978; Duca & Rosenthal, 1993; Munnell et al., 1996; Wheeler & Olson, 2015). However, this likelihood of denial declined drastically following the GF protests. In fact, after controlling for borrower and loan characteristics, the conditional likelihood of denial was close to zero after October 2020. This trend reverses in the later part of our sample with the likelihood of denial going back to around 9% in April 2023.

Thus, even though we observe changes in perceptions and credit access in the aftermath of the GF protests, similar to our earlier findings, these changes also did not persist. However, improvements in credit access persisted for at least two years following the GF protests relative to only one year in our earlier sample of protests that were smaller and covered less extensively by the news media.

7. Discussion and conclusion

Recent research highlights that socioeconomic disparities between Black or African American and White individuals continue to persist even long after the civil rights movement. However, much less attention has been given to how beliefs about the causes of these disparities—whether they are attributed to systemic discrimination or personal attributes like lack of motivation—affect outcomes for the Black community. We explore this question in the context of credit access, which offers significant social and economic benefits.

We argue that positive perceptions of minority groups can reduce discriminatory lending practices, leading to more equitable credit access. Additionally, public recognition of systemic discrimination may pressure financial institutions to address racial disparities and implement fairer lending systems. This awareness could also improve employment opportunities for minorities, helping them build better credit scores. Finally, societal shifts in racial perceptions might prompt regulators to enforce anti-discrimination rules in credit markets more effectively.

Using data from the GSS, we first examine how beliefs about the causes of racial disparities relate to mortgage denials for Black individuals at the county-year level. We find that when socioeconomic disparities are attributed to external factors like discrimination or lack of educational opportunities rather than to intrinsic traits such as a lack of motivation or in-born ability, there are fewer mortgage denials for Black applicants, but not for White applicants. This finding suggests a link between perceptions and credit access, which we explore in greater detail.

An empirical challenge in studying the causal effect of perceptions on credit access is reverse causality. That is, improved credit access might influence racial attitudes rather than vice versa. To address this challenge, we use public protests in response to police violence against Black civilians as a shock to perceptions. Prior research suggests that such public demonstrations change attitudes towards race, which we also find using the GSS data. We further employ an instrumental variables approach, using inclement weather to proxy for protest intensity (measured as crowd size) to address the endogeneity concern that general societal changes in attitudes could be affecting both the probability of protests and the provision of credit.

Our sample of protests includes ten U.S. states from 2000 to 2020. We gather details about the protests, including crowd size, protest length, incidence of arrests, and media coverage. We find that, following these protests, White respondents were more likely to attribute socioeconomic disparities to external factors like discrimination and lack of educational opportunities, particularly when the protests received media coverage for 90 days or more. We also find that following protests, more White respondents supported restricting civil liberties for individuals with racist views, endorsed affirmative action policies, and favored racial integration, underscoring the influence of protests and media coverage on public attitudes.

We then examine whether such improvements in perceptions lead to greater credit access for Black individuals, using protests as a proxy for shocks to perceptions. Utilizing

the instrumental variables approach, we find that mortgage denial rates decrease for Black applicants in the year following protests. However, similar to changes in perceptions, these effects are only observed for protests with media coverage lasting 90 days or more. We also find that the improvements in credit access are temporary, and dissipate in two to three years.

We then extend our analysis to a new sample of protests—those following the tragic death of George Floyd. The GF protests were widespread and received extensive media coverage. Although we find mixed results in changes in perceptions following these protests, consistent with our earlier findings, we observe a temporary improvement in mortgage access for Black applicants. However, credit access reverted to pre-protest levels two years after the protests, indicating that the effects were not long-lasting.

We contribute to the literature that studies socioeconomic disparities by examining the impact of perceptions on credit access. We highlight how changes in perceptions can improve mortgage access for minority applicants.

Our findings suggest several avenues for future research. For example, future research could investigate the long-term effects of changes in perceptions on other socioeconomic outcomes, such as employment, education, and health. Research could also investigate the mechanism through which changes in perceptions influence institutions, such as changes in corporate policies. Also, our work highlights the critical role of the media in changing perceptions, but there could be other mechanisms at work that future research could explore.

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Appendix A. Coding of GSS variables

Question	Coding
Progress in beliefs about racial differences	
On the average (Blacks/African Americans) have worse jobs, income, and housing than white people. Do you think these differences are... Because most (Blacks/African Americans) just don't have the motivation or will power to pull themselves up out of poverty?	Coded as 1 if "No" and 0 if "Yes"
On the average (Blacks/African Americans) have worse jobs, income, and housing than white people. Do you think these differences are... Because most (Blacks/African Americans) don't have the chance for education that it takes to rise out of poverty?	Coded as 1 if "Yes" and 0 if "No"
On the average (Blacks/African Americans) have worse jobs, income, and housing than white people. Do you think these differences are... Because most (Blacks/African Americans) have less in-born ability to learn?	Coded as 1 if "No" and 0 if "Yes"
On the average (Blacks/African Americans) have worse jobs, income, and housing than white people. Do you think these differences are... Mainly due to discrimination?	Coded as 1 if "Yes" and 0 if "No"
Believe that race issues dominate civil liberties	
There are always some people whose ideas are considered bad or dangerous by other people. Consider a person who believes that Blacks are genetically inferior. If some people in your community suggested that a book he wrote which said Blacks are inferior should be taken out of your public library, would you favor removing this book, or not?	Coded as 1 if "Remove" and 0 if "Not remove"
There are always some people whose ideas are considered bad or dangerous by other people. Consider a person who believes that Blacks are genetically inferior. Should such a person be allowed to teach in a college or university, or not?	Coded as 1 if "Not allowed" and 0 if "Yes, allowed to teach"
There are always some people whose ideas are considered bad or dangerous by other people. Consider a person who believes that Blacks are genetically inferior. If such a person wanted to make a speech in your community claiming that Blacks are inferior, should he be allowed to speak, or not?	Coded as 1 if "Not allowed" and 0 if "Yes, allowed to speak"
Suppose there is a community-wide vote on the general housing issue. There are two possible laws to vote on. Which law would you vote for? [A.] One law says that a homeowner can decide for himself whom to sell his house to, even if he prefers not to sell to (Blacks/African Americans). [B.] The second law says that a homeowner cannot refuse to sell to someone because of their race or color.	Coded as 1 if option B is chosen and 0 if option [A] or "Neither" is chosen

Support policies that favor affirmative action	
Some people say that because of past discrimination, Blacks should be given preference in hiring and promotion. Others say that such preference in hiring and promotion of Blacks is wrong because it discriminates against Whites. What about your opinion—are you for or against preferential hiring and promotion of blacks?	Coded as 1 if "Strongly favors" or "Not strongly favors"; and 0 if "Not strongly opposes" or "Strongly opposes"
We are faced with many problems in this country, none of which can be solved easily or inexpensively. I'm going to name some of these problems, and for each one I'd like you to tell me whether you think we're spending too much money on it, too little money, or about the right amount... Improving the conditions of Blacks	Coded as 1 if "Too little"; and 0 if "About right" or "Too much"
Some people think that (Blacks/African Americans) have been discriminated against for so long that the government has a special obligation to help improve their living standards. Others believe that the government should not be giving special treatment to (Blacks/African Americans). Where would you place yourself on this scale, or haven't you made up your mind on this?	Coded as 1 if "Government help" (options 1 & 2); and 0 if "Agree with both" or "No special treatment"
What do you think the chances are these days that a white person won't get a job or promotion while an equally or less qualified black person gets one instead? Is this very likely, somewhat likely, or not very likely to happen these days?	Coded as 1 if "Not very likely"; and 0 if "Very likely" or "Somewhat likely"
Favor social integration of races	
Now I'm going to ask you about different types of contact with various groups of people. In each situation would you please tell me whether you would be very much in favor of it happening, somewhat in favor, neither in favor nor opposed to it happening, somewhat opposed, or very much opposed to it happening? How about having a close relative or family member marry a Black person?	Coded as 1 if "Strongly favor" or "Favor"; and 0 if "Neither favor not oppose", "Oppose," and "Strongly oppose"
Now I'm going to ask you about different types of contact with various groups of people. In each situation would you please tell me whether you would be very much in favor of it happening, somewhat in favor, neither in favor nor opposed to it happening, somewhat opposed, or very much opposed to it happening? Living in a neighborhood where half of your neighbors were Blacks?	Coded as 1 if "Strongly favor" or "Favor"; and 0 if "Neither favor not oppose", "Oppose," and "Strongly oppose"
In general, how close do you feel to Blacks?	Coded as 1 if "Very Close" (options 6–9) and 0 if "Not at All Close" or "Neither One Feeling nor the Other"

Appendix B. Variable definitions

Variable	Definition	Source
Dependent Variables		
Denial	Indicator variable which takes the value of 1 if a mortgage application is denied by financial institution (Action Taken = 3) and 0 otherwise	HMDA
Denial Rate (Black)	Number of denials of mortgage loan applications scaled by total applications, for Black or African American applicants	HMDA
Denial Rate (White)	Number of denials of mortgage loan applications scaled by total applications, for White applicants	HMDA
Protest	Indicator variable which takes the value of 1 if a protest occurs in response to a fatal encounter, and 0 otherwise	Fatal Encounters database
Protest Crowd Size	Natural logarithm of the number of protesters in a protest	Inferred from articles in Factiva
Progress in beliefs about racial differences	Indicator variable which takes the value of 1 if any of the questions in this category (as described in Appendix A) are coded as a 1, and 0 otherwise	NORC GSS
Believe that race issues dominate civil liberties	Indicator variable which takes the value of 1 if any of the questions in this category (as described in Appendix A) are coded as a 1, and 0 otherwise	NORC GSS
Support policies that favor affirmative action	Indicator variable which takes the value of 1 if any of the questions in this category (as described in Appendix A) are coded as a 1, and 0 otherwise	NORC GSS
Favor social integration of races	Indicator variable which takes the value of 1 if any of the questions in this category (as described in Appendix A) are coded as a 1, and 0 otherwise	NORC GSS
Control Variables		
Age	Natural logarithm of the average age of the victims involved in a fatal encounter	Fatal Encounters database
County Population	Natural logarithm of the total population of a county, lagged by 1 year	U.S. Census

Democrat Vote Share	The county-level vote share of the Democratic Party in presidential elections, lagged by 1 year	MIT Election Lab
Female	Indicator variable which takes the value of 1 if the victim involved in a fatal encounter is female and 0 otherwise	Fatal Encounters database
Lethal Gunshot	Indicator variable which takes the value of 1 if gunshot is the cause of death for the victim involved in a fatal encounter and 0 otherwise	Fatal Encounters database
Lethal Violence	Indicator variable which takes the value of 1 if one of the following is the cause of death for the victim involved in a fatal encounter: tasered, asphyxiated/restrained, beaten/bludgeoned with instruments, or chemical agent/pepper spray, and 0 otherwise	Fatal Encounters database
Multiple Victims	Indicator variable which takes the value of 1 if more than one victim are involved in a fatal encounter	Fatal Encounters database
National News (Incident)	Indicator variable which takes the value of 1 if a fatal encounter is reported by either New York Times, New York Post, Washington Post, U.S.A. Today, or Wall Street Journal, and 0 otherwise	Hand-collected from Factiva
National News (Protest)	Indicator variable which takes the value of 1 if a protest is reported by either New York Times, New York Post, Washington Post, U.S.A. Today, or Wall Street Journal, and 0 otherwise	Hand-collected from Factiva
Per Capita Income	Natural logarithm of the average income earned per person in a county, lagged by 1 year	U.S. Bureau of Economic Analysis
Percent African American	The percentage of African American population within a county, lagged by 1 year	U.S. Census and authors' calculations

Precipitation (protest day) > 2mm	Indicator variable which takes the value of 1 if the amount of precipitation in a county on the day of protest is greater than 2 mm and 0 otherwise	NOAA Global Historical Climatology Network and authors' calculations
Precipitation (protest day) > 7-day-average	Indicator variable which takes the value of 1 if the amount of precipitation in a county on the day of protest is greater than the mean amount of precipitation on the seven days from the day of the incident to six days after the incident averaged over the past 30 years, and 0 otherwise	NOAA Global Historical Climatology Network and authors' calculations
Precipitation (week of incident) > 7-day-average	Indicator variable which takes the value of 1 if the mean amount of precipitation in a county in the week of incident is greater than the mean amount of precipitation on the seven days from the day of the incident to six days after the incident averaged over the past 30 years, and 0 otherwise	NOAA Global Historical Climatology Network and authors' calculations
Protest > 1 Day	Indicator variable which takes the value of 1 if a protest lasted longer than 1 day and 0 otherwise	Inferred from articles in Factiva
Protest News Coverage (#Articles)	Natural logarithm of the number of newspaper articles covering a protest	Hand-collected from Factiva
Protest News Coverage (Length)	Natural logarithm of the number of days for which there was media coverage of a protest	Hand-collected from Factiva
Unemployment Rate	The number of unemployed people as a proportion of the labor force in a county	U.S. Bureau of Labor Statistics
Vehicle	Indicator variable which takes the value of 1 if the victim involved in a fatal encounter died after being hit by a vehicle	Fatal Encounters database

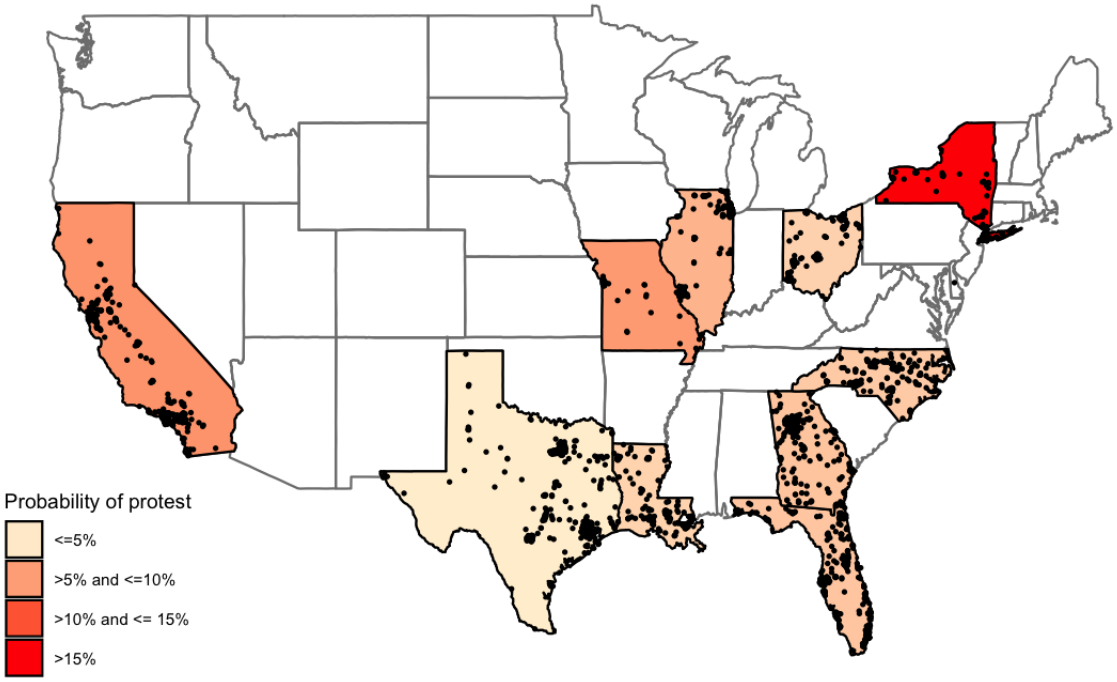
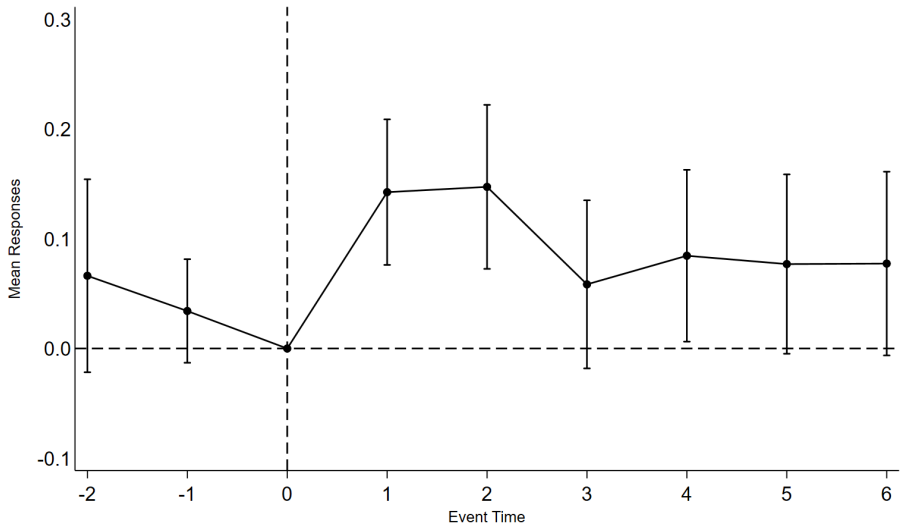
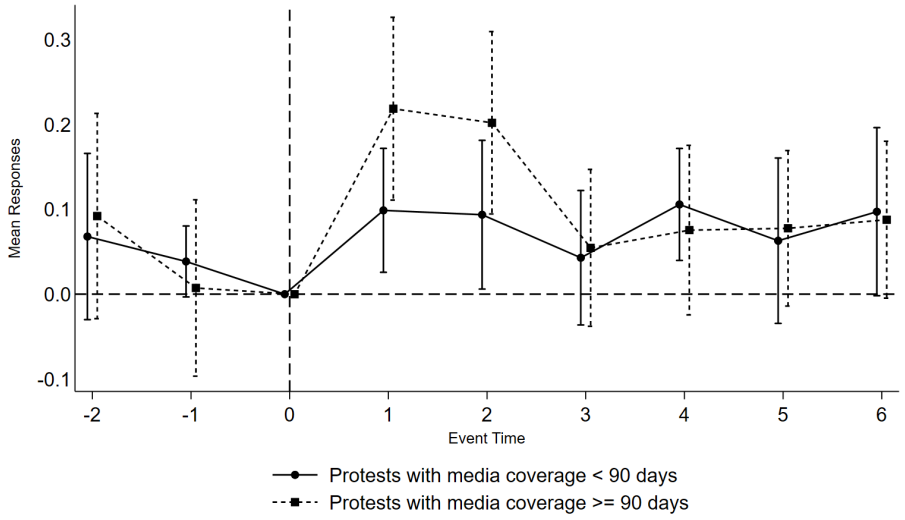


Figure 1: Location of fatal incidents and the probability of a protest

This figure shows the location of fatal incidents (dots on the map) and the probability that fatal incidents lead to protests in a state (shading of states). Probability of protest is the ratio of the number of protests associated with fatal incidents scaled by the total number of incidents in a state for 2000–2020.



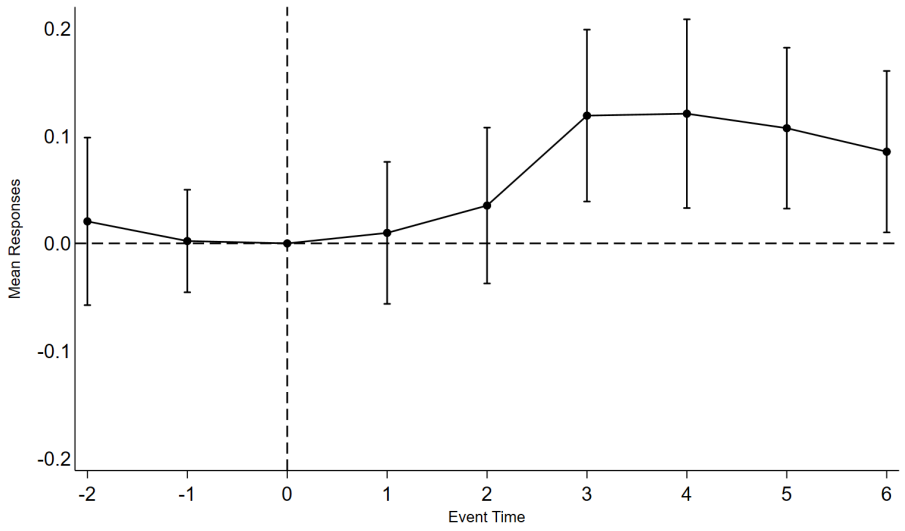
(a) All protests



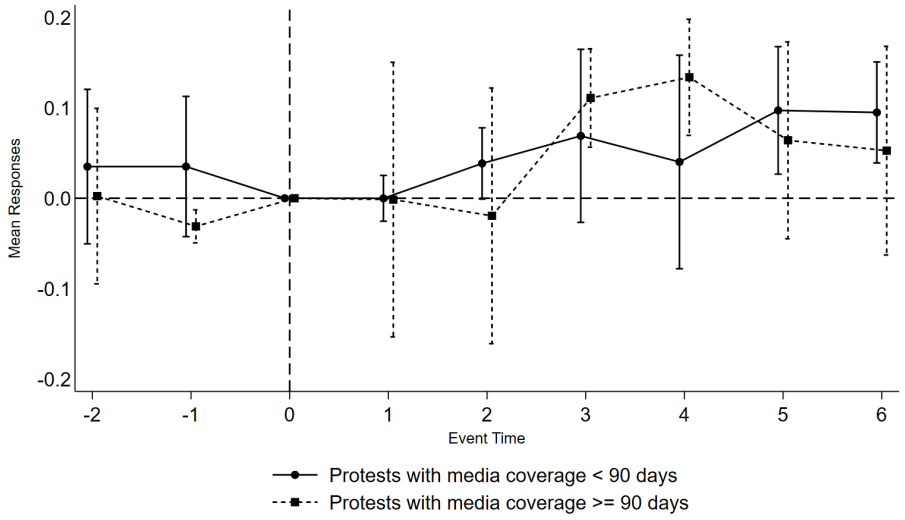
(b) Protests by media coverage

Figure 2: Difference-in-differences trends for *Progress in beliefs about racial differences* in event time

This figure displays the evolution of the race perceptions in event time. The figure shows trends in responses in counties with protests, relative to the control group of counties with no protests. The 95% confidence intervals are based on standard errors clustered by county.



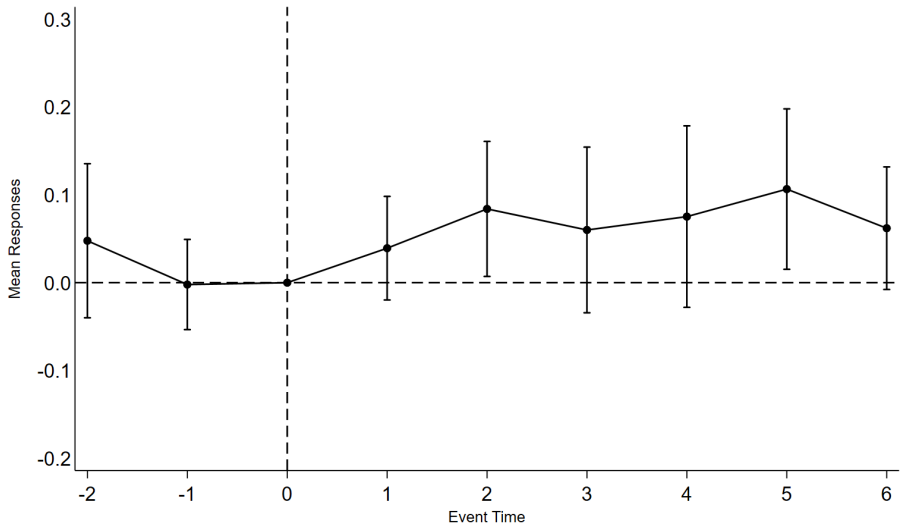
(a) All protests



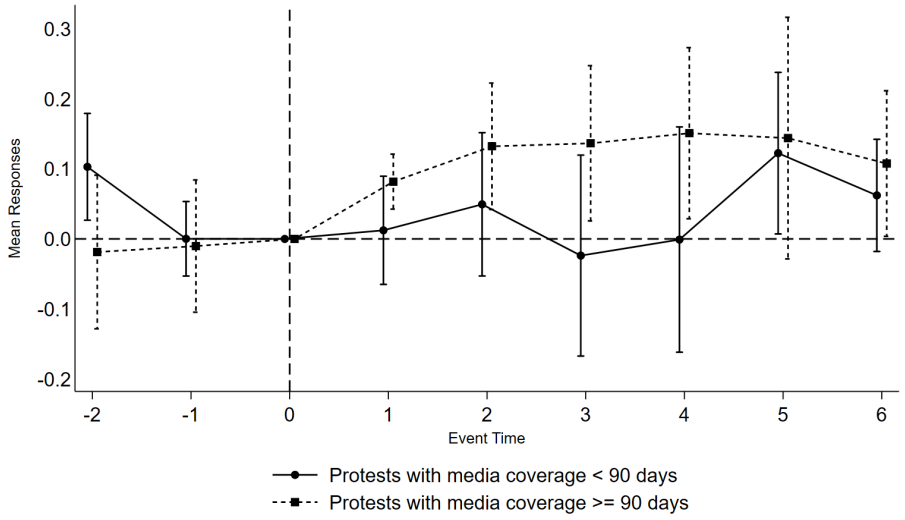
(b) Protests by media coverage

Figure 3: Difference-in-differences trends for *Believe that race issues dominate civil liberties* in event time

This figure displays the evolution of the race perceptions in event time. The figure shows trends in responses in counties with protests, relative to the control group of counties with no protests. The 95% confidence intervals are based on standard errors clustered by county.



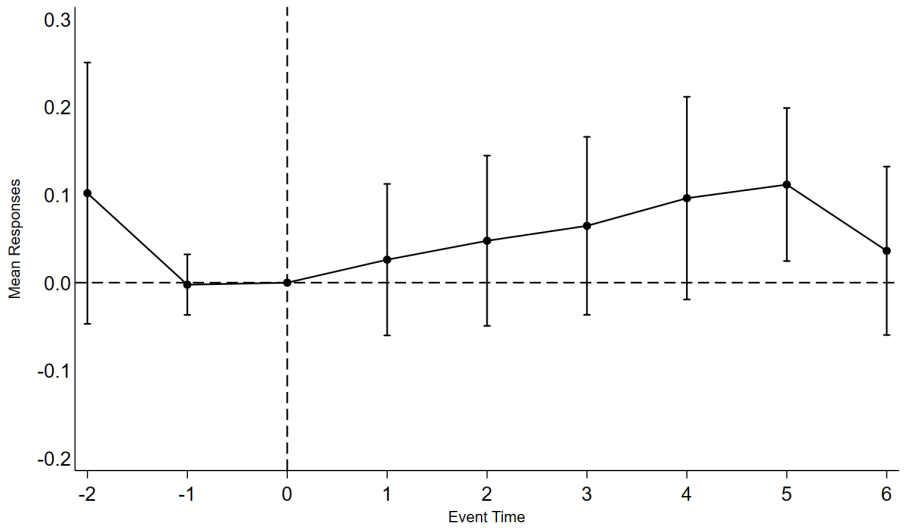
(a) All protests



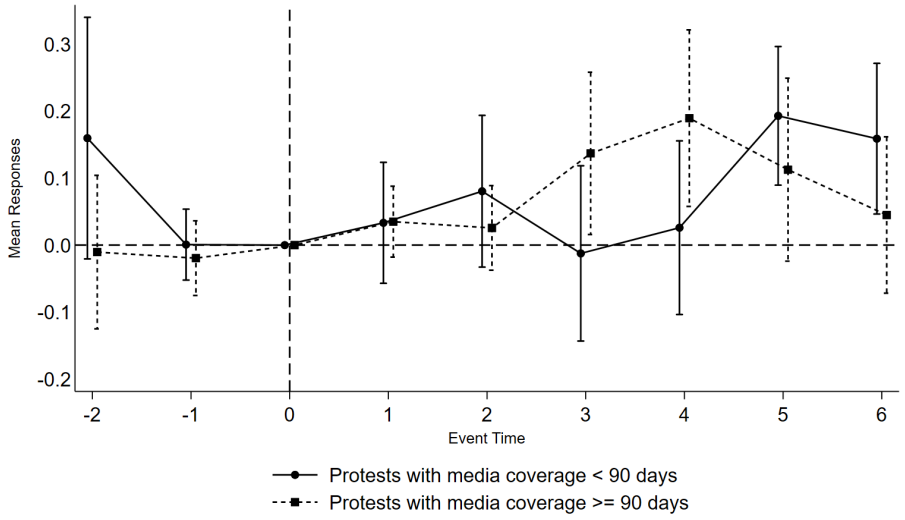
(b) Protests by media coverage

Figure 4: Difference-in-differences trends for *Support policies that favor affirmative action* in event time

This figure displays the evolution of the race perceptions in event time. The figure shows trends in responses in counties with protests, relative to the control group of counties with no protests. The 95% confidence intervals are based on standard errors clustered by county.



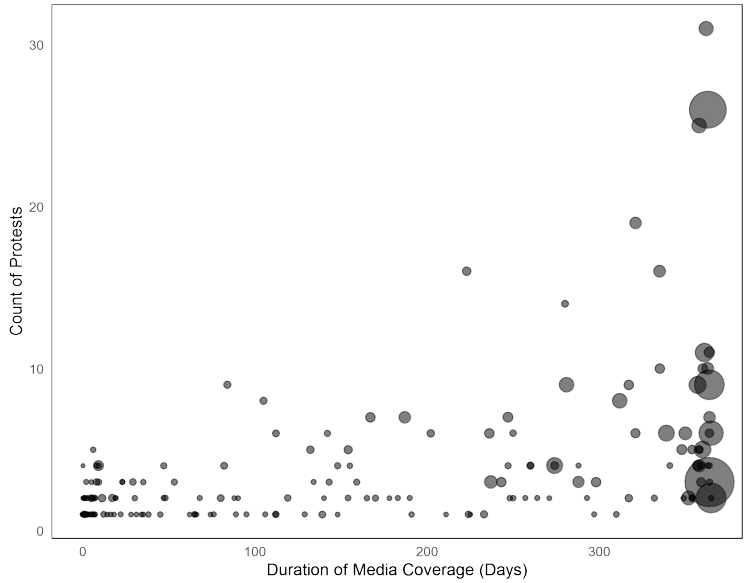
(a) All protests



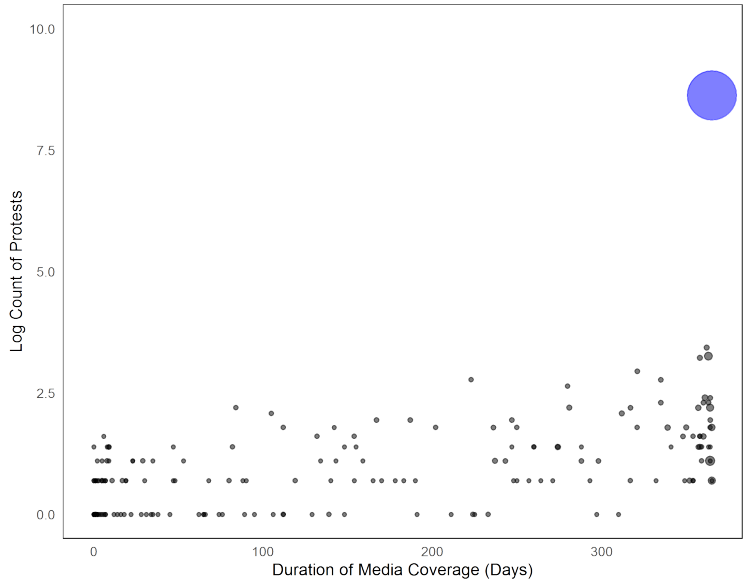
(b) Protests by media coverage

Figure 5: Difference-in-differences trends for *Favor social integration of races* in event time

This figure displays the evolution of the race perceptions in event time. The figure shows trends in responses in counties with protests, relative to the control group of counties with no protests. The 95% confidence intervals are based on standard errors clustered by county.



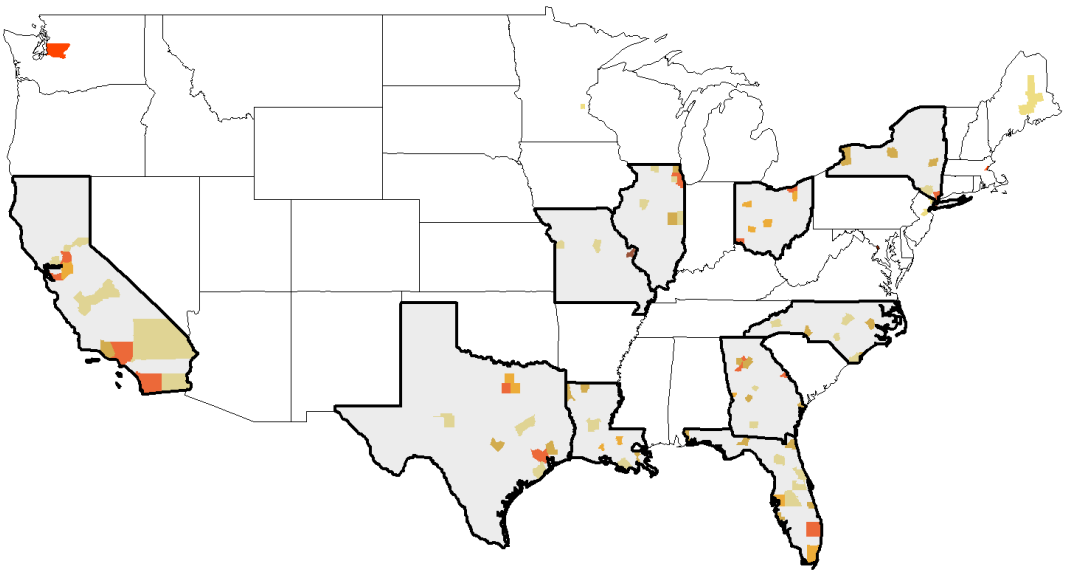
(a) Excluding the George Floyd incident



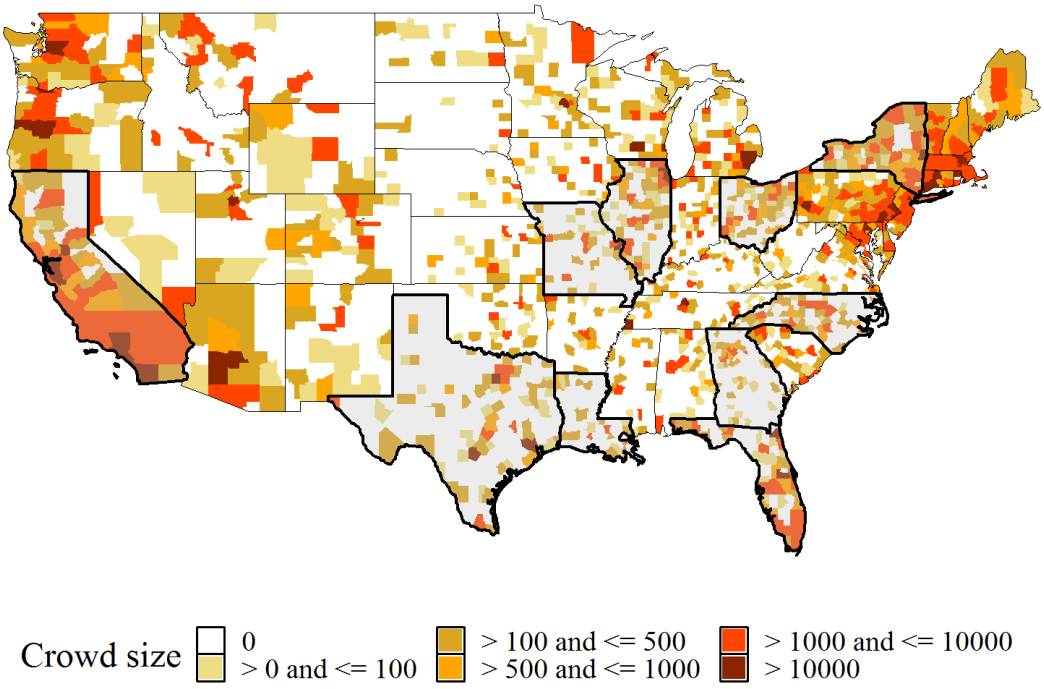
(b) Including the George Floyd incident

Figure 6: Protest count and duration of media coverage for incidents

This figure plots the duration of media coverage in days (X-axis) by the count of protest events per incident(Y-axis). The size of the bubble reflects the number of news articles that cover the protests. Panel A excludes the GF incident and plots the protests in the ten states in our sample. In Panel B, we include the GF incident, represented by the blue bubble.



Panel A



Panel B

Figure 7: Location of protests and crowd size

This figure shows the location and crowd size for protests following encounters of African American or Black civilians with the police. Panel A shows protests from 2000–2020 for the ten states in our main sample. Panel B shows protest events from May 2020–July 2020 for the George Floyd incident. The ten states in our main sample are emphasized in both panels.

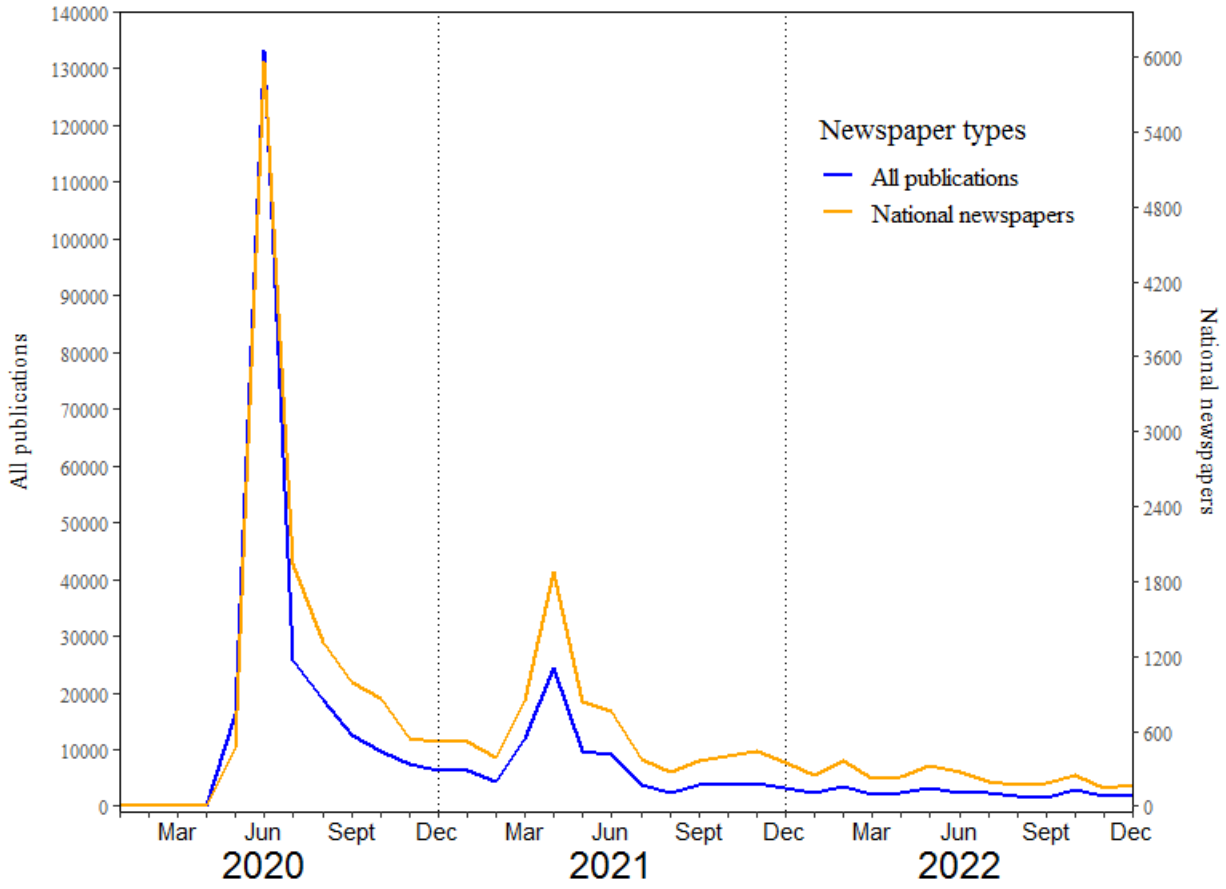
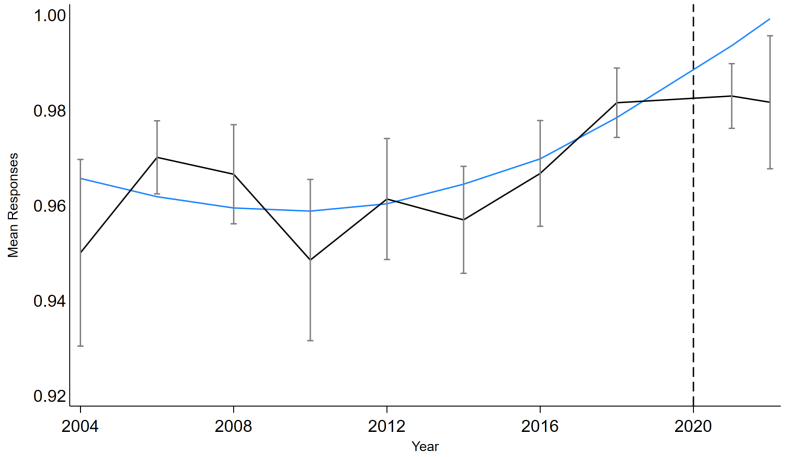
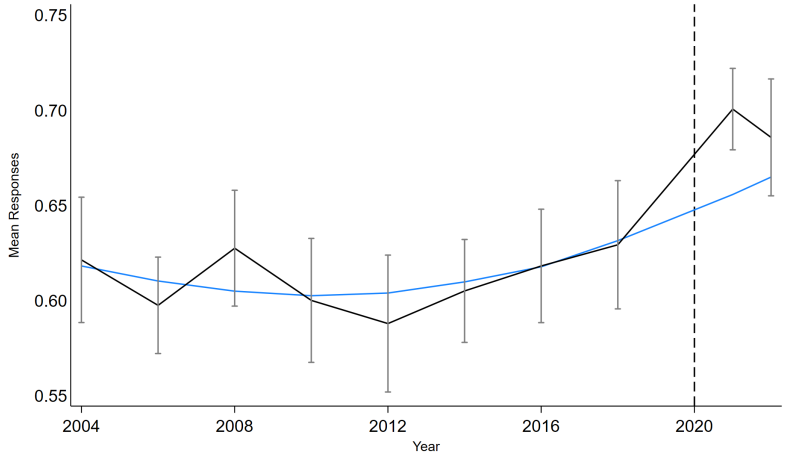


Figure 8: Media coverage of the George Floyd incident

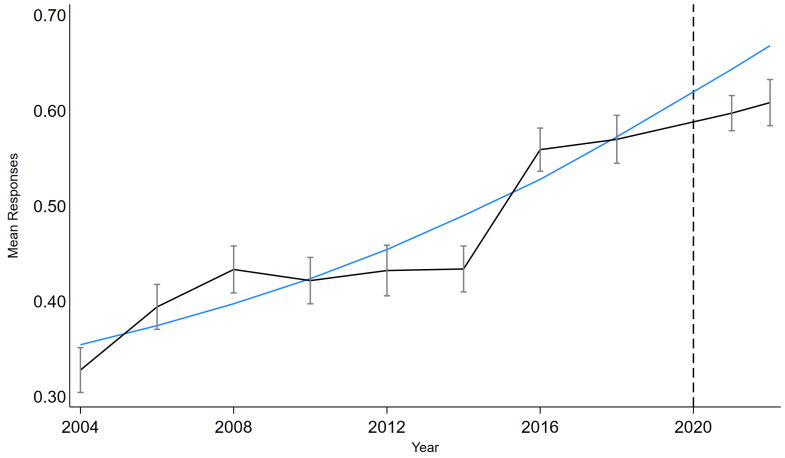
This figure shows trends in the number of news media articles covering the George Floyd incident. The data are sourced from the news archive Factiva.



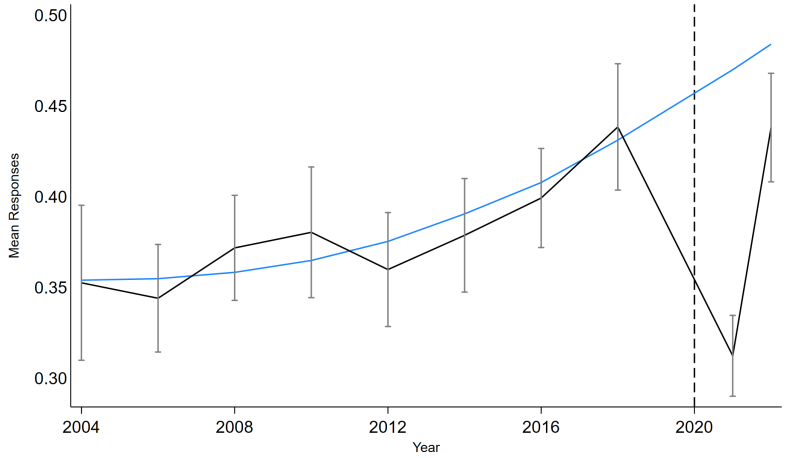
(a) Progress in beliefs about racial differences



(b) Believe that race issues dominate civil liberties



(c) Support policies that favor affirmative action



(d) Favor social integration of races

Figure 9: Time trends in attitudes towards race

This figure shows time trends in attitudes towards race. The dotted line indicates the year of the GF incident. The blue line fits a lowess curve to show trends in the data.

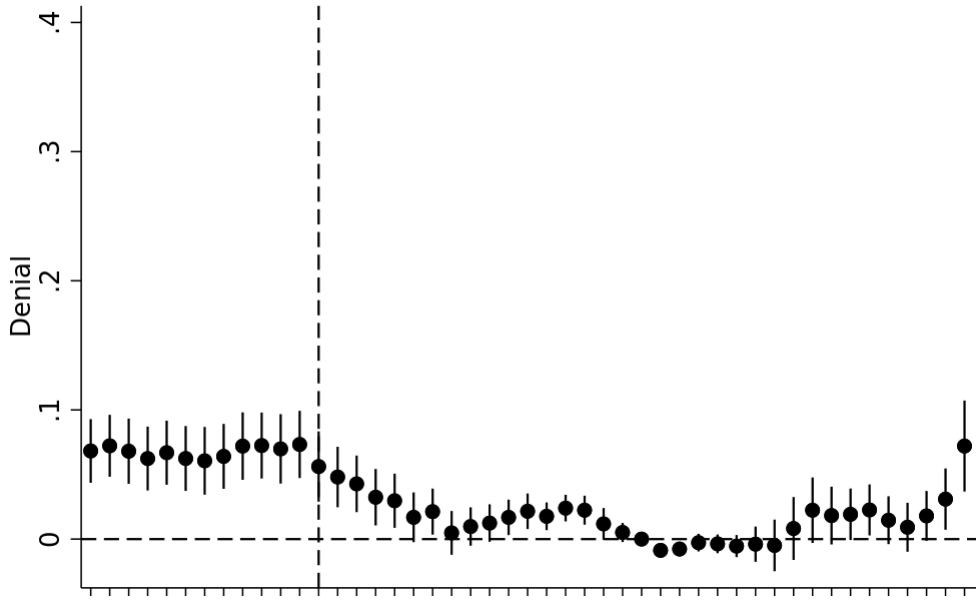


Figure 10: Coefficient plot of application denials for African American borrowers around the GF incident

This figure shows the monthly (X-axis) coefficient plot for the likelihood of denial (Y-axis) of mortgage applications from Black/African American borrowers around the GF incident. The sample period is from January 2018—April 2023. The dotted line represents June 2020, the month after the GF incident.

Table 1: Summary Statistics

This table presents the summary statistics for the variables used in this paper. Panel A presents respondent-year level summary statistics for our measures of race perceptions, Panel B presents summary statistics for variables at the level of fatal encounters and protests, whereas Panel C presents summary statistics for variables at the county-year level. All variables are defined in Appendix B.

Panel A: Respondent-year level summary statistics

	N	Mean	Sd	Min	Median	Max
Progress in beliefs about racial differences	5826	0.634	0.482	0	1	1
Believe that race issues dominate civil liberties	3936	0.810	0.392	0	1	1
Support policies that favor affirmative action	6609	0.437	0.496	0	0	1
Favor social integration of races	5690	0.455	0.498	0	0	1

Panel B: Incident or protest level summary statistics

	N	Mean	Sd	Min	Median	Max
Age	3357	3.373	0.391	0	3.367	4.533
Female	3357	0.085	0.279	0	0	1
Lethal Gunshot	3357	0.721	0.449	0	1	1
Lethal Violence	3357	0.074	0.261	0	0	1
Multiple Victims	3357	0.032	0.177	0	0	1
National News (Incident)	3357	0.091	0.288	0	0	1
National News (Protest)	728	0.556	0.497	0	1	1
Precipitation (protest day) > 2mm	728	0.242	0.428	0	0	1
Precipitation (protest day) > 7-day-average	728	0.202	0.402	0	0	1
Precipitation (week of incident) > 7-day-average	3357	0.346	0.476	0	0	1
Protest	3357	0.084	0.277	0	0	1
Protest Crowd Size	592	4.153	1.55	0	4.605	10.597
Protest > 1 Day	728	0.854	0.353	0	1	1
Protest News Coverage (#Articles)	728	3.274	2.056	0	3.258	8.271
Protest News Coverage (Length)	728	4.508	1.991	0	5.565	5.903
Vehicle	3357	0.155	0.362	0	0	1

Panel C: County-year level summary statistics

	N	Mean	Sd	Min	Median	Max
Denial Rate (Black)	1913	0.391	0.133	0.000	0.381	1.000
Denial Rate (White)	1941	0.231	0.075	0.039	0.222	0.714
County Population	1785	13.030	1.248	9.450	13.111	16.128
Democrat Vote Share	1785	0.523	0.135	0.197	0.518	0.902
Per Capita Income	1785	3.701	0.323	2.852	3.679	5.253
Percent African American	1785	0.210	0.145	0.009	0.175	0.677
Unemployment Rate	1785	0.064	0.029	0.022	0.057	0.289

Table 2: Factors associated with the probability and intensity of protests

This table presents coefficient estimates from an OLS model predicting the probability and intensity of protests. Column (1) presents coefficient estimates from predicting the probability of a protest following a fatal incident, whereas Columns (2) and (3) present coefficient estimates from predicting the intensity of protests. All variables are defined in Appendix B. The t-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	Protest	Protest Crowd Size	Protest > 1 Day
	(1)	(2)	(3)
Age	-0.055***	-0.286*	-0.068
	(-4.228)	(-1.882)	(-0.835)
Female	0.010	0.311**	0.032
	(0.680)	(2.830)	(0.347)
National News (Incident)	0.348***	0.430**	0.267***
	(6.503)	(2.839)	(5.313)
Lethal Gunshot	0.040**	0.155	-0.057
	(2.431)	(0.439)	(-0.505)
Lethal Violence	0.054*	-0.107	-0.086
	(1.978)	(-0.397)	(-0.630)
Vehicle	-0.038**	-0.023	0.115
	(-2.470)	(-0.074)	(1.140)
Multiple Victims	-0.003	-0.312	0.160
	(-0.100)	(-1.389)	(1.408)
County Population	-0.014***	-0.124**	0.002
	(-4.433)	(-2.367)	(0.071)
Percent African American	-0.093	3.268**	-0.512**
	(-1.115)	(2.751)	(-2.391)
Per Capita Income	0.094***	0.834***	-0.032
	(3.648)	(6.231)	(-0.693)
Unemployment Rate	0.336	-8.298	1.226
	(0.611)	(-1.718)	(0.760)
Democrat Vote Share	0.034	-1.089	0.233
	(0.441)	(-0.713)	(1.000)
Observations	3,357	592	728
Adjusted R^2	0.147	0.123	0.190
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Cluster s.e.	State	State	State

Table 3: Table showing an association between race perceptions and mortgage denial rates

This table presents the marginal effects from a fractional probit model of county-level mortgage denial rates in years *t+1 to t+5* on race-related perceptions and other control variables. In columns (1) to (5), the dependent variable is county-level denial rates for Black/African American applicants whereas in columns (6) to (10) it is the county-level denial rates for White applicants. *Race Perceptions* is the county-year average of the measure *Progress in beliefs about racial differences* described in Section 4 and Appendix A. The sample includes the even-numbered years from 2000–2018, for which location-level GSS data is available and includes all US states. All variables are defined in Appendix B. The z-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	Denial Rate (Black)	Denial Rate (Black)	Denial Rate (Black)	Denial Rate (Black)	Denial Rate (Black)	Denial Rate (White)	Denial Rate (White)	Denial Rate (White)	Denial Rate (White)	Denial Rate (White)
	t+1	t+2	t+3	t+4	t+5	t+1	t+2	t+3	t+4	t+5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Race Perceptions (t)	-0.013**	-0.011	-0.012*	-0.005	-0.008	-0.005	-0.003	-0.005	-0.005	-0.003
	(-2.304)	(-1.559)	(-1.720)	(-0.670)	(-1.208)	(-1.573)	(-1.090)	(-1.618)	(-1.552)	(-0.812)
Per Capita Income	-0.042	-0.081	-0.084	-0.013	-0.049	-0.267***	-0.254***	-0.255***	-0.251***	-0.265***
	(-0.811)	(-1.091)	(-1.305)	(-0.195)	(-0.697)	(-6.049)	(-5.958)	(-6.725)	(-5.602)	(-6.160)
Percent African American	0.026***	0.032***	0.032***	0.034***	0.030***	0.004*	0.004	0.004	0.004	0.003
	(3.693)	(4.141)	(4.483)	(4.218)	(4.342)	(1.656)	(1.516)	(1.569)	(1.575)	(1.457)
County Population	-0.169**	-0.197**	-0.217**	-0.260***	-0.216***	-0.128***	-0.122***	-0.121***	-0.113***	-0.106***
	(-2.050)	(-2.072)	(-2.545)	(-2.754)	(-2.637)	(-4.155)	(-3.765)	(-3.332)	(-3.835)	(-3.245)
Unemployment Rate	0.059***	0.036**	0.033**	0.051***	0.046**	0.039***	0.031**	0.032***	0.035***	0.029**
	(2.660)	(2.069)	(2.221)	(2.988)	(2.503)	(2.578)	(2.310)	(2.587)	(2.701)	(2.471)
Observations	1,913	1,913	1,912	1,702	1,700	1,941	1,941	1,941	1,728	1,728
Pseudo R^2	0.024	0.028	0.027	0.026	0.031	0.0200	0.0234	0.0192	0.0178	0.0184
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster s.e.	State	State	State	State	State	State	State	State	State	State

Table 4: Changes in perceptions following protests

This table presents difference-in-differences estimates of the change in race-related perceptions of survey respondents for the six years following a protest using the methodology presented in De Chaisemartin & d'Haultfoeuille (2020). The benchmark period is two years prior to the protest. The estimates are shown for the full sample and by the length of media coverage of the protest. Column (4) shows the difference in means between the estimates for Media coverage $\geq$ 90 days and Media coverage $<$ 90 days. The estimations include county and year fixed effects and the following control variables: *County Population, Democrat Vote Share, Per Capita Income, Percent African American* and *Unemployment Rate*. Standard errors are clustered by county.

	Estimate	z-statistic	N	Difference	t-statistic (Difference)
	(1)	(2)	(3)	(4)	(5)
Progress in beliefs about racial differences					
Full sample	0.102***	3.26	8607	0.041	0.79
Media coverage $\geq$ 90 days	0.125***	3.05	4476		
Media coverage $<$ 90 days	0.084***	2.63	4095		
Believe that race issues dominate civil liberties					
Full sample	0.076**	2.35	5808	0.006	0.11
Media coverage $\geq$ 90 days	0.057	1.24	2990		
Media coverage $<$ 90 days	0.051**	2.04	2779		
Support policies that favor affirmative action					
Full sample	0.069**	1.97	9958	0.093	1.45
Media coverage $\geq$ 90 days	0.125***	2.78	5177		
Media coverage $<$ 90 days	0.032	0.70	4790		
Favor social integration of races					
Full sample	0.061	1.54	8434	0.017	0.25
Media coverage $\geq$ 90 days	0.089**	2.07	4398		
Media coverage $<$ 90 days	0.072	1.36	4034		

Table 5: Inclement weather and the probability and intensity of protests

This table presents coefficient estimates from an OLS model predicting the protest crowd size (columns (1)–(2)) and the probability of a protest (column (3)). *Protest Crowd Size* is the natural logarithm of the number of participants at the protest event. *Protest* is an indicator for whether the fatal encounter resulted in a protest event. Incident-level controls include *Age, Female, National News, Lethal Gunshot, Lethal Non Gunshot, Vehicle* and *Multiple Victims*. County level controls are lagged by a year and include *County Population, Percent African American, Per Capita Income, Unemployment Rate* and *Democrat Vote Share*. All variables are defined in Appendix B. Standard errors are adjusted for the small number of clusters using a wild cluster bootstrap (Cameron et al., 2008). The t-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	Protest Crowd Size	Protest Crowd Size	Protest
	(1)	(2)	(3)
Precipitation (protest day) > 7-day-average	-0.266**		
	(-2.349)		
Precipitation (protest day) > 2mm		-0.243	
		(-1.765)	
Precipitation (week of incident) > 7-day-average			0.008
			(1.009)
Observations	592	592	3,357
Adjusted R^2	0.116	0.116	0.143
Incident-level controls	Yes	Yes	Yes
County-level controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Cluster s.e.	State	State	State

Table 6: Impact of protests on mortgage loan denials for Black/African American borrowers

This table presents coefficient estimates from a 2SLS model predicting denial of loan applications from Black/African American borrowers. The sample consists of all originated and denied loan applications by Black/African American borrowers. Columns (1) and (2) include protests that are covered in the news media for a period of $\geq$ 90 days, whereas Columns (3) and (4) include protests that are covered for a period of $<$ 90 days. *Denied* is an indicator for whether the mortgage loan application was denied; *Protest Crowd Size* is the natural logarithm of the number of participants at the protest event. County level controls are lagged by a year and include *County Population, Percent African American, Per Capita Income, Unemployment Rate* and *Democrat Vote Share*. Loan level controls include loan purpose and occupancy status of the property, and loan type. All variables are defined in Appendix B. The t-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	1-year window		1-year window	
	Media coverage $\geq$ 90 days		Media coverage $<$ 90 days	
	Denied	Denied	Denied	Denied
	(1)	(2)	(3)	(4)
$\widehat{\text{Protest Crowd Size}}$	-0.072**	-0.053**	0.050*	0.046**
	(-2.224)	(-1.984)	(1.689)	(2.062)
First stage F-Statistic for precipitation (protest day)	17.30	12.95	23.21	30.14
Observations	671,461	656,286	1,033,386	1,010,009
Adjusted R^2	0.016	0.071	0.036	0.085
County-level controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Loan-level controls	No	Yes	No	Yes
Cluster s.e.	Lender	Lender	Lender	Lender

Table 7: Impact of protests on mortgage loan denials for Black/African American borrowers (For protests with media coverage $\geq$ 90 days)

This table presents coefficient estimates from a 2SLS model predicting denial of loan applications from Black/African American borrowers for the sample of protests that are covered in the news media for a period $\geq$ 90 days. The sample consists of all originated and denied loan applications by Black/African American borrowers. Columns (1) and (2) include loan applications in the first two years after the protest events, whereas Columns (3) and (4) include loan applications in the first three years after the protest events. *Denied* is an indicator for whether the mortgage loan application was denied; *Protest Crowd Size* is the natural logarithm of the number of participants at the protest event. County level controls are lagged by a year and include *County Population, Percent African American, Per Capita Income, Unemployment Rate* and *Democrat Vote Share*. Loan level controls include loan purpose and occupancy status of the property, and loan type. All variables are defined in Appendix B. The t-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	2-year window		3-year window	
	Media coverage $\geq$ 90 days		Media coverage $\geq$ 90 days	
	Denied	Denied	Denied	Denied
	(1)	(2)	(3)	(4)
$\widehat{\text{Protest Crowd Size}}$	-0.023	-0.000	-0.021	-0.001
	(-1.198)	(-0.027)	(-1.331)	(-0.127)
First stage F-Statistic for precipitation (protest day)	13.97	12.01	20.84	20.38
Observations	1,259,713	1,223,406	1,812,042	1,745,392
Adjusted R^2	0.027	0.081	0.025	0.084
County-level controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Loan-level controls	No	Yes	No	Yes
Cluster s.e.	Lender	Lender	Lender	Lender