Triggers and barriers to political empowerment. Evidence from Black Lives Matter.

Annalí Casanueva Artís*

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Abstract

This paper studies the triggers, barriers and factors favoring political empowerment through protest in the context of the Black Lives Matter movement (BLM) in the period 2014–2018 in the US. Using high-profile police-caused deaths of Blacks as a quasi-exogenous national protest trigger, and two-way fixed effects for counties and days, I study the differential effects of various local characteristics on offline protest behavior and online BLM activity. After confirming that police-related Black deaths are an important predictor of protests, and more so in places with a higher share of Black population, results show the following: 1) Past protest in the county itself and in surrounding areas increase the likelihood of observing a BLM event after a new trigger, even more so if past protest are larger, are closer geographically to the county or are closer in time to the date of a new trigger; 2) past local police-related deaths are linked to an increase in BLM protest and online discussion after a non-local police-related death that gained national media attention 3) economic resource deprivation reduces both protest behavior and online engagement in BLM debates, suggesting the existence of a "protest poverty trap"; 4) higher inequality increases the number of protests but not the likelihood of observing a first protest in a county that has never protested before, suggesting that unfavorable local context can be reinterpreted after exposure to a more negative narrative about it (for example during a protest); 5) more social links are related to an increase of the number of protests but not to the likelihood of observing a first protest, suggesting that having experienced a protest can reveal information about others' political preferences in the region, allowing individuals to be less reluctant when taking advantage of their social network to push forward their protest agenda; 6) a higher ability to participate in formal ways in the political debate (such as participating in elections) reduces the protest behavior, suggesting that formal and informal means of political participation substitute each other.

Keywords: protest, online, BLM, inequality, protest poverty trap, political participation
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*Paris School of Economics.

1 Introduction

Protests are important in shaping economic, social, and political institutions (Collins and Margo, 2007; Madestam et al., 2013; El-Mallakh et al., 2018; Mazumder, 2019). They are crucial in keeping governments and institutions accountable (Acemoglu et al., 2017) and can empower traditionally disempowered groups (Larreboure and González, 2021). Even purely online protest that do not have a clear offline translation can cause notable effects on beliefs and behaviors (Enikolopov et al., 2018; Levy and Mattsson, 2020).

The factors that could affect the rise of a social mobilization have been debated in the theoretical literature (Goodwin and Jasper, 2014; Della Porta and Diani, 2015) and some scholars have empirically documented different factors correlated to protest (Dalton et al., 2010; Williamson et al., 2018). Yet, the determinants of protest remain poorly understood (Chenoweth and Ulfelder, 2017; Choi and Kim, 2019), even more so if we refer to the determinants of online protest.

I build on this literature and study how economic, social and political characteristics and past experiences of a region can affect offline protest behavior and online participation in the discussion created around a protest movement. In particular, I take as a case study the Black Lives Matter movement from 2014 to 2018 in the US.

The Black Lives Matter (BLM) movement is a well-suited case to study protest determinants, first and most straightforwardly because it was born online and has maintained a high level of online activity but has also spawned massive offline protests all over the US territory, which allows us to study both the online and the offline parts of the movement.

Second, BLM protests occur mainly in response to well-determined triggers, namely high-profile, highly-mediatized police-related death of Black people. This characteristic allows us to study the determinants at different points in time, making it less likely to have spurious correlations with another event happening around the same time and affecting the probability of the occurrence of the protest trigger and its protest response. This offers an advantage compared to analyses that rely on a one-time triggering event for several reasons. First, a multi-trigger analysis of BLM is less likely to be capturing the effect of confounder characteristics, i.e., characteristics that are related at the same time to the characteristic that we want to study, to the probability of occurrence of a trigger, and to the protest response. Second, this allows studying the determinants that matter across different historical moments and political environments. The period I study (2014–2018) covers the Obama and the Trump presidencies, both having very different ideologies. Third, having multiple triggers allows the study of the factors affecting the first time a region hosts a BLM protest separately from overall protests.

Finally, BLM triggers and protests have been widely geographically distributed which ensures enough variation of county characteristics.

More generally, the study of BLM local determinants can be of particular interest because it is a movement that has had an impact on different measurable outcomes (Mazumder, 2019; Campbell, 2021). The study of this movement will shed light on the factors encouraging and preventing the mobilization for a movement that has been able to achieve some of its goals.

I construct a county-day level database of BLM protests, Black police-related deaths, deaths receiving national media attention, Twitter activity related to BLM, and several demographic, economic, social and political characteristics at the county or state level over 3,100 US counties and 4 years. I use this database to study the direct effect of high-profile Black deaths at the hands of the police—that I will call "notable deaths"—on protests and online activity; the differential reaction to this trigger in counties with a higher percentage of Black population; and the differential reaction to notable deaths in counties with both a higher percentage of Black population and some county characteristics of interest.

The empirical strategy uses notable deaths as a quasi-exogenous shock and adds day and county fixed effects, as well as lower-level interaction terms in cases when the triple interaction is conducted. This does not make the interpretation of the differential effect of protest based on county characteristics causal but does ensure that what we capture is indeed the effect of a protest trigger—and not the effect of another unobservable affecting both the presence of a trigger and the protest reaction. The inclusion of the interaction between notable deaths and Black population in the triple-interaction specification ensures that the result is not driven by the correlation between the studied characteristic and the percentage of Black people in the county.

It is likely that the mechanisms underlying the organization of the first protest in a county are different from those of subsequent protests, particularly in the presence of non-linearities in the decision to protest (González, 2020; Bursztyn et al., 2021). To allow the analysis of possible different determinants of the first protest rather than for protest in general, I also conduct the analysis restricting it to the sub-sample of county-day observations before or on the day of the first demonstration in a county. Finally, in order to be able to document the determinants of online BLM activity, I also use the number of tweets mentioning BLM as an outcome.

Results show the following: first, they confirm that Black police-related deaths are a trigger of BLM protest, and that they are a stronger trigger where there exists a proportionally larger Black population. This is true for overall protest, first-time protest and online activity.

Second, they show that past protest in own county itself and surrounding areas increase the likelihood of observing a BLM event after a new trigger. The effect is even stronger if past protest are larger, are closer geographically to the county or are closer in time to the date of a new trigger.

Third, they show that cumulative past experiences at the local level play a role in explaining subsequent protest behavior. In particular, past exposure to Black police-related deaths in the county is associated with a higher protest response.

Fourth, a relative deprivation of economic resources (measured by the percentage of Black people below the poverty line and the percentage of Black people in unemployment) is associated with lower participation in protest, with a lower probability of having a first BLM protest in the county following a notable Black police-related death, and, notably, economic deprivation also prevents online political participation. These results suggest the existence of a "protest poverty trap" where, paradoxically, the groups that could potentially benefit the most from protesting are the least able to do so.

Fifth, higher inequality (measured as the over-representation of Blacks among the unemployed and by the Gini index) increases the number of protests but neither the likelihood of observing a first protest in a county that had never protested before, nor BLM activity on Twitter. Inequality seems then to fuel protest behavior in this setting, as previously found in the literature (Iacoella et al., 2021), but only after a first protest experience. Exposure to a BLM protest may result in protesters (and the whole region via spill-over effects) being exposed to a different narrative about an unfavorable local context. They may then feel more aggrieved about their situation. Indeed, people living in counties with higher inequality levels may be accustomed to this inequality and consider that as part of the norm. The presence of a BLM event in the county can serve to expose people to a different narrative about their situation and to increase their internal grievances.

Sixth, contrary to other findings in the literature (Algan et al., 2020), I find that a higher social capital (measured as the number of either religious or civic organizations) is linked with an increase in the number of protests but no increase in first protests. Preexisting social networks can have several effects that favor protest, including acting as an echo-chamber for a certain ideology or reducing coordination cost (Enikolopov et al., 2020). The results suggest that those effects only operate once the network has been exposed to a first BLM demonstration. The cost-benefit analysis of taking advantage of preexisting social networks (created for other purposes) may change after an external informational shock (Lohmann, 1994) such as the presence of a BLM event. Indeed, a BLM event can i) inform about the general feeling in the local population about the protest (and thus give a better idea on whether an attempt to use the preexisting social relationships for mobilization purposes will be welcome or not) and ii) increase motivation to protest by exposure to new information.

Finally, I document that a higher ability to participate in formal ways in the political debate (such as participating in elections) reduces both offline protest and online political participation in BLM-related discussions, suggesting that formal and informal means of political participation substitute each other.

Overall, this paper shows that local experiences play a role in determining the reaction to protest triggers. In particular, it has four main contributions. First, it suggests that regional informational shocks, both as a signal of others' beliefs and as exposure to alternative narratives, may play a role in explaining differences in protest behavior. Second, it documents the possible existence of a "protest poverty trap" where more deprived individuals are not able to gain resources through protest because they don't have enough resources to protest and are trapped in this equilibrium. Third, it provides evidence suggesting that subjective feelings of inequality can increase protest participation. Finally, it suggests that formal and informal forms of political participation may be substitutes rather than complements.

This paper contributes to different strands of the literature, starting with the literature studying the determinants of protest (Bozzoli and Brück, 2010; Dalton et al., 2010; Williamson et al., 2018; Cantoni et al., 2019; Sánchez and Namhata, 2019; Massoud et al., 2019; Manacorda and Tesei, 2020; Algan et al., 2020; Bursztyn et al., 2021). I add to this literature in two ways, first by not only studying the determinants of offline protest but also of online discussion about BLM; second by analyzing not only the determinants of overall protest but also more specifically the determinants of the first BLM protest in a county. This paper also relates to the literature studying the effects of exposure to changes in available information (Lohmann, 1994; DellaVigna and Kaplan, 2007; Ferraz and Finan, 2008; Allcott and Gentzkow, 2017; Durante et al., 2019; Manacorda and Tesei, 2020; Barrera et al., 2020; Bursztyn et al., 2021). I add to this literature by providing suggestive evidence that protests can act as information shocks, providing new information about other people's preferences and beliefs and exposing individuals to alternative narratives about their own circumstances and surroundings.

The rest of this paper is organized as follows: in Section 2, I give some background on the BLM movement; in Section 3, I describe the structure of my dataset; in Section 4, I present the empirical strategy. I describe the results in Section 5, present some robustness checks in Section 6, and finally conclude in Section 7.

2 Background and Motivating Evidence

The Black Lives Matter (BLM) movement was born on social media after the acquittal of George Zimmerman in the deadly shooting of a Black teenager named Trayvon Martin.

The movement was founded in July 2013 by three Black activists, Alicia Garza, Patrisse Cullors and Opal Tometi, who gave birth to the Twitter hashtag #BlackLivesMatter.

Black Lives Matter arose as a reaction to police brutality against Black people and particularly to the use of deadly force. The lifetime risk of dying from an interaction with the police is about 500 per million inhabitants for Blacks, while it is 270 per million inhabitants for the overall population (Edwards et al., 2019). Black police-related deaths are neither infrequent nor regionally isolated. Among all US counties, 476 (15.1 %) had at least one Black police-related death over my period of study, and deaths took place in 203 of the 204 weeks in the period. Moreover, there is a widespread perception that absuse of force by police goes unpunished and that agents using deadly force are not prevented from using it again[1].

Beyond criticism of police brutality, BLM was created with the aim of ending systemic racism, abolishing white supremacy and state-sanctioned violence (Black Lives Matter, 2020).

In August 2014, around one year after the online birth of the movement, the fatal shooting of Michael Brown by a police officer triggered a large wave of offline protest in the city of Ferguson, Missouri. These protests were widely covered by both national and international media, and consequences of the shooting rippled through all American society, mobilizing protesters and counter-protesters far beyond the city's borders.

In the subsequent months and years, other Black police-related deaths gained media attention and triggered mobilizations all over the country. Some examples include the deaths of Tamir Rice, Freddie Gray, Sandra Bland or Philando Castile. Figure 1 shows the number of protests per week and the timing of these "notable deaths". Figure 2 shows the number of tweets mentioning BLM two weeks before and after each notable death. We see that notable Black deaths have an effect on the online intensity of the discussion about BLM as well. Figure 3 shows the cumulative number of counties having hosted at least one BLM protest. We see that since BLM started its offline activity, counties have gradually been engaging in protest, generally after a notable death acting as trigger. In the middle of 2018, 319 counties (10.1%) had held at least one BLM protest.

However, when confronted to the same national trigger, not all regions reacted, and, among those which reacted, not all did it with the same intensity. Why do some counties protest and others do not after a national trigger? Our intuition would tell us that counties with a higher proportion of people affected by the object of the protest have a higher potential for protesting. Figure 4 clearly shows that counties with an above-median share of Black population react more to protest triggers, with the reaction measured as the number of BLM events per 100,000 inhabitants.

Past exposure to local police brutality can also affect the reaction to a non-local trigger. Counties with a higher percentage of Black population and, within that population, a higher risk of having a deadly encounter with the police might react differently to a "new" non-local notable death. Figure 5 shows that indeed, among counties with above the median percentage of Black population, the more a county has been exposed to past local police use of deadly force, the higher the protest reaction to a notable death in the US.

Beyond past experiences, other local characteristics are thought to impact protest behavior. Inequality is one of the factors that has, for a long time, been linked with social unrest and protest (Muller, 1985). Its role as a fuel for protest has been largely debated in the literature (Acemoglu and Robinson, 2001; Solt, 2015; Justino and Martorano, 2016; Kołczyńska, 2020; Iacoella et al., 2021). Figure 6 shows the levels of protest in reaction to a notable death depending on the level of inequality, measured in two different ways:

[1] The Washington Post

the Gini index and the ratio of Black unemployment rate over total unemployment rate. Both graphs take only the subsample of counties with an above-median percentage of Black population. Inequality seems to indeed also play a role in shaping protest behavior in the BLM context. Among counties with an above-median percentage of Black population, counties with higher inequality react systematically more than counties with lower inequality.

To sum up, this motivating evidence delivers four takeaways. First, notable deaths trigger BLM protest and online participation in the BLM discussion. Second, not all counties react the same to the same national trigger. Third, having a higher percentage of the population being affected by the protest's demands increases BLM protest. Fourth, among regions with a higher proportion of "concerned population", local experiences and characteristics still play an important role in determining the level of protest response to a notable death.

I use these observations to guide the empirical analysis. I start by establishing a credible causal link between BLM trigger and BLM protest, distinguishing between the presence of the very first BLM protest and the total number of protests in a county. Then I show that a higher share of Black population is key in explaining protest. I then analyze the correlates between different county characteristics—grouped into past experiences, economic factors, social factors and political factors—and different protest reactions to a same trigger.

3 Data

The data set includes information from various sources connecting the occurrence and scope of BLM events to exposure to police violence against Black people. I complement this information with manually scraped data about deaths receiving particular attention from the media, and traditional socio-economic variables at the county level from representative surveys. I create a data set at the county-day level spanning August 2014 to July 2018, both included. This data set is constituted of more than 4 million observations. I provide some descriptive statistics for all variables used in the analysis in Table 1.

Black Lives Matter protests This data comes from the crowd-sourced platform Elephrame. It provides information on the place and date of each BLM protest and an estimated number of participants, as well as a link to a news article covering the protest. I extracted all protests' records from August 2014 to July 2018 and geo-coded their location. Figure 1 shows the total number of events over time, and Figure 7 shows their distribution within counties. Among all US counties, 319 had at least one BLM protest over the period 2014–2018. This represents about 10% of counties. Over the 204 weeks of the period of study, 177 (87%) had at least one BLM protest.

Notable deaths data I scrape data on all notable Black deaths that have occurred in the country for the period August 2014–July 2018. Not every death of a Black person at the hands of the police gets media coverage, which is crucial for generating public discourse and action. I put together details of deaths of all Black people at the hands of the police authorities that got media coverage. Notable deaths are defined as deaths that were covered in a major national news source like the Washington Post or CNN and/or has a dedicated Wikipedia page. The timing of the notable deaths is represented as vertical lines in Figure 1, and Figure 8 shows their locations.

Twitter Twitter data is an important source of information when studying social events and protests. I collected tweets using the Twitter Academic Research API. In particular, I collected all tweets that contain the keywords "BLM", "Black Lives Matter" or "Black Life Matters",[2] excluding retweets. Due to the usage limits of the Twitter Academic Research API, I did not collect all tweets mentioning BLM published during the four year period. I instead focus on tweets posted within 14 days of a notable death. For each tweet, I extract the time and text of the tweet, and the user's name, stated location, and account creation date. I then assign the tweets to geographical locations using the location provided by the user in their profile. The location of Tweets is challenging. First, not all users indicate a location and among those who do, not all give a valid location (e.g., "in the heart of Justin Bieber") so I restrict the sample to the users that provide a valid location that can be matched to a USA county (in particular, I exclude users whose location only mentions a state). Second, the location is an arbitrary text field which is not meant to be machine-readable. I use the Nominatim geocoding engine (based on the Open Street Map database) to find the coordinates of the most likely match for the location. I then filter out all locations outside the US and locations that are too vague (i.e. that map to the whole country or an entire state). Finally, I map these coordinates to counties using the US Census Bureau cartographic boundary files. I end up with 1.35 million tweets.

Use of deadly force by police I obtain this information from the collaborative platform Fatal Encounters. This organization started collecting police-related deaths in 2014. Available information include, notably, the race of the victim, the specific address where the death occurred and whether the death is considered a suicide (for example, a suicide during or just after an arrest). I geocoded the location of these events. I only use the number of police-related deaths of Black victims. Figure 9 show their spatial distribution.

County level characteristics I obtain county-level characteristics from the American Community Survey. The characteristics I use are the total population, the percentage of Black population, the overall unemployment rate, the Black unemployment rate, the Black poverty rate, and the county's Gini index. To avoid concerns of endogeneity, all variables are measured in 2013 using the 5-year estimates. GDP per county in 2013 is obtained from the Bureau of Economic Analysis, and divided by the population to obtain the per-capita GDP for the county.

Voting and registration data I obtain data on voter registration and actual participation in national elections in November 2014 by state and race from the Census Bureau's Current Population Survey[3].

Social capital data I also rely on county-level social capital measures produced by Rupasingha et al. (2006). They use secondary data covering the entire United States, the County Business Patterns, collected by the Census Bureau, to compile an extensive and comprehensive set of variables representing membership organizations at the county level. I use the number of civic groups and religious organizations per 1,000 inhabitants.

[2]These keywords are matched both when appearing separated with spaces, or without spaces as a hashtag (e.g. #BlackLivesMatter).

[3]https://www.census.gov/data/tables/time-series/demo/voting-and-registration/p20-577.html

4 Empirical strategy

The empirical strategy relies on the quasi-exogenous time variation of the exposure to police brutality against Black people. In particular, I use the presence of a notable death (i.e. a high-profile, highly mediatized Black police-related death) as a protest trigger and study the differential protest response to this trigger driven by local characteristics. I use a two-way fixed effects model which follows the logic of a difference in differences estimation and absorbs many of the concerns regarding unobserved heterogeneity. Notably, the inclusion of county fixed effects allows to account for characteristics of the county that remain constant over the period of study (2014–2018).

The occurrence of a notable death on a given day outside the county in which it happens can be considered quasi-exogenous as it is unlikely that time-varying county characteristics are related to a notable death occurring in another county. However, in the county where the notable death took place, time-varying characteristics can be associated with both the occurrence of a police-related death and with protest. To avoid this, for each notable death, I exclude the county where it took place from the sample for the 14 days following the death. Neighboring counties of the county in which the death occurred could have similar time-varying characteristics. Thus, as a robustness check, I exclude all counties of the state where the death occurred.

The first step is to establish that notable deaths can indeed predict protests. Since notable deaths are aggregated nationally, it is not possible to include time fixed effects in this specification. I still include county fixed effects to control for characteristics of the counties. The equation of my model is then the following:

$$\text{BLM events}_{c,d} = \beta_1 \text{Notable deaths in last 14 days}_{c,d} + \alpha_c + \varepsilon_{c,d} \tag{1}$$

where $\text{BLM events}_{c,d}$ is the number of BLM events in county c during day d. The variable $\text{Notable deaths in last 14 days}_{c,d}$ is the number of notables deaths of Black people during days $d-13$ to d. I consider this variable missing if one of the notable death in the interval occurred in the county c.[4] α_c are county fixed effects and $\varepsilon_{c,d}$ is the error term. β_1 is the coefficient of interest. I cluster standard errors at the county-treatment level.[5] The sample consists of all county-day observations from 2014 to 2018, excluding, for each notable death, the county where the death occurred.

Then, I interact the number of notable deaths with the percentage of Black population in a county. This allows to center the study on the protest behavior of the population that is the most likely to protest.[6] Using the interaction between Black population and notable deaths allows to better capture the effect of different characteristics on protest behavior: let us consider an extreme case where the only people that ever protest are Black, or in other words, all non-Blacks are never takers. In that case, if we studied the effect of a factor that were highly relevant in predicting protest in a county without Black people, we would still not find any result. The study of different local factors in counties with a higher percentage of "potentially protesting population" (or possible compliers) allows gaining statistical power. The equation of the model I use is the following:

[4]This is why the variable is indexed with both the county c and the date d, even though notable deaths are used as national shocks.

[5]Following Bertrand et al. (2004), I create for each county several clusters, one before the treatment and one during the treatment. Each notable death is considered to be a different treatment: we obtain one cluster per county and period during which the "notable deaths in the last 14 days" variable is constant.

[6]The population most likely to protest is Black people, particularly over the period of study (2014-2018), when there were fewer white allies than during the wave of protest following George Floyd's murder. The study of the recruitment of allies is the subject of another chapter of this thesis.

$$\begin{aligned} \text{BLM events}_{c,d} = & \ \delta_1 \text{Notable deaths in last 14 days}_{c,d} \times \text{Ratio of Black population}_c \\ & + \alpha_c + \gamma_d + \varepsilon_{c,d} \end{aligned} \tag{2}$$

where Ratio of Black population$_c$ is the ratio of Black population to the total population in the county, and γ_d are day fixed effects. Notable deaths in last 14 days$_{c,d}$ is not included, as it is now absorbed by the time fixed effects. The coefficient of interest is δ_1, and it is expected it to be positive.

After confirming, as expected, that the effect of protest triggers is higher in places with a higher share of Black population, I build on the above model and analyze the link between different regional characteristics and protest in places with a higher percentage of Black population. Using a triple interaction allows in part to increase statistical power, as explained above. The resulting coefficients for the double and triple interactions can not be interpreted causally. Indeed, this strategy does not guarantee that when interacting with a county characteristic the differential effect that is captured is not driven by other characteristic correlated to the one of interest. Still, the triple interaction helps alleviate some of the endogeneity concerns. When doing a triple interaction, the lower-degree interaction terms are also included, notably the interaction between the presence of a notable death and the percentage of Black population. This accounts for the possible correlation between the regional variable of interest and the share of Black population. Let us consider another extreme example: all poor people are Black people. Then, if we use a simple interaction between notable deaths and poverty rate in a county, we would not be able to disentangle the role of the poverty rate from the role of the Black population rate. Doing a triple interaction allows to compare counties with the same level of Black population but different poverty rates. There could be, however, other characteristics correlated to poverty that are not taken into account. This is a limitation of this empirical strategy. The equation that I estimate writes as follows:

$$\begin{aligned} & \text{BLM events}_{c,d} \\ & = +\sigma_1 \text{Notable deaths in the last 14 days}_{c,d} \times \text{Ratio of black population}_c \times \ \mathrm{X}_c \\ & \quad + \sigma_2 \text{Notable deaths in the last 14 days}_{c,d} \times \text{Ratio of black population}_c \\ & \quad + \sigma_3 \text{Notable deaths in the last 14 days}_{c,d} \times \ \mathrm{X}_c + \alpha_c + \gamma_d + \varepsilon_{c,d} \end{aligned} \tag{3}$$

where X_c is a characteristic of interest (or *mediator)* of county *c*. δ_1 is the coefficient of interest. The regional characteristics of the county are measured in 2013, just before the period of analysis, to avoid concerns about reverse causality. As in the previous equation, as the presence of a notable death does not vary over counties, the number of notable deaths is included in the time fixed effects.

In order to specifically study the role of different characteristics on the probability of having a first protest, I use as an alternative outcome for all previous specifications a dummy variable equal to zero if the county has not had any BLM protest yet, equal to one if the county had its first BLM protest during the day, and is set to missing for all the days following the first protest, thus excluding them from the regression sample.

Finally, to study the link between different local characteristics and online BLM activity, I also use the number of tweets mentioning BLM in each county (i.e. coming from an account that I was able to map to a particular county) as an outcome of interest. Because of data collection constraints, I only collect the tweets that mention BLM published 14 days before and 14 days after each notable death occurred. Contrary to the other two outcomes that I use, for which I have data for every day during the four years of study, the sample of for the tweets is thus restricted to 28 days around each notable death. It is important to note two limitations of this data. First, tweets mentioning BLM can be tweets in favor of the movement or against. Thus, the measure of online activity that I use cannot be interpreted as a measure of online protest but rather as the intensity of the online discussion of BLM. Second, the accounts I am able to map to a geographical location may have different characteristics from the ones I am not able to map.

Overall, this empirical strategy ensures that I am estimating the effects of notable deaths and not the effects of something else. This is the case for multiple reasons. First, I study the effect of *several* notable deaths. If I were studying the effects of a one-time trigger, I should be worried it may have happened at the exact same time as another event that is causing the protest. In contrast, the study of several events makes it less likely that the timings of different notables deaths coincide systematically, by chance, with other such events, particularly since Black police-related deaths and their notable character are somewhat unpredictable. Second, the county fixed effects ensure that county-invariant characteristics over the period 2014–2018 are not driving the results. Finally, the exclusion of the county (or the state in the robustness check) in which the notable death took place ensures that there are no time-varying characteristics of the county that could be explaining the effect.

As explained above, one limitation of this strategy is that the coefficients estimated to analyze the role of local characteristics on protest behavior cannot be interpreted as causal. In other words, we are correctly measuring the effect of a notable death, but we might be measuring the differential effect of other characteristics (not necessarily time-varying) correlated to the one we want to measure.

Another limitation of this strategy is that it can only give insights on the determinants of protest triggered by notable deaths. Yet, notable deaths are not the only triggers of Black Lives Matter protests: in Figure 1, we observe other peaks of BLM protests that do not match with notable deaths. Some of them can be related to other events such as the shooting of a Black church in Charleston by a white supremacist in June 2015, and the Unite the Right white supremacist rally in Charlottesville in August 2017. As the list of these events is less clearly defined, I do not include them in my analysis.

5 Results

In this section I start by establishing that high-profile police-related deaths covered by major national media outlets –notable deaths– act as triggers for protest, and more so in regions with a higher ratio of Black population. Then I analyze the role of local factors on propensity to protest (both overall and for the first time) and on the intensity of the BLM debate online, measured by the number of tweets talking about BLM. I first study whether local past Black police-related deaths play a role in explaining the reaction to a protest trigger. Second, I study the role of local economic factors: measures of economic resource deprivation, mean GDP and inequality. Third, I analyze the role of social links and finally the role of political resources, namely the percentage of people registered to vote and the percentage that voted.

5.1 Notable deaths as a trigger

Table 2 presents the effect of notable deaths on offline protest participation and online BLM debate. Columns 1, 3 and 5 show that the number of notable Black police-related deaths in the last two weeks[7] increases both the number of BLM events on a given day and the probability of having the first protest. Notable deaths also increase the number of tweets mentioning BLM. The interaction with the percentage of Black population (columns 2, 4 and 6) indicates that the effect of protest triggers is higher in regions with a higher share of Black population. This is true for both the effect on the total number of BLM events and for the probability of having a first BLM event as well as for the BLM online activity measure.

5.2 Dynamics of protest and spillovers

In this subsection, I present the analysis of the dynamics of protest and the presence of spillovers. In particular, I study how the reaction to past notable deaths in the county itself or in surrounding regions affect subsequent reaction to a notable death. To do that, I interact the presence of a notable death with a certain spillover measure. I use four different spillover measures: (i) the cumulative number of past BLM events (taking into account all past reaction to notable deaths); (ii) the number of BLM events triggered by the previous notable death (taking into account events triggered by only one notable death); (iii) the cumulative number of large past BLM events (all BLM events until the day that had at least 10 thousand participants and (iv) the number of large BLM events triggered by the previous notable death. I conduct the analysis considering the past protest behavior at three different levels: past protest in the county itself, in neighboring counties and all counties of a same state (excluding the county of analysis). I present the results in Table 3. Panel A show the results for the past protest behavior in the county; panel B for past protest in neighboring counties while panel C at the level of the state. Columns 1 and 2 show the results for the number of events while columns 3 and 4 for the number of large events. Columns 1 and 3 presents the estimates for the cumulative number of events since the beginning of BLM and column 2 and 4 for the number of events triggered only by the preceding notable death. In general terms, results show that past protest behavior in county itself and surrounding counties can impact the likelihood of observing a BLM event after a new trigger.

For the past protest in the county itself, results are positive and significant when considering the total protest history but are not significant when considering the electoral behavior triggered by only the previous notable death. In general, magnitudes are higher than for surrounding regions.

For the past protest in surrounding areas, results show that past protest increase the probability of a BLM protest after a new trigger. This is true when considering both past behavior in neighboring counties and in the other counties in the whole state. However, magnitudes are higher for neighboring counties than counties in all the state, showing the importance of geographical closeness in behavior imitation. Magnitudes are also higher when considering events triggered by the preceding notable death suggesting that there might be a short memory effect were past events months or years ago are less relevant than more recent events. Finally, the coefficients are also higher when considering only large events showing that large events have a higher impact in increasing future probability of protesting.

[7]Note that I consider the number of BLM events at a county-day level, and there are few instances of a county having more than one event in a day, so the outcome "number of BLM events" can, with little error, be interpreted as the probability of observing a protest in a given county in a given day.

5.3 Factors favoring or preventing protest

5.3.1 Past exposure to usage of deadly force by the police

Block (I) of Table 4 presents the effect of past local exposure to the use of deadly force by the police against Black people. Column 1 of Panel A shows the estimate with the number of BLM events on a given day as the outcome while Panel B shows the first day with a protest as outcome. Higher past exposure to local police-related deaths of Black people per Black population is associated with higher protest response to a notable death outside the county. Similarly, higher past exposure of a county to Black deaths at the hands of the police is related to an increase in the number of tweets talking about BLM (Panel C). These results are consistent with previous literature showing that personal past grievances are an important factor determining future political attitudes (Madestam and Yanagizawa-Drott, 2012; Marchais et al., 2021).

5.3.2 Economic determinants: poverty and inequality

Columns 2-6 (or Block (II)) of Table 4 show the differential effects of notable deaths depending on five local economic indicators: two measuring resource deprivation, one measuring average income in the county and two measuring economic inequality. Columns 2 and 3 present the two measures of economic deprivation: respectively, the percentage of Blacks that are below the poverty line and the unemployment rate among Blacks.[8] Column 4 presents the estimates for the GDP per capita (as a proxy for average income in the county). Finally, columns 5 and 6 present the differential effect of two different inequality measures: the relative unemployment rate of Blacks over the total unemployment rate and the Gini index. Panel A presents the results for the number of BLM events; Panel B for the presence of the first protest during the week; and Panel C for the online activity around BLM.

Results show that a lack of economic resources is linked with a lower protest behavior. Indeed, counties with higher percentage of poor Blacks and higher Black unemployment rates are less likely to protest after a notable death (columns 2 and 3). Along the same line, having a higher per-capita GDP is associated with an increase in offline protests and online BLM activity (column 4). This economic obstacle exists both for all protests taken together and for the likelihood of protesting for the first time after a trigger. This may indicate a higher opportunity cost to protest for economically deprived people. Notably, an economic obstacle seems to exist as well for tweeting about BLM, a less costly form of political participation.[9] Research shows a positive effect of BLM protest both in reduction of police-caused Black deaths (Campbell, 2021) and in reduction of white prejudice (Mazumder, 2019). This suggests that the most vulnerable groups could benefit of protesting to improve their livelihoods. If however they cannot engage in it because they do not have the necessary resources, they are trapped in an equilibrium, which I call a "protest poverty trap". Such a negative relationship between poverty and protest, even if it has been theoretically hypothesized by political scientists under the name "resource mobilization theory" (McCarthy and Zald, 1977), goes in the opposite direction from the empirical findings in the literature that show a positive relationship between

[8] Note that both the Black poverty rate and the Black unemployment rate can be interpreted as the percentage of poor Blacks and unemployed Blacks over total population because we interact the protest trigger with the percentage of Black population and the Black poverty rate or the Black unemployment rate.

[9] This result is particularly remarkable because in the United States in 2014–2018, it is difficult to attribute it to a lack of access to Twitter.

economic poverty and social unrest (Berazneva and Lee, 2013; Hagemann and Kufenko, 2016; Sánchez and Namhata, 2019; Manacorda and Tesei, 2020).

The different variables I use to proxy for economic deprivation are likely to be correlated. Indeed, it might be a significant overlap between Black poor people and Black unemployed people. In order to disentangle the differential effect of those variables I run a regression including both at the same time. Results are shown in column 1 of Table 5. The coefficient for Black poverty rate and GDP per capita remain negative and significant. On the contrary, Black unemployment rate change signs and become positive ans significant. This could indicate that once we account for the income effect of unemployed we are able to observe a positive effect of unemployment probably coming from a reduced opportunity cost of protesting.

On the other hand, inequality seems to fuel protest, but only in counties that already had a BLM protest (columns 5 and 6). The two measures of inequality that I use (the ratio of Black unemployment rate over the unemployment rate of the entire population and the Gini index) are positively associated with the overall number of protests after a notable death (Panel A, columns 5 and 6). This result does not hold for the likelihood of observing the first protest in the county nor for the number of tweets mentioning BLM in the county (Panels B and C, columns 5 and 6). One possible explanation is that people living in counties with higher inequality levels may be accustomed to it, considering that as part of normality or thinking that the benefit of protesting is not high enough to surpass the costs. The presence of a first BLM protest can serve as an external signal of other people's beliefs and willingness to protest, thus changing the perception of the possible benefits of protesting. A BLM protest can also expose participants, and more generally, the region in which it takes place if there are spill-over effects, to a different narrative about inequality. As a consequence, people may perceive inequality more strongly or give it a stronger negative moral value, increasing their feelings of grievance. It is already well established in the literature that the perception of grievances—and not the objective situation—is what matters for mobilization (Justino and Martorano, 2016; Passarelli and Tabellini, 2017; Power, 2018).

In order to establish what type of inequality (racial or economic) is driving the results, I conduct a "horse race" where I include in the same regression the proxy variable I have for racial inequality (the ratio of the unemployment rate of Black people over the unemployment rate over the whole population) and the Gini index (accounting for economic inequality. I study the number of total BLM events as the outcome of interest. Results are presented in column 2 of Table 5. Both estimates remain positive and significant with similar magnitudes. This seems to indicate that both racial and economic inequality fuel the protest behavior.

5.3.3 Pre-existing social links and networks

Block (III) of Table 4 shows the influence of pre-existing social interactions and links on BLM protest and discussion activity after a notable death. Contrary to the literature (Algan et al., 2020), I find that counties with a higher number of religious and civic organizations (which can be consider a proxy for social interactions and links) protest relatively more and engage also relatively more in online BLM discussion after a trigger (columns 8 and 9, Panel A and C). This effect does not hold, however, for the probability of observing a first protest in a county (columns 8 and 9, Panel B). Pre-existing social networks can have several effects that favor protest, such as acting as an echo-chamber for a certain ideology or reducing coordination costs (Enikolopov et al., 2020). The results suggest that those effects only operate once the network has been exposed to a first BLM demonstration. Unlike social media, where discussion topics can be extremely diverse, offline civic and religious organizations usually center around a particular activity (for example playing chess, climbing mountains or doing charitable activities). People may be more reluctant to take advantage of those links to organize protests regarding another quite different topic. They may need an additional incentive (either internal, e.g. they feel a higher level of grievances, or external, e.g. they feel that the environment is more receptive to this "new" cause) to be willing to use those types of networks. The occurrence of BLM protests in the county can provide new information affecting both internal and external incentives to mobilize those networks.

5.3.4 Political determinants: formal political voice

Columns 10 and 11 (or block (IV)) of Table 4 show the estimates for the triple interaction with two mediators measuring the level of formal political voice available to Black people: the percentage of the Black population in the state that is registered to vote and the percentage of Black population that voted in 2014 mid-term elections. For both measures, the higher the magnitude, the higher the relative ability of Black people to voice their grievances trough formal electoral channels. Results show that the higher the ability to participate in traditional ways in the political debate, the lower the level of protest and informal political participation. This negative link between formal voice and protest holds for the total number of BLM events (Panel A, columns 10 and 11); for the likelihood of occurrence of the first BLM protest in a county (Panel B, the columns 10 and 11) and for the intensity of the Twitter BLM debate (Panel C, columns 10 and 11). These results suggest that formal political participation (such as electoral participation) and informal political participation (such as street protests) are substitutes rather than complements. This evidence contradicts one of the main theoretical mechanisms that political scientists and sociologists use to explain the determinants of social movements: the modernization theory. According to this theory, as regions develop, become more urban, more educated and richer, individuals' values change and they place greater importance on political and civil rights.

6 Robustness

Excluding the state of notable deaths In the main specification, I exclude county-day observations for counties where a notable death took place in the last 14 days, as the death might not be exogenous to these counties. As a robustness check, I also remove the entire state where the notable death took place, as the characteristics of the county were the death took place may be correlated with those of neighboring counties. Results are presented in Panel B of Table A1 (corresponding to Table 2) and Panel B of Tables A2, A3 and A4 corresponding respectively to Panels A, B, C of the main Table 4.[10] For all the estimates, both the magnitude and significance of the coefficients are very similar to those of the main specification.

Including all counties In the main specification, I exclude county-day observations for counties where a notable death took place in the last 14 days, as a robustness check I

[10]All robustness checks for the results on the effect of notable deaths and notable deaths interacted with Black population percentage are presented in Table A1. For the results using the triple interaction, each of the outcomes is presented in a different table (Tables A2, A3 and A4). For all tables, each Panel represents a different check. To make comparison easier, Panel A always repeats the main specification.

include those observations in the analysis. Results are presented in Panel B of Table A5 and Panels A and B of Table A6. Results show similar but slightly higher in magnitude for Table A5. For Table A6 we see similar results with slightly higher magnitudes. In addition, two coefficients become significant: unemployment ratio and number of civic organizations for the presence of a first BLM protest in a county (panel B). This results must be interpreted with caution as the inclusion of the county were a notable death took place adds endogeneity. Indeed, the probability of observing a notable death can be correlated with some characteristics of the county that can at their turn be related to the probability of observing a protest.

Different fixed effect structure As a control for possible time-varying characteristics of the county correlated both with police-related deaths and protest, I add different types of fixed effects to the specification. In Panel C of Tables A1, A2, A3 and A4, I add fixed effects for all state-month groups (i.e. groups formed by observations in a given state in a given month) in addition to county and day fixed effects. This controls for month-varying characteristics of states (but not counties). The results are robust to the use of this fixed effects structure.

As a more demanding version of this specification, I add state-day fixed effects instead of state-month (in addition to county fixed effects). This accounts for punctual events such as information shocks at the state level (for example, a tweet from a state governor) that are not long-lived but that can have punctual effects. Panel D of Tables A1, A2, A3 and A4 present the results. As this specification includes fixed effects at the day-level and the notables deaths are also measured in a given day, I cannot present the results for the estimation of the effect of a notable death on protest in Table A1 and instead only present the interaction estimates with the Black population. Overall, results remain robust. All estimates that were significant remain significant. Magnitudes are higher (almost double) for the differential effect of having a higher percentage of Black population for all outcomes (columns 2, 4 and 6 of Table A1). The magnitudes are also higher for the estimates using the two measures of political voice as a mediator term for all outcomes (Block (IV) of Tables A2, A3 and A4) One coefficient that was not significant before becomes significant (Table A3, column 5, Panel D). I interpret that as a type I error.

Including county time trends To account for county-specific trends in characteristics, I add county-fixed trends, i.e. a per-county linear trend. The results, presented in Panel E, remain the same in terms of significance and very similar in magnitude.

Controlling for notable deaths instead of day fixed effects Including day fixed effects, as in my preferred specification, removes the possibility of controlling for the presence of a notable death on a given day. As a robustness check, I remove the time fixed effects and control for the presence of a notable death at a given day. Results are shown in Panel F of Tables A1, A2, A3 and A4. Results are almost identical both in magnitude and in significance levels, suggesting that day fixed effects capture mainly variation of the presence or absence of a notable death in the day.

Varying the trigger window I test that the results are robust to changing the time window used for triggers. In the main specification, BLM events on day d are predicted using the notable deaths during days $d - 13$ to d. This allows a trigger to have an effect during the two following weeks. I restrict here this window allowing a notable death to have an effect only during the following week. Results are shown in Panel G of Tables A1, A2, A3 and A4. The significance of the results are similar to the main specification. The magnitudes of the results are in general higher (between 1,5 and 2 times higher than for the main specification). This is consistent with the fact that we expect any reaction to a death to take place rather shortly after the death took place. Restricting the window to one week increases the power of the estimates as the effect of the trigger is less diluted with the following days.

7 Conclusion

Protests are important in shaping institutions and bringing about social change. Yet, their determinants remain poorly understood. In this paper, I investigate which local characteristics are associated with different offline protest and online discussion reaction to a BLM national protest trigger: the death of a Black person in the hand of the police covered by the national media.

In particular, I use panel data to estimate a two-way fixed effects model to study the differential effects of local characteristics in counties with a high percentage of Black population—which is the most concerned population and the one most likely to protest in this particular period–0-to a high-profile, nationally mediatized Black death caused by the police. I am interested in three different outcomes: the number of BLM protests, the probability of observing the first protest in a county and the number of tweets mentioning BLM (as a proxy for the intensity in the online discussion about BLM).

I find that local past-experiences, economic resources, inequality, social networks and political resources can account for part of the different regional protest and online activity response to a same trigger. In particular, I find that: 1) Past protest in the county itself and in surrounding areas increase the likelihood of observing a BLM event after a new trigger, even more so if past protest are larger, are closer geographically to the county or are closer in time to the date of a new trigger. 2) Past-exposure to police use of deadly force in the region is linked to a higher response. 3) Resource deprivation is linked to a lower protest response. 4) Inequality is linked to a higher number of protests but not to a higher probability of having a first protest. 5) Pre-existing social and religious organizations is linked to a higher number of protests but, again, not to a higher probability of having a first protest and 6) higher level of political voice of Black people is linked to a lower protest response.

Overall, this paper provides empirical evidence for several takeaways. First, the existence of a "protest poverty trap" where individuals who could benefit the most by protesting are not able to do so. This obstacle is also present for less costly ways of political participation: tweeting about BLM. Second, local protest can act as an informational shock to the region. They can provide information about other people's political preferences and expose people to narratives about their economic, political and social situation to which they have not been exposed before. This new information can change the interpretation of one's own social context, increasing grievance and allowing individuals to be less reluctant when taking advantage of their social network to push forward their protest agenda. These information shocks can in turn change how local characteristics affect the response to a protest trigger, suggesting the possibility of dynamic (rather than constant) patterns of the effect of local characteristics. Third, formal ways of expressing political preferences or grievances, such as voting, may be substitutes to informal ways of expressing it, such as protesting.

References

1. **Acemoglu, Daron and James A Robinson**, "A theory of political transitions," *American Economic Review*, 2001, *91* (4), 938–963.

2. ______ **, Tarek A Hassan, and Ahmed Tahoun**, "The power of the street: Evidence from egypt's arab spring," *The Review of Financial Studies*, 2017, *31* (1), 1–42.

3. **Algan, Yann, Clément Malgouyres, and Claudia Senik**, "Territories, well-being and public policy," *Notes du conseil d'analyse économique, 2020/1*, 2020, *55* (1), 1–12.

4. **Allcott, Hunt and Matthew Gentzkow**, "Social media and fake news in the 2016 election," *Journal of economic perspectives*, 2017, *31* (2), 211–36.

5. **Barrera, Oscar, Sergei Guriev, Emeric Henry, and Ekaterina Zhuravskaya**, "Facts, alternative facts, and fact checking in times of post-truth politics," *Journal of Public Economics*, 2020, *182*, 104123.

6. **Berazneva, Julia and David R Lee**, "Explaining the African food riots of 2007–2008: An empirical analysis," *Food Policy*, 2013, *39*, 28–39.

7. **Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan**, "How much should we trust differences-in-differences estimates?," *The Quarterly journal of economics*, 2004, *119* (1), 249–275.

8. **Black Lives Matter**, "Home - Black Lives Matter," https://blacklivesmatter.com/ 2020. Accessed: 2020-10-31.

9. **Bozzoli, Carlos and Tilman Brück**, "Determinants of protests: Longitudinal evidence from Ukraine's Orange Revolution," 2010.

10. **Bursztyn, Leonardo, Davide Cantoni, David Y Yang, Noam Yuchtman, and Y Jane Zhang**, "Persistent political engagement: Social interactions and the dynamics of protest movements," *American Economic Review: Insights*, 2021, *3* (2), 233–50.

11. **Campbell, Travis**, "Black Lives Matter's Effect on Police Lethal Use-of-Force," *Available at SSRN*, 2021.

12. **Cantoni, Davide, David Y Yang, Noam Yuchtman, and Y Jane Zhang**, "Protests as strategic games: experimental evidence from Hong Kong's antiauthoritarian movement," *The Quarterly Journal of Economics*, 2019, *134* (2), 1021–1077.

13. **Chenoweth, Erica and Jay Ulfelder**, "Can structural conditions explain the onset of nonviolent uprisings?," *Journal of Conflict Resolution*, 2017, *61* (2), 298–324.

14. **Choi, Chonghyun and Dongwook Kim**, "The Determinants of Anti-Government Protests in Asia," *Journal of East Asian Studies*, 2019, *19* (3), 315–338.

15. **Collins, William J and Robert A Margo**, "The economic aftermath of the 1960s riots in American cities: evidence from property values," *The Journal of Economic History*, 2007, *67* (4), 849–883.

16. **Dalton, Russell, Alix Van Sickle, and Steven Weldon**, "The individual–institutional nexus of protest behaviour," *British journal of political science*, 2010, *40* (1), 51–73.

17. **DellaVigna, Stefano and Ethan Kaplan**, "The Fox News effect: Media bias and voting," *The Quarterly Journal of Economics*, 2007, *122* (3), 1187–1234.

18. **Durante, Ruben, Paolo Pinotti, and Andrea Tesei**, "The political legacy of entertainment TV," *American Economic Review*, 2019, *109* (7), 2497–2530.

19. **Edwards, Frank, Hedwig Lee, and Michael Esposito**, "Risk of being killed by police use of force in the United States by age, race–ethnicity, and sex," *Proceedings of the National Academy of Sciences*, 2019, *116* (34), 16793–16798.

20. **El-Mallakh, Nelly, Mathilde Maurel, and Biagio Speciale**, "Arab spring protests and women's labor market outcomes: Evidence from the Egyptian revolution," *Journal of Comparative Economics*, 2018, *46* (2), 656–682.

21. **Enikolopov, Ruben, Alexey Makarin, and Maria Petrova**, "Social media and protest participation: Evidence from Russia," *Econometrica*, 2020, *88* (4), 1479–1514.

22. **______, Maria Petrova, and Konstantin Sonin**, "Social media and corruption," *American Economic Journal: Applied Economics*, 2018, *10* (1), 150–74.

23. **Ferraz, Claudio and Frederico Finan**, "Exposing corrupt politicians: the effects of Brazil's publicly released audits on electoral outcomes," *The Quarterly journal of economics*, 2008, *123* (2), 703–745.

24. **González, Felipe**, "Collective action in networks: Evidence from the Chilean student movement," *Journal of Public Economics*, 2020, *188*, 104220.

25. **Goodwin, Jeff and James M Jasper**, *The social movements reader: Cases and concepts*, John Wiley & Sons, 2014.

26. **Hagemann, Harald and Vadim Kufenko**, "Economic, structural and socio-psychological determinants of protests in Russia during 2011–2012: Empirical analysis on a regional level," *Economics of Transition*, 2016, *24* (1), 3–30.

27. **Iacoella, Francesco, Patricia Justino, and Bruno Martorano**, "Do pandemics lead to rebellion? Policy responses to COVID-19, inequality, and protests in the USA," Technical Report, World Institute for Development Economic Research (UNU-WIDER) 2021.

28. **Justino, Patricia and Bruno Martorano**, "Inequality, distributive beliefs and protests: A recent story from Latin America," 2016.

29. **Kołczyńska, Marta**, "Changes or cross-national differences? Effects of economic inequality on protest participation," *Social Science Quarterly*, 2020, *101* (1), 256–268.

30. **Larreboure, Magdalena and Felipe González**, "The impact of the Women's March on the US House Election," *Documento de Trabajo IE-PUC*, 2021, (560).

31. **Levy, Roee and Martin Mattsson**, "The effects of social movements: Evidence from# MeToo," *Available at SSRN 3496903*, 2020.

32. **Lohmann, Susanne**, "Information aggregation through costly political action," *The American Economic Review*, 1994, pp. 518–530.

33. **Madestam, Andreas and David Hans Yanagizawa-Drott**, "Shaping the nation: The effect of Fourth of July on political preferences and behavior in the United States," *HKS Faculty Research Working Paper Series*, 2012.

34. **______, Daniel Shoag, Stan Veuger, and David Yanagizawa-Drott**, "Do political protests matter? evidence from the tea party movement," *The Quarterly Journal of Economics*, 2013, *128* (4), 1633–1685.

35. **Manacorda, Marco and Andrea Tesei**, "Liberation technology: Mobile phones and political mobilization in Africa," *Econometrica*, 2020, *88* (2), 533–567.

36. **Marchais, Gauthier, Christian M Mugaruka, Raúl Sanchez de la Sierra, and David Qihang Wu**, "The Forging of a Rebel," Technical Report, National Bureau of Economic Research 2021.

37. **Massoud, Tansa George, John A Doces, and Christopher Magee**, "Protests and the Arab Spring: an empirical investigation," *Polity*, 2019, *51* (3), 429–465.

38. **Mazumder, Soumyajit**, "Black Lives Matter for Whites' Racial Prejudice: Assessing the Role of Social Movements in Shaping Racial Attitudes in the United States," 2019.

39. **McCarthy, John D. and Mayer N. Zald**, "Resource Mobilization and Social Movements: A Partial Theory," *American Journal of Sociology*, 1977, *82* (6), 1212–1241.

40. **Muller, Edward N**, "Income inequality, regime repressiveness, and political violence," *American sociological review*, 1985, pp. 47–61.

41. **Passarelli, Francesco and Guido Tabellini**, "Emotions and political unrest," *Journal of Political Economy*, 2017, *125* (3), 903–946.

42. **Porta, Donatella Della and Mario Diani**, *The Oxford handbook of social movements*, Oxford University Press, 2015.

43. **Power, Séamus A**, "The deprivation-protest paradox: how the perception of unfair economic inequality leads to civic unrest," *Current Anthropology*, 2018, *59* (6), 765–789.

44. **Rupasingha, Anil, Stephan J Goetz, and David Freshwater**, "The production of social capital in US counties," *The journal of socio-economics*, 2006, *35* (1), 83–101.

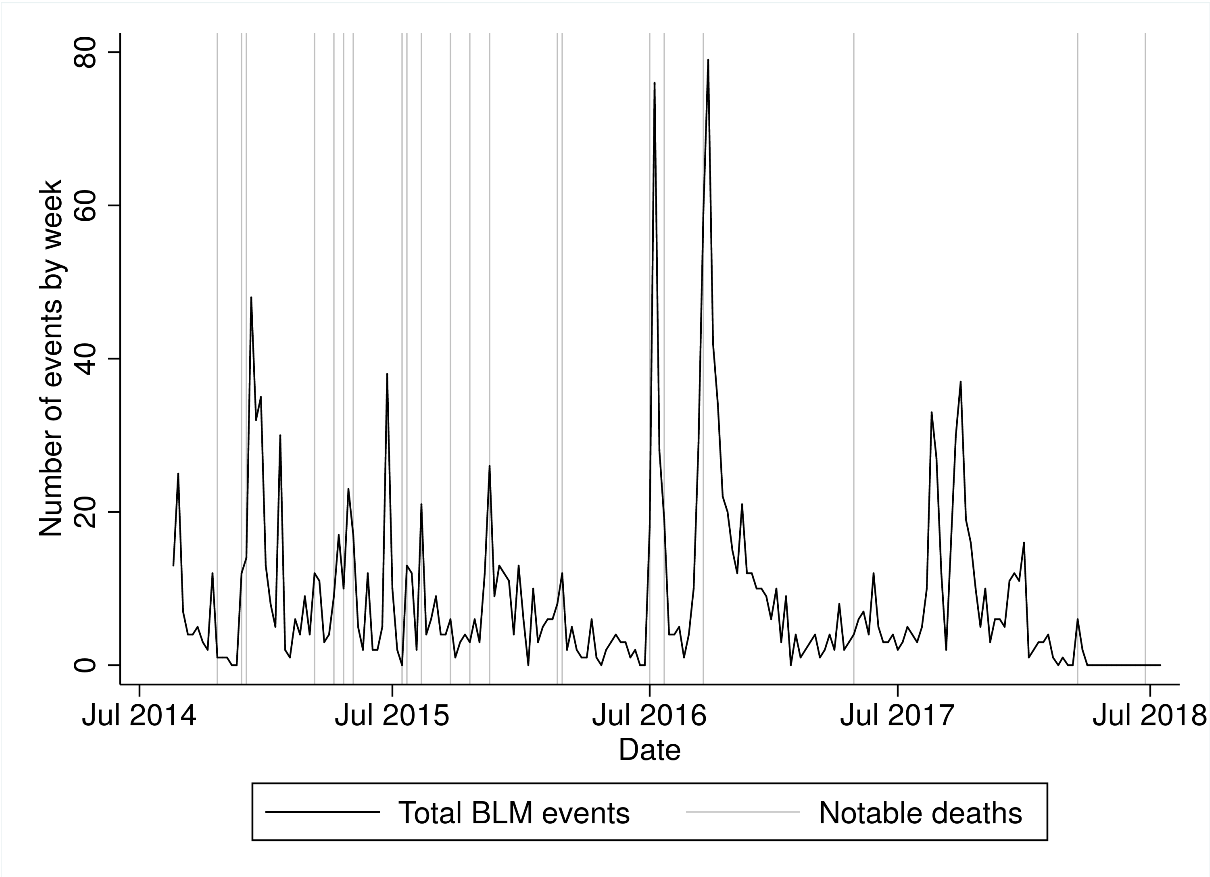
45. **Sánchez, Alfonso and Chandreyee Namhata**, "What feeds protest participation in sub-Saharan Africa? An empirical analysis," *Global Food Security*, 2019, *23*, 74–84.

46. **Solt, Frederick**, "Economic inequality and nonviolent protest," *Social Science Quarterly*, 2015, *96* (5), 1314–1327.

47. **Williamson, Vanessa, Kris-Stella Trump, and Katherine Levine Einstein**, "Black lives matter: Evidence that police-caused deaths predict protest activity," *Perspectives on Politics*, 2018, *16* (2), 400–415.

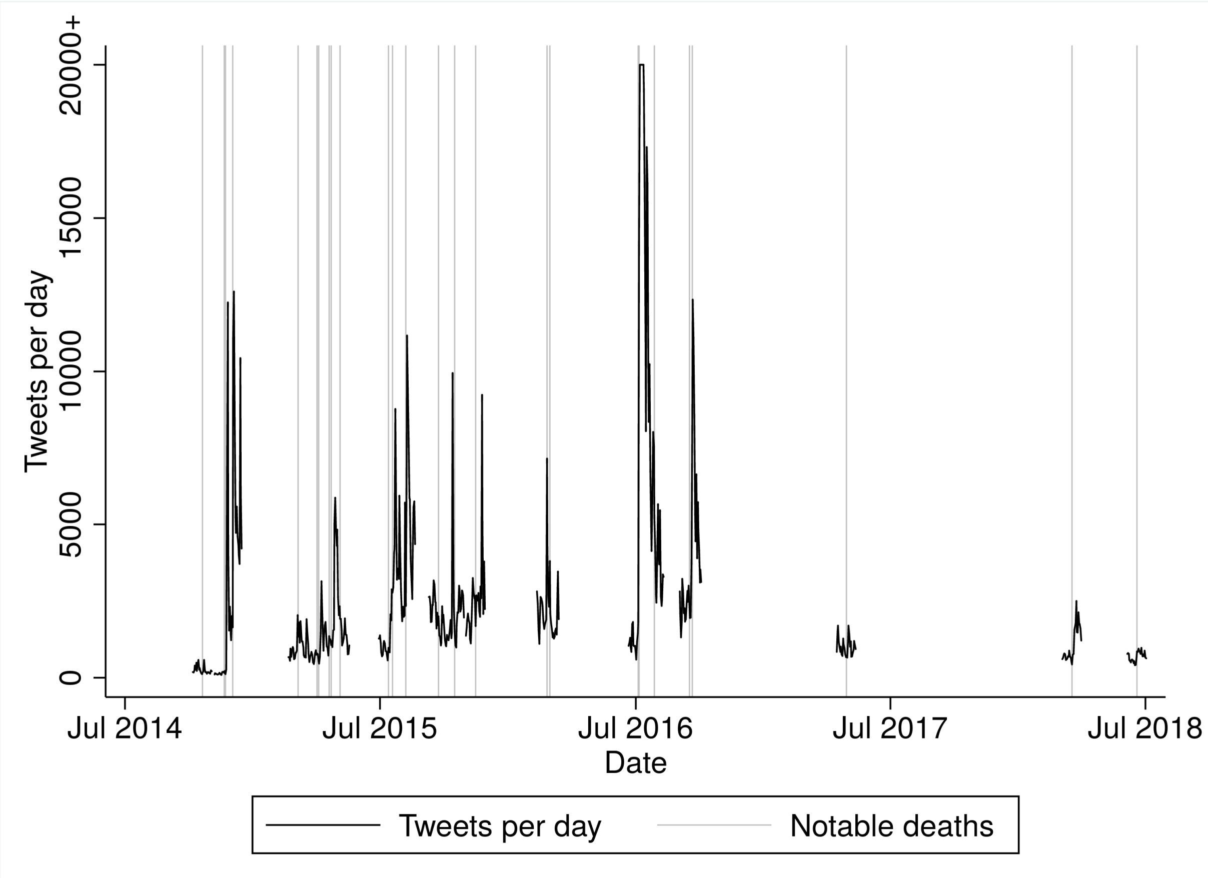
8 Figures

Figure 1: BLM events and notable deaths over time



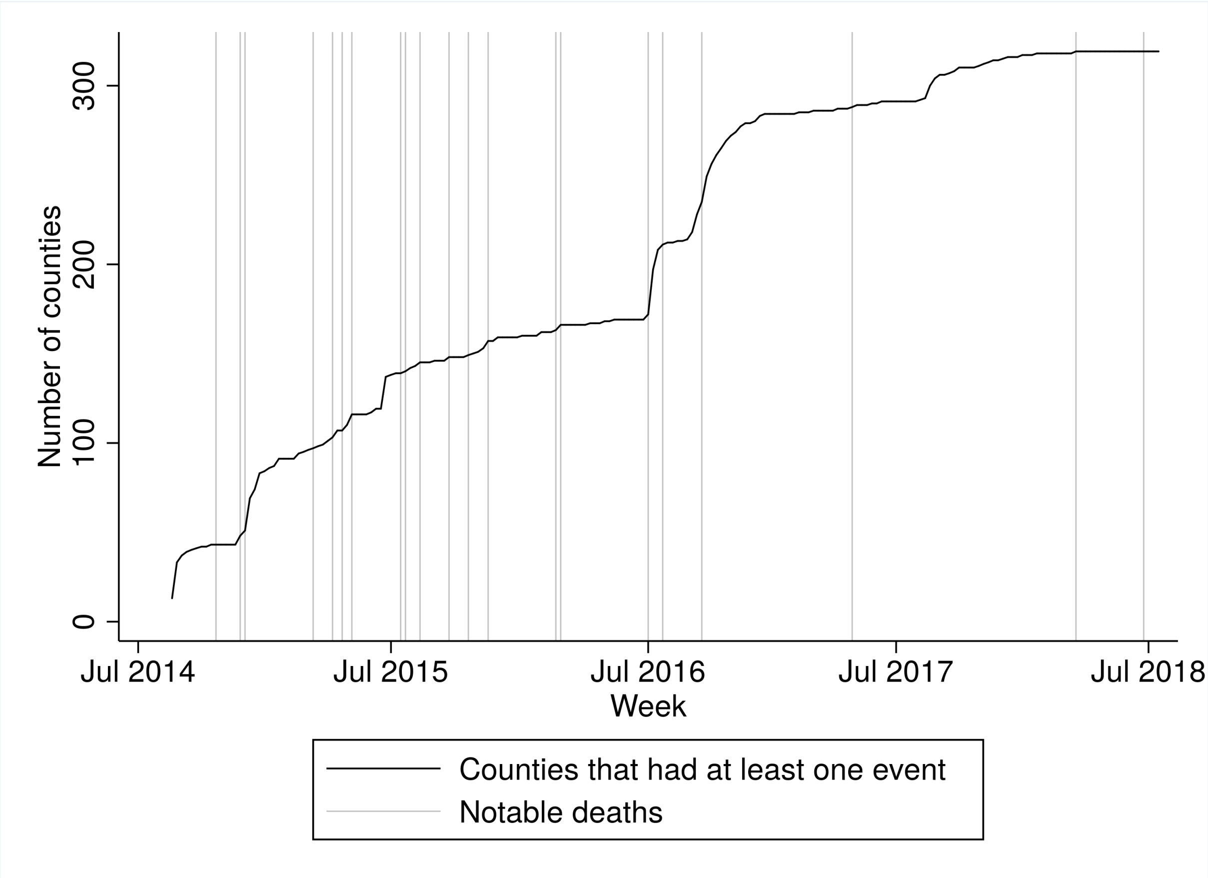
Note: Graph of the number of BLM events each week over time, summed over all counties. Grey vertical lines represent the weeks of notable police-related Black deaths.

Figure 2: Number of tweets over time



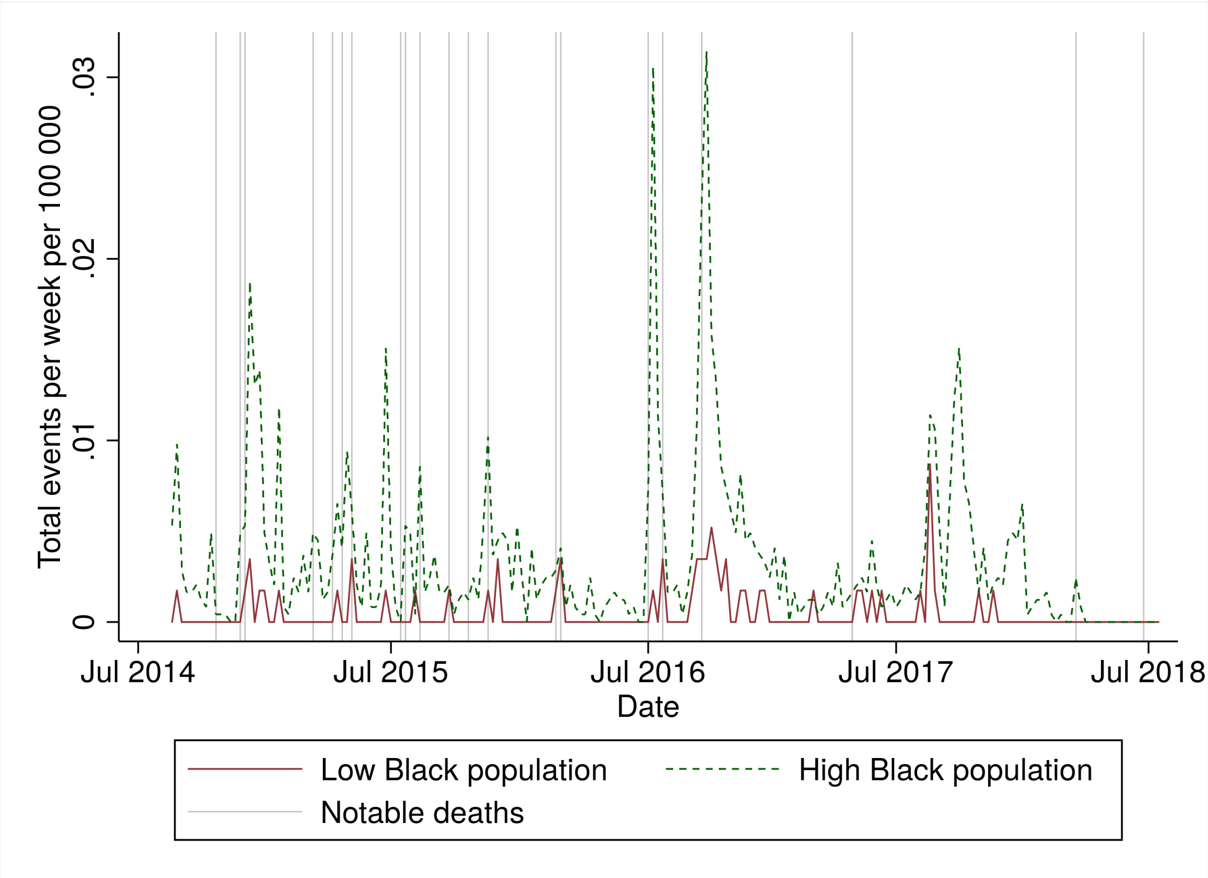
Note: Graph of the number of tweets mentioning BLM each day over time, summed over all counties. Grey vertical lines represent the days of notable police-related Black deaths. Tweets have been collected for 14 day before and after each notable deaths.

Figure 3: Cumulative number of counties that had at least one BLM event



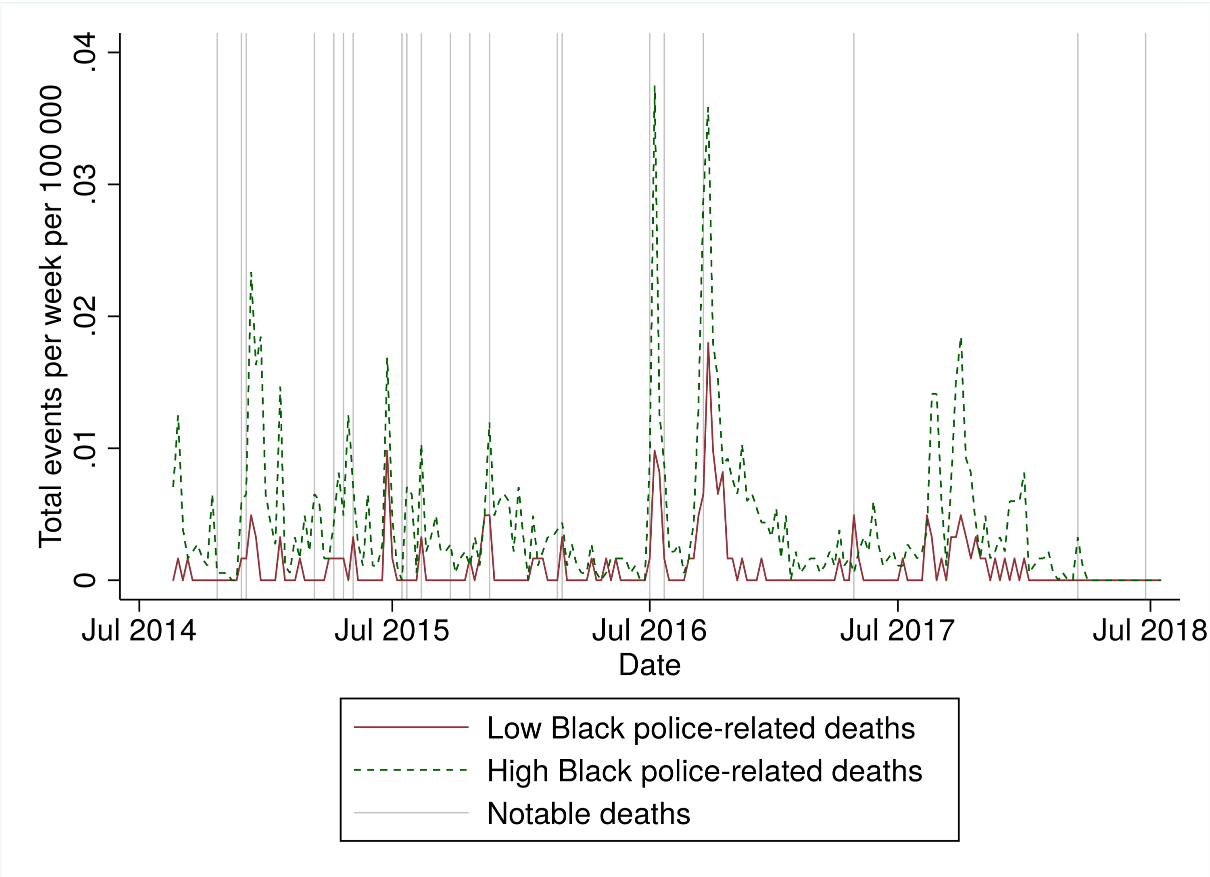
Note: Graph of the cumulative number of counties that have had at least one BLM event over time. Grey vertical lines represent the weeks of notable police-related Black deaths.

Figure 4: BLM events over time, counties with low and high Black population



Note: Graph of the number of BLM events per 100 000 inhabitants each week over time, for the groups of counties with below-median and above-median Black population percentage. The median Black population percentage is 2.2%. Grey vertical lines represent the weeks of notable police-related Black deaths.

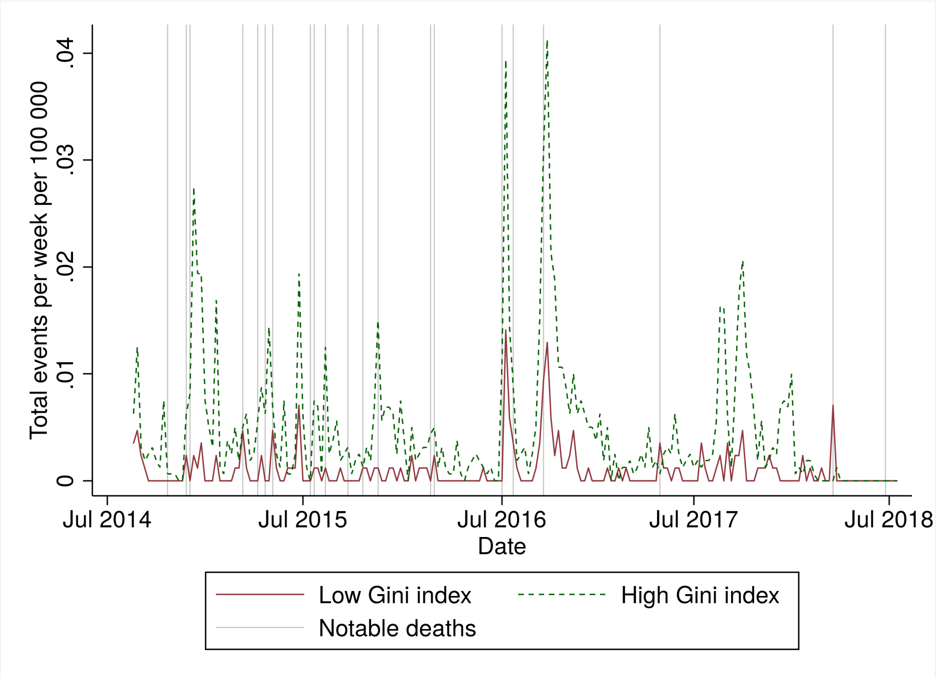
Figure 5: BLM events over time, counties with high Black population, split by previous experiences with police brutality



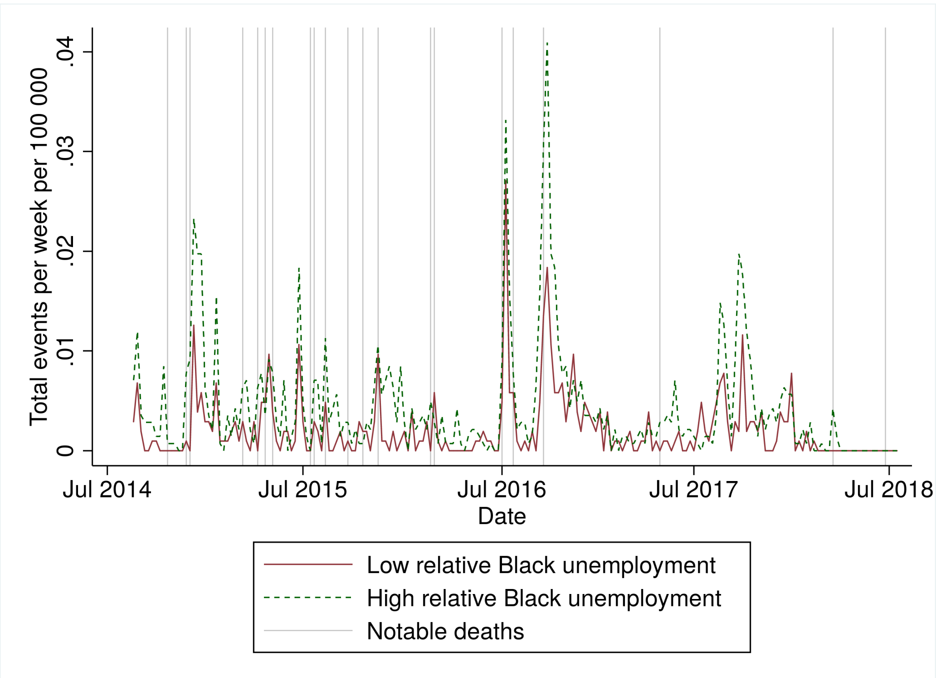
Note: Graph of the number of BLM events per 100 000 each week over time. The sample is restricted to counties with above-median Black percentage. Among these, counties are split between counties with below-median and above-median Black police-related deaths per black population. Grey vertical lines represent the weeks of notable police-related Black deaths.

Figure 6: BLM events over time, counties with high Black population, split by county characteristics

(a) Low and high Gini index



(b) Low and high relative Black unemployment



Note: Graph of the number of BLM events per 100 000 each week over time. The sample is restricted to counties with above-median Black percentage. Among these, counties are split between counties with below-median and above-median characteristics. Figure (a) separates counties with below and above-median Gini index. Figure (b) separates counties with below and above-median relative Black unemployment, i.e. the ratio of Black unemployment over general unemployment. Grey vertical lines represent the weeks of notable police-related Black deaths.

Figure 7: Spatial distribution of BLM events

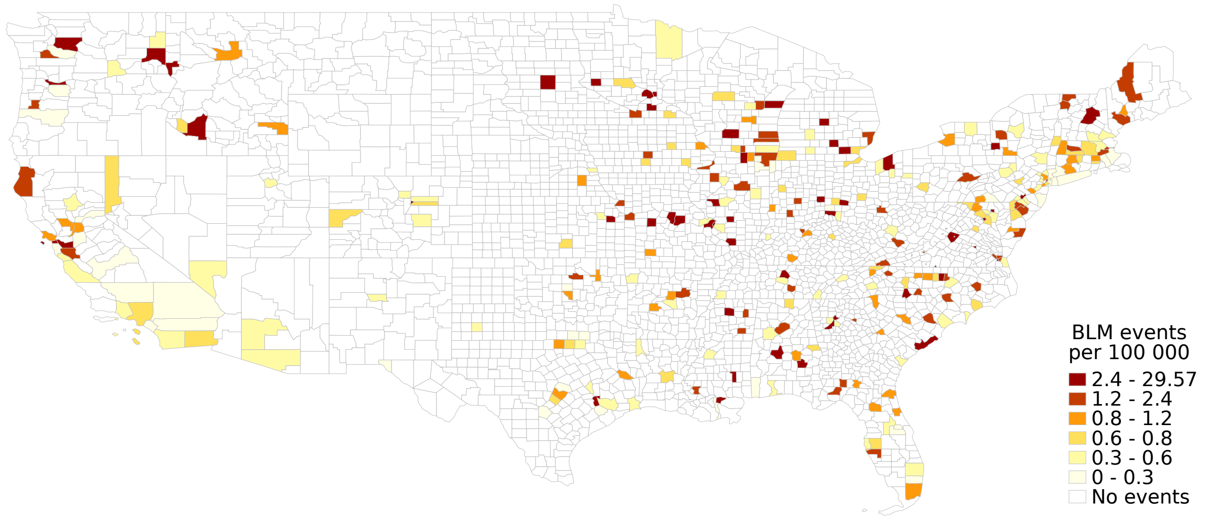


Figure 8: Spatial distribution of notable deaths

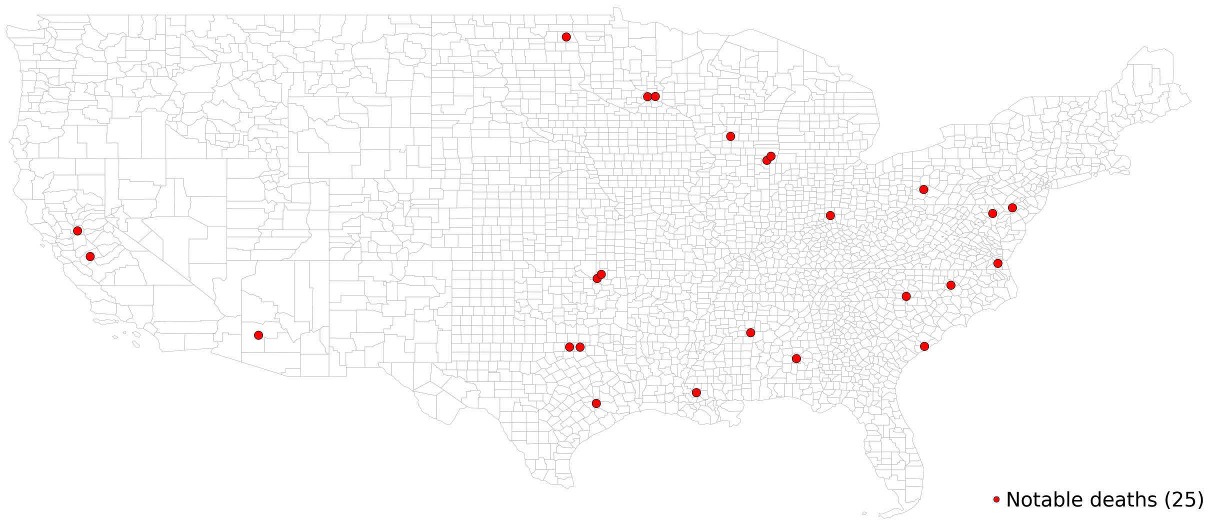
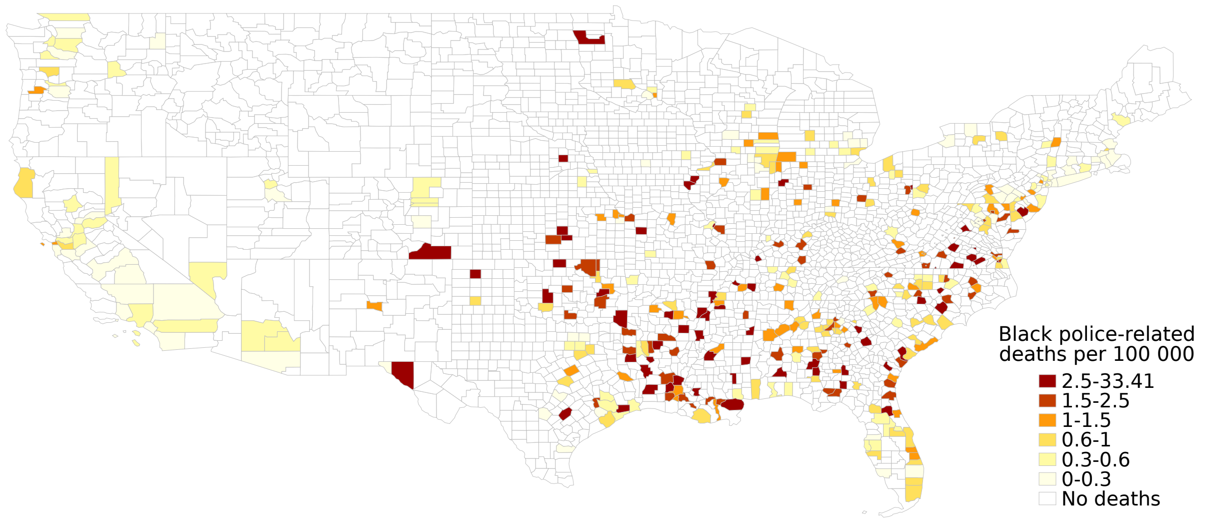


Figure 9: Spatial distribution of Black police-related deaths



9 Tables

Table 1: Descriptive statistics

Variable	obs.	mean	sd	min	median	max
BLM events	4445619	0.0004	0.022	0.000	0.000	7.000
Notable deaths (national)	4445619	0.0175	0.131	0.000	0.000	1.000
Tweets	1515057	0.8926	15.26	0.000	0.000	4863.000
Share of Black population	4445619	0.0904	0.146	0.000	0.022	0.862
Past police-related deaths (per Black pop.)	4302719	0.0001	0.002	0.000	0.000	0.200
Black poverty rate	4186970	33.0540	22.458	0.000	31.200	100.000
Unemployment rate, Black	4008345	16.9501	18.002	0.000	14.400	100.000
GDP per capita	4445619	52.5551	220.613	6.874	37.307	10340.104
Unemployment ratio (Black/all)	4006916	2.0202	3.310	0.000	1.478	55.556
County Gini Index	4445619	0.4381	0.035	0.332	0.436	0.599
Civic organizations	4445619	8.3658	20.920	0.000	2.000	546.000
Religious organizations	4445619	59.1067	125.815	0.000	24.000	3275.000
% Black registered to vote	3538204	59.7532	8.346	34.600	59.700	83.200
% Black who voted in 2014	3538204	37.2727	6.994	17.200	38.000	51.200

Table 2: Black Lives Matter protest triggers

VARIABLES	Number of BLM events		First day with BLM events		Number of tweets mentioning BLM	
	(1)	(2)	(3)	(4)	(7)	(8)
Notable deaths (last 14 days)	0.000350***		7.70e-05***		0.772***	
	(3.32e-05)		(1.39e-05)		(0.0661)	
Notable deaths (last 14 days) × Ratio black population		0.00191***		0.000295**		4.269***
		(0.000308)		(0.000118)		(0.808)
Mean of dep. var.	0.000387	0.000387	7.67e-05	7.67e-05	0.885	0.885
Observations	4,445,263	4,445,263	4,147,562	4,147,562	1,514,707	1,514,707
Day fixed effects		Y		Y		Y
County fixed effects	Y	Y	Y	Y	Y	Y

Note: Regression of the number of BLM events on protest triggers and protest triggers interacted with the proportion of Black population in the county. Observations correspond to county-day combinations. Proportion of black population at the county level measured in 2013. Columns 3 and 4 exclude all observations after the first BLM event in a county. Column 5 and 6 use tweets as outcome and are restricted to dates within 14 days of a notable death. All models include county fixed effects, columns 2 and 4 additionally include week fixed effects. Standard errors, in parentheses, are clustered at the county-treatment level. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Spillover effects

	Outcome: Number of BLM events			
Spillover measure:	Number of events		Number of events > 10 000	
	Cumulative	Previous death	Cumulative	Previous death
	(1)	(2)	(3)	(4)
	Panel A: Past protests in county			
Notable deaths (last 14 days)	0.000515***	0.000806	0.0103**	-0.00311
× *Spillover measure*	(0.000139)	(0.00181)	(0.00507)	(0.0144)
	Panel B: Neighboring counties			
Notable deaths (last 14 days)	2.46e-08**	2.03e-06***	1.69e-06	0.000161**
× *Spillover measure*	(9.86e-09)	(4.75e-07)	(1.10e-06)	(7.01e-05)
	Panel C: Same state			
Notable deaths (last 14 days)	2.62e-09**	1.22e-07**	7.87e-07***	3.88e-05***
× *Spillover measure*	(1.14e-09)	(6.11e-08)	(2.65e-07)	(1.23e-05)
Observations	4,445,263	4,202,625	4,445,263	4,202,625
Mean of dependent variable	0.000387	0.000392	0.000387	0.000392
County fixed effects	Y	Y	Y	Y

Note: Regression of the number of BLM events on protest triggers and protest triggers interacted with a measure of past protest close to the county. Panel A considers past protest in the county itself. Panel B considers protest in counties bordering the county of interest. Panel C considers all counties in the same state, except the county of interest. Column 1 and 2 use the number of protests as a measure, column 3 and 4 use the number of protests with more than 10 000 participants. Columns 1 and 3 consider all historical protests, column 2 and 4 consider only protests in the 14 days following the previous notable death. All models include county fixed effects. Standard errors, in parentheses, are clustered at the county-treatment level. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Effect of resources on protest

	Block I Experience	Block II Economic					Block III Social		Block IV Political	
Mediator:	Black police-related deaths	Black poverty rate	Black unemployment rate	GDP per capita	Unemployment ratio (Black/ all)	Gini index	Civic orgs.	Religious orgs.	Blacks registered to vote (%)	Blacks who voted (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)	(10)	(11)
	Panel A: Outcome: Number of BLM events									
Notable deaths × Ratio black × *Mediator*	29.42***	-0.000161***	-7.90e-05***	0.000188***	0.00312***	0.0290***	0.000306***	3.59e-05***	-0.000158***	-0.000263***
	(8.062)	(2.50e-05)	(2.49e-05)	(3.51e-05)	(0.000635)	(0.0100)	(9.23e-05)	(1.22e-05)	(3.10e-05)	(7.43e-05)
Mean dep. var.	0.000400	0.000411	0.000430	0.000387	0.000430	0.000387	0.000387	0.000387	0.000465	0.000465
Observations	4,302,363	4,186,614	4,007,989	4,445,263	4,006,560	4,445,263	4,445,263	4,445,263	3,537,862	3,537,862
	Panel B: Outcome: First BLM event									
Notable deaths × Ratio black × *Mediator*	4.695**	-3.61e-05***	-3.75e-05***	1.86e-05***	0.000223	-0.00479	0.000124	1.53e-05	-2.86e-05**	-8.40e-05**
	(1.948)	(1.16e-05)	(1.22e-05)	(6.42e-06)	(0.000146)	(0.00310)	(7.92e-05)	(1.18e-05)	(1.21e-05)	(4.22e-05)
Mean dep. var.	7.94e-05	8.18e-05	8.57e-05	7.67e-05	8.57e-05	7.67e-05	7.67e-05	7.67e-05	8.75e-05	8.75e-05
Observations	4,004,662	3,888,913	3,710,288	4,147,562	3,708,859	4,147,562	4,147,562	4,147,562	3,267,434	3,267,434
	Panel C: Outcome: Number of tweets									
Notable deaths × Ratio black × *Mediator*	47,330***	-0.627***	-0.377***	0.196***	0.0655	-3.617	0.382**	0.102**	-0.431***	-0.873***
	(7,905)	(0.149)	(0.114)	(0.0524)	(1.334)	(37.33)	(0.186)	(0.0453)	(0.0839)	(0.220)
Mean dep. var.	0.912	0.934	0.972	0.885	0.972	0.885	0.885	0.885	1.044	1.044
Observations	1,466,007	1,426,560	1,365,685	1,514,707	1,365,198	1,514,707	1,514,707	1,514,707	1,205,476	1,205,476
Day fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Regression of BLM events outcomes on the triple interaction of notable deaths in the last two weeks, the proportion of black population in the country, and county characteristics. Panel A and B use the number of BLM events as an outcome, panel B excludes all county-week observations after the first BLM event in a county. Panel C uses the number of tweets mentioning BLM as outcome, and is restricted to observations within 14 days of a notable death. Mediators are indicated as column headers. Black police-related deaths are the number of previous police-related deaths of Blacks divided by the Black population of the county. Unemployment ratio is the ratio of the Black unemployment rate over the general unemployment rate. The coefficients of lower-level interaction terms are omitted. All models include county and week fixed effects. Standard errors, in parentheses, are clustered at the county-treatment level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Horseraces, BLM events

	Number of BLM events	
	(1)	(2)
. . . × Black poverty rate	-6.47e-05***	
	(2.22e-05)	
. . . × Black unemployment rate	0.000119***	
	(3.95e-05)	
. . . × Unemployment ratio (Black / all)		0.00267***
		(0.000606)
. . . × Gini index		0.0261**
		(0.0103)
Observations	4,005,131	4,006,560
Mean of dependent variable	0.000430	0.000430
Day fixed effects	Y	Y
County fixed effects	Y	Y

Note: Regression of tweet outcomes on the triple interaction of notable deaths in the last two weeks, the proportion of black population in the country, and county characteristics. Unemployment ratio is the ratio of the Black unemployment rate over the general unemployment rate. The coefficients of lower-level interaction terms are omitted. All models include county and week fixed effects. Standard errors, in parentheses, are clustered at the county-treatment level. *** p<0.01, ** p<0.05, * p<0.1

A Appendix

Table A1: Robustness: Black Lives Matter protest triggers

VARIABLES	Number of BLM events		First day with BLM events		Number of tweets mentioning BLM	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Main specification						
Notable deaths (last 14 days)	0.000350***		7.70e-05***		0.772***	
	(3.32e-05)		(1.39e-05)		(0.0661)	
Notable deaths (last 14 days) × Ratio black population		0.00191***		0.000295**		4.269***
		(0.000308)		(0.000118)		(0.808)
Mean of dep. var.	0.000387	0.000387	7.67e-05	7.67e-05	0.885	0.885
Observations	4,445,263	4,445,263	4,147,562	4,147,562	1,514,707	1,514,707
Panel B: Excluding state of event						
Notable deaths (last 14 days)	0.000350***		7.62e-05***		0.776***	
	(3.41e-05)		(1.41e-05)		(0.0683)	
Notable deaths (last 14 days) × Ratio black population		0.00191***		0.000309**		4.383***
		(0.000320)		(0.000123)		(0.850)
Mean of dep. var.	0.000386	0.000386	7.58e-05	7.58e-05	0.880	0.880
Observations	4,412,393	4,412,393	4,116,366	4,116,366	1,482,521	1,482,521
Panel C: State-month fixed effects						
Notable deaths (last 14 days)	0.000327***		8.32e-05***		0.796***	
	(4.04e-05)		(1.79e-05)		(0.0764)	
Notable deaths (last 14 days) × Ratio black population		0.00240***		0.000386***		5.233***
		(0.000380)		(0.000145)		(0.941)
Mean of dep. var.	0.000387	0.000387	7.67e-05	7.67e-05	0.885	0.885
Observations	4,445,263	4,445,263	4,147,562	4,147,562	1,514,707	1,514,707
Panel D: State-day fixed effects						
Notable deaths (last 14 days) × Ratio black population		0.00356***		0.000558**		9.426***
		(0.000630)		(0.000231)		(1.543)
Mean of dep. var.	0.000387	0.000387	7.67e-05	7.67e-05	0.885	0.885
Observations		4,443,834		4,146,821		1,514,220
Panel E: County trends						
Notable deaths (last 14 days)	0.000340***		7.54e-05***		0.790***	
	(3.45e-05)		(1.41e-05)		(0.0689)	
Notable deaths (last 14 days) × Ratio black population		0.00178***		0.000299**		4.321***
		(0.000316)		(0.000124)		(0.843)
Mean of dep. var.	0.000387	0.000387	7.67e-05	7.67e-05	0.885	0.885
Observations	4,445,263	4,445,263	4,147,562	4,147,562		
Panel F: No time fixed effects						
Notable deaths (last 14 days)	0.000350***	0.000177***	7.70e-05***	5.17e-05***	0.772***	0.386***
	(3.32e-05)	(2.48e-05)	(1.39e-05)	(1.28e-05)	(0.0661)	(0.0504)
Notable deaths (last 14 days) × Ratio black population		0.00191***		0.000295**		4.268***
		(0.000309)		(0.000118)		(0.813)
Mean of dep. var.	0.000387	0.000387	7.67e-05	7.67e-05	0.885	0.885
Observations	4,445,263	4,445,263	4,147,562	4,147,562	1,514,707	1,514,707
Panel G: 7 day interval						
Notable deaths (last 7 days)	0.000411***		0.000108***		1.044***	
	(4.70e-05)		(2.21e-05)		(0.110)	
Notable deaths (last 7 days) × Ratio black population		0.00286***		0.000663***		5.576***
		(0.000506)		(0.000238)		(1.327)
Mean of dep. var.	0.000392	0.000392	7.67e-05	7.67e-05		
Observations	4,445,444	4,445,444	4,147,590	4,147,590	880,238	880,238

Note: Regression of the number of BLM events on protest triggers and protest triggers interacted with the proportion of Black population in the county. Observations correspond to county-day combinations. Proportion of black population at the county level measured in 2013. Columns 3 and 4 exclude all observations after the first BLM event in a county. Different panels correspond to different specifications. Column 5 and 6 use tweets as outcome and are restricted to dates within 14 days of a notable death (or 7 days for Panel G). Panel A repeats the main specification. Panel B excludes the state where a notable death happened from the sample in the 14 days after the death. Panels A to E and G include county fixed effects, and time fixed effects for columns 2, 4, and 6. Panel F only includes county fixed effects and controls by notable deaths. Panel C and D add state-month and state-day fixed effects respectively, and Panel E adds county trends. In Panel G, notable deaths are counted as having an influence for 7 days only, and tweet observations are restricted to 7 days around notable deaths. Standard errors, in parentheses, are clustered at the county-treatment level. *** p<0.01, ** p<0.05, * p<0.1

Table A2: Robustness: Effect of resources on BLM events

	Outcome: Number of BLM events									
	Block I Experience	Block II Economic					Block III Social		Block IV Political	
Mediator:	Black police-related deaths	Black poverty rate	Black unemployment rate	GDP per capita	Unemployment ratio (Black/ all)	Gini index	Civic orgs.	Religious orgs.	Blacks registered to vote (%)	Blacks who voted (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)	(10)	(11)
	Panel A: Main specification									
Notable deaths	29.42***	-0.000161***	-7.90e-05***	0.000188***	0.00312***	0.0290***	0.000306***	3.59e-05***	-0.000158***	-0.000263***
× Ratio black × *Mediator*	(8.062)	(2.50e-05)	(2.49e-05)	(3.51e-05)	(0.000635)	(0.0100)	(9.23e-05)	(1.22e-05)	(3.10e-05)	(7.43e-05)
Mean dep. var.	0.000400	0.000411	0.000430	0.000387	0.000430	0.000387	0.000387	0.000387	0.000465	0.000465
Observations	4,302,363	4,186,614	4,007,989	4,445,263	4,006,560	4,445,263	4,445,263	4,445,263	3,537,862	3,537,862
	Panel B: Excluding state of event									
Notable deaths	29.45***	-0.000161***	-7.43e-05***	0.000195***	0.00317***	0.0302***	0.000300***	3.49e-05***	-0.000158***	-0.000280***
× Ratio black × *Mediator*	(8.373)	(2.59e-05)	(2.58e-05)	(3.72e-05)	(0.000658)	(0.0104)	(9.38e-05)	(1.25e-05)	(3.16e-05)	(7.78e-05)
Mean dep. var.	0.000399	0.000410	0.000428	0.000386	0.000428	0.000386	0.000386	0.000386	0.000463	0.000463
Observations	4,270,073	4,154,908	3,977,439	4,412,393	3,976,052	4,412,393	4,412,393	4,412,393	3,505,720	3,505,720
	Panel C: State-month fixed effects									
Notable deaths	27.74***	-0.000156***	-9.29e-05***	0.000165***	0.00281***	0.0218**	0.000277***	3.24e-05***	-0.000213***	-0.000357***
× Ratio black × *Mediator*	(7.962)	(2.48e-05)	(2.43e-05)	(3.11e-05)	(0.000586)	(0.00933)	(8.99e-05)	(1.20e-05)	(4.16e-05)	(8.65e-05)
Mean dep. var.	0.000400	0.000411	0.000430	0.000387	0.000430	0.000387	0.000387	0.000387	0.000465	0.000465
Observations	4,302,363	4,186,614	4,007,989	4,445,263	4,006,560	4,445,263	4,445,263	4,445,263	3,537,862	3,537,862
	Panel D: State-day fixed effects									
Notable deaths	26.53***	-0.000154***	-0.000117***	0.000154***	0.00271***	0.0165*	0.000305***	3.12e-05**	-0.000372***	-0.000492***
× Ratio black × *Mediator*	(8.163)	(2.63e-05)	(2.45e-05)	(2.99e-05)	(0.000595)	(0.00943)	(0.000100)	(1.23e-05)	(7.95e-05)	(0.000118)
Mean dep. var.	0.000400	0.000411	0.000430	0.000387	0.000430	0.000387	0.000387	0.000387	0.000465	0.000465
Observations	4,300,934	4,185,185	4,006,560	4,443,834	4,005,131	4,443,834	4,443,834	4,443,834	3,536,433	3,536,433
	Panel E: County trends									
Notable deaths	25.22***	-0.000152***	-8.90e-05***	0.000172***	0.00267***	0.0242**	0.000269***	3.04e-05**	-0.000153***	-0.000258***
× Ratio black × *Mediator*	(7.585)	(2.55e-05)	(2.52e-05)	(3.49e-05)	(0.000644)	(0.0102)	(9.33e-05)	(1.28e-05)	(3.21e-05)	(7.64e-05)
Mean dep. var.	0.000400	0.000411	0.000430	0.000387	0.000430	0.000387	0.000387	0.000387	0.000465	0.000465
Observations	4,302,363	4,186,614	4,007,989	4,445,263	4,006,560	4,445,263	4,445,263	4,445,263	3,537,862	3,537,862
	Panel F: No time fixed effects									
Notable deaths	29.93***	-0.000161***	-7.90e-05***	0.000188***	0.00312***	0.0290***	0.000306***	3.59e-05***	-0.000158***	-0.000263***
× Ratio black × *Mediator*	(8.103)	(2.51e-05)	(2.49e-05)	(3.53e-05)	(0.000635)	(0.0101)	(9.27e-05)	(1.23e-05)	(3.12e-05)	(7.48e-05)
Mean dep. var.	0.000400	0.000411	0.000430	0.000387	0.000430	0.000387	0.000387	0.000387	0.000465	0.000465
Observations	4,302,363	4,186,614	4,007,989	4,445,263	4,006,560	4,445,263	4,445,263	4,445,263	3,537,862	3,537,862
	Panel G: 7 day interval									
Notable deaths	47.34***	-0.000212***	-0.000105***	0.000229***	0.00296***	0.0399**	0.000387***	5.45e-05***	-0.000219***	-0.000389***
× Ratio black × *Mediator*	(11.49)	(3.98e-05)	(3.95e-05)	(5.27e-05)	(0.000873)	(0.0160)	(0.000142)	(1.90e-05)	(5.03e-05)	(0.000123)
Mean dep. var.	0.000406	0.000417	0.000435	0.000392	0.000436	0.000392	0.000392	0.000392	0.000471	0.000471
Observations	4,302,544	4,186,795	4,008,170	4,445,444	4,006,741	4,445,444	4,445,444	4,445,444	3,538,036	3,538,036

Note: Regression of BLM events on the triple interaction of notable deaths in the last two weeks, the proportion of black population in the country, and county characteristics. Mediators are indicated as column headers. Panel A repeats the main specification. Panel B excludes the state where a notable death happened from the sample in the 14 days after the death. Panels A to E and G include time and county fixed effects. Panel F only includes county fixed effects and controls by notable deaths. Panel C and D add state-month and state-day fixed effects respectively, and Panel E adds county trends. In Panel G, notable deaths are counted as having an influence for 7 days only. The coefficients of lower-level interaction terms are omitted. Standard errors, in parentheses, are clustered at the county-treatment level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A3: Robustness: Effect of resources on first BLM events

	Outcome: First BLM event									
	Block I Experience	Block II Economic					Block III Social		Block IV Political	
Mediator:	Black police-related deaths	Black poverty rate	Black unemployment rate	GDP per capita	Unemployment ratio (Black/ all)	Gini index	Civic orgs.	Religious orgs.	Blacks registered to vote (%)	Blacks who voted (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)	(10)	(11)
Panel A: Main specification										
Notable deaths	4.695**	-3.61e-05***	-3.75e-05***	1.86e-05***	0.000223	-0.00479	0.000124	1.53e-05	-2.86e-05**	-8.40e-05**
× Ratio black × *Mediator*	(1.948)	(1.16e-05)	(1.22e-05)	(6.42e-06)	(0.000146)	(0.00310)	(7.92e-05)	(1.18e-05)	(1.21e-05)	(4.22e-05)
Mean dep. var.	7.94e-05	8.18e-05	8.57e-05	7.67e-05	8.57e-05	7.67e-05	7.67e-05	7.67e-05	8.75e-05	8.75e-05
Observations	4,004,662	3,888,913	3,710,288	4,147,562	3,708,859	4,147,562	4,147,562	4,147,562	3,267,434	3,267,434
Panel B: Excluding state of event										
Notable deaths	5.266***	-3.46e-05***	-3.39e-05***	2.17e-05***	0.000242	-0.00437	0.000132	1.61e-05	-2.72e-05**	-8.90e-05**
× Ratio black × *Mediator*	(2.043)	(1.20e-05)	(1.24e-05)	(6.96e-06)	(0.000152)	(0.00325)	(8.12e-05)	(1.21e-05)	(1.22e-05)	(4.42e-05)
Mean dep. var.	7.85e-05	8.09e-05	8.48e-05	7.58e-05	8.48e-05	7.58e-05	7.58e-05	7.58e-05	8.65e-05	8.65e-05
Observations	3,974,046	3,858,881	3,681,412	4,116,366	3,680,025	4,116,366	4,116,366	4,116,366	3,236,966	3,236,966
Panel C: State-month fixed effects										
Notable deaths	4.525**	-3.70e-05***	-3.83e-05***	1.78e-05***	0.000233	-0.00471	0.000122	1.56e-05	-4.01e-05***	-0.000107**
× Ratio black × *Mediator*	-0.00462**	(1.16e-05)	(1.18e-05)	(6.44e-06)	(0.000147)	(0.00309)	(8.03e-05)	(1.19e-05)	(1.53e-05)	(4.85e-05)
Mean dep. var.	7.94e-05	8.18e-05	8.57e-05	7.67e-05	8.57e-05	7.67e-05	7.67e-05	7.67e-05	8.75e-05	8.75e-05
Observations	4,004,662	3,888,913	3,710,288	4,147,562	3,708,859	4,147,562	4,147,562	4,147,562	3,267,434	3,267,434
Panel D: State-day fixed effects										
Notable deaths	4.024**	-3.28e-05***	-3.72e-05***	1.59e-05**	0.000263*	-0.00369	0.000123	1.64e-05	-8.98e-05***	-0.000162**
× Ratio black × *Mediator*	(1.846)	(1.17e-05)	(1.20e-05)	(6.40e-06)	(0.000153)	(0.00309)	(8.15e-05)	(1.20e-05)	(2.68e-05)	(6.45e-05)
Mean dep. var.	7.94e-05	8.18e-05	8.57e-05	7.67e-05	8.57e-05	7.67e-05	7.67e-05	7.67e-05	8.75e-05	8.75e-05
Observations	4,003,921	3,888,172	3,709,547	4,146,821	3,708,118	4,146,821	4,146,821	4,146,821	3,266,693	3,266,693
Panel E: County trends										
Notable deaths	4.326**	-3.35e-05***	-3.62e-05***	1.80e-05***	0.000218	-0.00498	0.000116	1.42e-05	-2.88e-05**	-8.29e-05*
× Ratio black × *Mediator*	(1.953)	(1.18e-05)	(1.24e-05)	(6.38e-06)	(0.000148)	(0.00327)	(7.58e-05)	(1.19e-05)	(1.20e-05)	(4.46e-05)
Mean dep. var.	7.94e-05	8.18e-05	8.57e-05	7.67e-05	8.57e-05	7.67e-05	7.67e-05	7.67e-05	8.75e-05	8.75e-05
Observations	4,004,662	3,888,913	3,710,288	4,147,562	3,708,859	4,147,562	4,147,562	4,147,562	3,267,434	3,267,434
Panel F: No time fixed effects										
Notable deaths	5.061**	-3.62e-05***	-3.75e-05***	1.86e-05***	0.000225	-0.00481	0.000123	1.52e-05	-2.87e-05**	-8.41e-05**
× Ratio black × *Mediator*	(1.965)	(1.16e-05)	(1.22e-05)	(6.43e-06)	(0.000145)	(0.00311)	(7.93e-05)	(1.18e-05)	(1.21e-05)	(4.23e-05)
Mean dep. var.	7.94e-05	8.18e-05	8.57e-05	7.67e-05	8.57e-05	7.67e-05	7.67e-05	7.67e-05	8.75e-05	8.75e-05
Observations	4,004,662	3,888,913	3,710,288	4,147,562	3,708,859	4,147,562	4,147,562	4,147,562	3,267,434	3,267,434
Panel G: 7 day interval										
Notable deaths	8.694**	-6.85e-05***	-7.17e-05***	3.25e-05***	0.000156	-0.00563	0.000142	2.97e-05	-5.89e-05***	-0.000177**
× Ratio black × *Mediator*	(3.545)	(2.23e-05)	(2.41e-05)	(1.14e-05)	(0.000244)	(0.00637)	(0.000125)	(2.21e-05)	(2.21e-05)	(8.91e-05)
Mean dep. var.	7.94e-05	8.18e-05	8.57e-05	7.67e-05	8.57e-05	7.67e-05	7.67e-05	7.67e-05	8.75e-05	8.75e-05
Observations	4,004,690	3,888,941	3,710,316	4,147,590	3,708,887	4,147,590	4,147,590	4,147,590	3,267,455	3,267,455

Note: Regression of first BLM events on the triple interaction of notable deaths in the last two weeks, the proportion of black population in the country, and county characteristics. Mediators are indicated as column headers. The sample is restricted to observations before or on the day of the first protest in a county. Panel A repeats the main specification. Panel B excludes the state where a notable death happened from the sample in the 14 days after the death. Panels A to E and G include time and county fixed effects. Panel F only includes county fixed effects and controls by notable deaths. Panel C and D add state-month and state-day fixed effects respectively, and Panel E adds county trends. In Panel G, notable deaths are counted as having an influence for 7 days only. The coefficients of lower-level interaction terms are omitted. Standard errors, in parentheses, are clustered at the county-treatment level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4: Robustness: Effect of resources on number of tweets

	Outcome: Number of tweets									
	Block I Experience	Block II Economic					Block III Social		Block IV Political	
Mediator:	Black police-related deaths	Black poverty rate	Black unemployment rate	GDP per capita	Unemployment ratio (Black/ all)	Gini index	Civic orgs.	Religious orgs.	Blacks registered to vote (%)	Blacks who voted (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)	(10)	(11)
Panel A: Main specification										
Notable deaths	47,330***	-0.627***	-0.377***	0.196***	0.0655	-3.617	0.382**	0.102**	-0.431***	-0.873***
× Ratio black × *Mediator*	(7,905)	(0.149)	(0.114)	(0.0524)	(1.334)	(37.33)	(0.186)	(0.0453)	(0.0839)	(0.220)
Mean dep. var.	0.912	0.934	0.972	0.885	0.972	0.885	0.885	0.885	1.044	1.044
Observations	1,466,007	1,426,560	1,365,685	1,514,707	1,365,198	1,514,707	1,514,707	1,514,707	1,205,476	1,205,476
Panel B: Excluding state of event										
Notable deaths	48,355***	-0.642***	-0.383***	0.204***	0.0825	-0.663	0.381**	0.103**	-0.418***	-0.854***
× Ratio black × *Mediator*	(8,304)	(0.157)	(0.121)	(0.0547)	(1.388)	(39.49)	(0.189)	(0.0465)	(0.0833)	(0.225)
Mean dep. var.	0.908	0.929	0.967	0.880	0.968	0.880	0.880	0.880	1.042	1.042
Observations	1,434,395	1,395,508	1,335,753	1,482,521	1,335,308	1,482,521	1,482,521	1,482,521	1,174,018	1,174,018
Panel C: State-month fixed effects										
Notable deaths	47,566***	-0.637***	-0.386***	0.199***	0.0472	-2.061	0.454**	0.103**	-0.515***	-0.994***
× Ratio black × *Mediator*	(7,721)	(0.149)	(0.114)	(0.0556)	(1.317)	(37.58)	(0.201)	(0.0458)	(0.101)	(0.253)
Mean dep. var.	0.912	0.934	0.972	0.885	0.972	0.885	0.885	0.885	1.044	1.044
Observations	1,466,007	1,426,560	1,365,685	1,514,707	1,365,198	1,514,707	1,514,707	1,514,707	1,205,476	1,205,476
Panel D: State-day fixed effects										
Notable deaths	47,984***	-0.671***	-0.447***	0.201***	0.319	-6.435	0.674***	0.107**	-0.923***	-1.399***
× Ratio black × *Mediator*	(7,618)	(0.149)	(0.115)	(0.0654)	(1.302)	(38.99)	(0.250)	(0.0475)	(0.199)	(0.386)
Mean dep. var.	0.912	0.934	0.972	0.885	0.972	0.885	0.885	0.885	1.044	1.044
Observations	1,465,520	1,426,073	1,365,198	1,514,220	1,364,711	1,514,220	1,514,220	1,514,220	1,204,989	1,204,989
Panel E: County trends										
Notable deaths	47,762***	-0.635***	-0.382***	0.199***	0.0944	-3.726	0.383**	0.102**	-0.437***	-0.884***
× Ratio black × *Mediator*	(8,125)	(0.155)	(0.120)	(0.0545)	(1.392)	(38.96)	(0.193)	(0.0471)	(0.0876)	(0.229)
Mean dep. var.	0.912	0.934	0.972	0.885	0.972	0.885	0.885	0.885	1.044	1.044
Observations	1,466,007	1,426,560	1,365,685	1,514,707	1,365,198	1,514,707	1,514,707	1,514,707	1,205,476	1,205,476
Panel F: No time fixed effects										
Notable deaths	50,061***	-0.627***	-0.377***	0.196***	0.0617	-3.639	0.382**	0.102**	-0.431***	-0.874***
× Ratio black × *Mediator*	(8,194)	(0.150)	(0.115)	(0.0527)	(1.339)	(37.54)	(0.187)	(0.0456)	(0.0845)	(0.221)
Mean dep. var.	0.912	0.934	0.972	0.885	0.972	0.885	0.885	0.885	1.044	1.044
Observations	1,466,007	1,426,560	1,365,685	1,514,707	1,365,198	1,514,707	1,514,707	1,514,707	1,205,476	1,205,476
Panel G: 7 day interval										
Notable deaths	63,777***	-0.810***	-0.490***	0.266***	0.406	0.171	0.495	0.128*	-0.576***	-1.179***
× Ratio black × *Mediator*	(12,308)	(0.241)	(0.186)	(0.0885)	(2.166)	(60.99)	(0.309)	(0.0759)	(0.140)	(0.367)
Mean dep. var.	1.033	1.057	1.100	1.002	1.101	1.002	1.002	1.002	1.183	1.183
Observations	851,938	829,015	793,640	880,238	793,357	880,238	880,238	880,238	700,540	700,540

Note: Regression of tweets mentioning BLM on the triple interaction of notable deaths in the last two weeks, the proportion of black population in the country, and county characteristics. Mediators are indicated as column headers. The sample is restricted dates within 14 days (or 7 days for Panel G) around notable deaths. Panel A repeats the main specification. Panel B excludes the state where a notable death happened from the sample in the 14 days after the death. Panels A to E and G include time and county fixed effects. Panel F only includes county fixed effects and controls by notable deaths. Panel C and D add state-month and state-day fixed effects respectively, and Panel E adds county trends. In Panel G, notable deaths are counted as having an influence for 7 days only. The coefficients of lower-level interaction terms are omitted. Standard errors, in parentheses, are clustered at the county-treatment level. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Black Lives Matter protest triggers, including county of notable deaths

VARIABLES	Number of BLM events		First day with BLM events		Number of tweets mentioning BLM	
	(1)	(2)	(3)	(4)	(5)	(6)
Notable deaths (last 14 days)	0.000409***		8.04e-05***		0.777***	
	(3.79e-05)		(1.40e-05)		(0.0676)	
Notable deaths (last 14 days) × Ratio Black population		0.00253***		0.000337***		4.321***
		(0.000402)		(0.000119)		(0.830)
Mean of dependent variable	0.000402	0.000402	7.79e-05	7.79e-05	0.893	0.893
Observations	4,445,619	4,445,619	4,147,632	4,147,632	1,515,057	1,515,057
Day fixed effects		Y		Y		Y
County fixed effects	Y	Y	Y	Y	Y	Y

Note: Regression of the number of BLM events on protest triggers and protest triggers interacted with the proportion of Black population in the county. The county where a notable death happened is NOT excluded from the sample. Observations correspond to county-day combinations. Proportion of black population at the county level measured in 2013. Columns 3 and 4 exclude all observations after the first BLM event in a county. Column 5 and 6 use tweets as outcome and are restricted to dates within 14 days of a notable death. All models include county fixed effects, columns 2 and 4 additionally include week fixed effects. Standard errors, in parentheses, are clustered at the county-treatment level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A6: Effect of resources on protest, including county of notable death

	Block I Experience	Block II Economic					Block III Social		Block IV Political	
Mediator:	Black police-related deaths	Black poverty rate	Black unemployment rate	GDP per capita	Unemployment ratio (Black/ all)	Gini index	Civic orgs.	Religious orgs.	Blacks registered to vote (%)	Blacks who voted (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)	(10)	(11)
Panel A: Outcome: Number of BLM events										
Notable deaths	37.86***	-0.000208***	-0.000110***	0.000223***	0.00385***	0.0392***	0.000364***	5.00e-05***	-0.000177***	-0.000251***
× Ratio black × *Mediator*	(9.085)	(3.46e-05)	(2.79e-05)	(3.80e-05)	(0.000712)	(0.0119)	(9.69e-05)	(1.44e-05)	(3.19e-05)	(7.88e-05)
Mean dep. var.	0.000415	0.000427	0.000446	0.000402	0.000446	0.000402	0.000402	0.000402	0.000483	0.000483
Observations	4,302,719	4,186,970	4,008,345	4,445,619	4,006,916	4,445,619	4,445,619	4,445,619	3,538,204	3,538,204
Panel B: Outcome: First BLM event										
Notable deaths	5.052**	-3.82e-05***	-4.10e-05***	2.09e-05***	0.000305**	-0.00436	0.000140*	1.73e-05	-3.00e-05**	-8.27e-05**
× Ratio black × *Mediator*	(1.970)	(1.16e-05)	(1.24e-05)	(6.55e-06)	(0.000155)	(0.00310)	(7.97e-05)	(1.18e-05)	(1.21e-05)	(4.22e-05)
Mean dep. var.	8.07e-05	8.31e-05	8.71e-05	7.79e-05	8.71e-05	7.79e-05	7.79e-05	7.79e-05	8.91e-05	8.91e-05
Observations	4,004,732	3,888,983	3,710,358	4,147,632	3,708,929	4,147,632	4,147,632	4,147,632	3,267,490	3,267,490
Panel C: Outcome: Number of tweets										
Notable deaths	48,379***	-0.631***	-0.378***	0.199***	0.104	-2.454	0.386**	0.102**	-0.432***	-0.871***
× Ratio black × *Mediator*	(8,042)	(0.153)	(0.118)	(0.0528)	(1.366)	(38.21)	(0.189)	(0.0458)	(0.0871)	(0.229)
Mean dep. var.	0.920	0.942	0.980	0.893	0.981	0.893	0.893	0.893	1.054	1.054
Observations	1,466,357	1,426,910	1,366,035	1,515,057	1,365,548	1,515,057	1,515,057	1,515,057	1,205,812	1,205,812
Day fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Regression of BLM events outcomes on the triple interaction of notable deaths in the last two weeks, the proportion of black population in the country, and county characteristics. The county where a notable death happened is NOT excluded from the sample. Panel A and B use the number of BLM events as an outcome, panel B excludes all county-week observations after the first BLM event in a county. Panel C uses the number of tweets mentioning BLM as outcome, and is restricted to observations within 14 days of a notable death. Mediators are indicated as column headers. Black police-related deaths are the number of previous police-related deaths of Blacks divided by the Black population of the county. Unemployment ratio is the ratio of the Black unemployment rate over the general unemployment rate. The coefficients of lower-level interaction terms are omitted. All models include county and week fixed effects. Standard errors, in parentheses, are clustered at the county-treatment level. *** p<0.01, ** p<0.05, * p<0.1