Race-Specific Provider Performance: Evidence from Black Lives Matter Protests *

Haizhen Lin[†] Yanhao Wang[‡] Jia Xiang [§]

December 2025

Abstract

This paper studies whether hospital performance for Black patients is malleable and how it shapes racial disparities in healthcare. Using local Black Lives Matter protests as an exogenous shock to providers' racial awareness and social pressure, we find that exposed hospitals experienced significant declines in 30-day mortality among Black heart attack patients, with no detectable change for non-Black patients. Evidence from emergency department admissions and non-exposed patients supports a supply-side response. We observe no changes in resource utilization but substantial productivity gains, partly driven by an increased likelihood of Black patients being treated by high-productivity physicians.

JEL Codes: I10, I14, J15

Keywords: racial disparity, BLM protests, patient mortality, provider productivity

*We thank Mike Baye, Andrew Butters, Christopher (Kitt) Carpenter, Yiqun Chen, Matt Grennan, John Maxwell, Matt Notowidigdo, Alberto Ortega, Harold A. Pollack, Dan Sacks, Amanda Starc, Kosali Simon, Coady Wing, and conference/seminar participants at the 2025 Midwest Health Economics Conference, Indiana University, University of Southern California, and UNC-Chapel Hill for their useful comments. All errors are our own.

[†]Kelley School of Business, Indiana University and NBER (email: hzlin@iu.edu).

[‡]Alberta School of Business, University of Alberta (email: yanhao.wang@ualberta.ca).

[§]Kelley School of Business, Indiana University (email: xiangjia@iu.edu).

1 Introduction

Racial disparities in healthcare remain a persistent issue in the U.S., with the Black population experiencing an age-adjusted mortality rate that is 30% higher than that of their White counterpart (Kochanek et al., 2023). These disparities also exist across a wide range of healthcare services, from basic care to the most advanced diagnostic and therapeutic interventions (Nelson, 2002). Prior studies have identified various contributing factors, including disparities in patients' socioeconomic status (Cutler et al., 2006), barriers for patients in accessing high-quality hospitals (Chandra et al., 2024), racial discordance between providers and patients (Alsan et al., 2019), provider discretion (Chandra and Staiger, 2010; Singh and Venkataramani, 2022; Corredor-Waldron et al., 2024; Philip and Ozkaya, 2024), among others. In this paper, we examine the role of race-specific provider performance in shaping racial disparities in healthcare. We present new evidence that, even within a hospital, hospital performance for Black patients is malleable, and that improving this performance can help reduce racial disparities without compromising the care quality of other patient groups.

Race-based social movements provide a unique opportunity for empirically estimating the malleability of race-specific provider performance. Specifically, we study local Black Lives Matter (BLM) protests, a major racial justice movement, as a natural experiment to examine the role of provider performance in addressing racial disparities. BLM protests, first triggered by high-profile police killings of unarmed Black Americans, generated substantial attention to racial justice, reshaped public discourse, and heightened awareness of racial bias (Reny and Newman, 2021; Dunivin et al., 2022; Gethin and Pons, 2024). In particular, exposure to BLM protests might enhance providers' racial awareness and amplify societal pressures through public scrutiny, media attention, and societal expectations, thereby altering how providers engage with Black patients and potentially improving health outcomes for Black patients.[1]

We study patients admitted to hospitals with acute myocardial infarction (AMI), more commonly known as heart attack. There are several reasons for choosing this setting. First, AMI is a leading cause of death and imposes a substantial financial burden on patients and payers, with annual costs estimated at $84.9 billion in 2016 dollars (Bishu et al., 2020). Second, there are stark racial disparities in AMI care; for example, Black patients face up to 1.5 times the mortality risk of White patients after cardiac surgeries (Khera et al., 2015). Third, measures for hospital performance, such as 30-day risk-adjusted mortality rate, are well defined and extensively validated in this context (Doyle et al., 2019). Finally, and

[1] We suspect, and provide evidence, that BLM protests do not simultaneously alter patients' underlying medical risks or preferences regarding hospitals.

more importantly for our identification, AMI is an acute condition that typically requires hospitalization and timely medical intervention, highlighting the role of providers, rather than patient preferences, in determining health outcomes (Chandra and Staiger, 2010).

We link information on BLM protests to Medicare claims data to examine how social movements affect patient outcomes. Our empirical strategy leverages the staggered onset of local BLM protests across U.S. cities between 2014 and 2016. During this period, approximately 700 cities experienced their first BLM protest, which we use to define our set of treated hospitals. Specifically, we construct three calendar-time cohorts based on the year of initial exposure (2014, 2015, or 2016) and designate as controls those hospitals that did not experience a protest until during or after 2020, yet did so by 2021. Employing a stacked difference-in-differences framework, we compare within-hospital changes in the 30-day risk-adjusted mortality rate between treated and control hospitals. Our identification relies on the assumption that, absent BLM protests, treated and control hospitals would have exhibited parallel trends in their underlying risk-adjusted mortality.

We find that hospitals exposed to BLM protests experienced an immediate reduction of 4.6 percentage points in their 30-day risk-adjusted mortality rate for Black patients. This improvement represents approximately one-fifth of a standard deviation in hospital-level risk-adjusted mortality within our sample. In magnitude, the effect is comparable to moving a Black patient from a hospital at the 25th percentile up to one at the 32nd percentile of hospital quality ranking. The improvement in patient outcomes persists for up to three years following the initial exposure.

Meanwhile, we find no discernible changes in health outcomes for White, Asian, or Non-Black Hispanic (hereafter "Hispanic") patients. In combination, these results offer evidence that hospital performance is race-specific and that the Black-patient-specific performance is malleable. The null effect on non-Black patients suggests that the observed mortality reduction for Black patients is plausibly attributable to BLM protests instead of driven by unobserved factors that might otherwise affect all patients in local markets. Moreover, the absence of spillover effects also highlights an important policy implication: improvements in outcomes for Black patients can be achieved without adversely affecting non-Black patients.

We next present evidence that the observed improvements in health outcomes are primarily driven by supply-side responses, as opposed to demand-side confounds, such as patients' riskiness and preferences. First, we show that patient demographics, risk factors, predicted mortality based on patient characteristics, and the volume of Black patients all remain stable within a given hospital following BLM protests. This finding mitigates concerns that the observed effects are driven by shifts in the underlying health of Black patients or by patient

selection into certain hospitals in response to the protests.[2] Second, we observe comparable reductions in mortality among Black patients who were admitted through emergency departments, where patients and their families have little influence over hospital choice or treatment decisions. Finally, we analyze a subsample of "non-exposed" patients who were admitted to exposed hospitals prior to any BLM protests occurring in their home cities and therefore should not have responded to BLM protests by themselves. We find consistent results among this group of patients, thus further corroborating the argument that the mortality reductions are not likely driven by demand-side responses.

To further strengthen our identification, we conduct a series of placebo and permutation tests to confirm that our findings capture the causal effect of BLM protests on Black patients' health outcomes. In the placebo analysis, we find the closest match for each treated hospital from the control group and find no significant effects for these "placebo-treated" hospitals. In the permutation test, we construct a series of "pseudo-treated" groups by randomly assigning fake protest timings to control hospitals and repeatedly re-estimate the model. The actual treatment effect lies at the extreme tail of the distribution for estimated effects from permutation regressions, indicating that the observed effect is highly unlikely to have occurred by chance. Additionally, our results remain robust across a range of alternative specifications, including the difference-in-differences estimator proposed by Callaway and Sant'Anna (2021).

We note that the effect of BLM protests can be unequal for different hospitals in different markets. Through several heterogeneity analyses, we find that mortality reductions are more pronounced following protests with more participants involved. These effects are also concentrated in hospitals with lower baseline performance in treating Black patients and in those located in Democratic-leaning counties.

The fact that we find a reduction in Black patients' mortality rates after BLM protests does not necessarily indicate any discriminatory intent by providers ex ante. Rather, salient external events appear to have prompted greater provider attentiveness, resulting in better outcomes for Black patients. To understand further how hospitals achieve better outcomes for Black patients only, we examine two potential mechanisms: increased resource use and enhanced productivity with the same resources. We find no significant changes in key indicators of resource use, including length of stay; number of tests and exams; surgery rates; Diagnosis-Related Group (DRG) weights; physicians' relative value units (RVUs); or post-discharge care, such as being transferred to skilled nursing or rehabilitation facilities. These

[2]Regarding potential changes in population health caused by BLM-related events, prior research documents poorer mental health among Black adults following police killings of unarmed Black Americans (Bor et al., 2018).

results suggest that the observed improvements likely reflect improved productivity in treating Black patients, rather than an increase in the intensity of care delivery. Consistent with this interpretation, we document a substantial increase in hospitals' Black-specific total factor productivity, estimated using a patient-level health production function, following Chandra et al. (2016a,b).

Finally, we consider two possible pathways through which productivity gains are realized. The first one is the probability of Black patients being treated by higher-productivity physicians. We show that Black patients are about 6% more likely than before to be treated by higher-productivity physicians, which accounts for approximately one-third of the overall productivity gains.[3] Importantly, physician quality for non-Black patients remains largely unchanged. The second pathway is the probability of Black patients being treated by Black physicians. Previous literature has documented the benefits of such racial concordance (e.g., Alsan et al., 2019). However, we find no evidence of increased racial concordance between Black patients and their physicians in our context, regardless of the reduction in mortality rates.

Our study contributes to the literature examining the underlying causes and potential solutions for racial disparities in healthcare. Such disparities stem from a variety of factors, including social determinants of health (Cutler et al., 2006), differences in insurance coverage (Yearby, 2011), unequal access to high-quality hospitals (Chandra et al., 2024), and limited racial concordance between minority patients and healthcare providers (Alsan et al., 2019; Ye and Yi, 2023). Within this line of research, our paper is most closely related to Chandra and Staiger (2010), Singh and Venkataramani (2022); Corredor-Waldron et al. (2024), and Philip and Ozkaya (2024), all of which study the role of provider discretion in allocating resources and choosing treatment for Black versus non-Black patients. In contrast, we leverage BLM protests as a race-specific external shock to assess whether provider performance can be improved for Black patients. We also extend the earlier literature by showing that, beyond differences in resource utilization and treatment choices, variation in providers' productivity across patient racial groups also contributes to racial disparities in health outcomes. Our results highlight provider productivity as a distinct and potentially more actionable channel for addressing these disparities. In contrast, interventions targeting the socioeconomic conditions of Black patients tend to operate slowly, while policies redirecting patients to higher-quality hospitals face geographic and logistical constraints, particularly in emergency care. Likewise, initiatives promoting racial concordance are limited by the low representation of Black physicians in the medical workforce.

[3]Prior to the protests, Black and non-Black patients were equally likely to be treated by a high-productivity physician, which provides no evidence of preexisting discriminatory assignment.

Our study also contributes to the literature on social movements by examining their impact on the performance of organizations that are not directly connected to those movements. Prior research shows that social movements can heighten public awareness, shift public sentiment, and affect targeted institutions (Madestam et al., 2013; Soule, 2018; Wasow, 2020; Dunivin et al., 2022), while more recent work (Acemoglu et al., 2018; Luo and Zhang, 2022; Ba et al., 2023; Lins et al., 2024) reveals spillover effects of social movements on domains connected with the immediate target(s) of those movements. For example, Acemoglu et al. (2018) find that, Egypt's Arab Spring protests, aimed at challenging political regimes, reduced market valuations of politically connected firms. We extend this literature by exploring how social movements influence *non-connected* institutions. In this vein, our paper complements studies that document the broader impacts of social movements on corporate board diversity (Bogan et al., 2021), credit access (Garcia and Ortega, 2024), research collaboration (Gertsberg, 2022), venture capital investment in Black-founded startups (Marx et al., 2025), and judicial decision-making in gender-based violence cases (Cai et al., 2025). Related research also shows that social movements shape consumer behavior, including increased crime reporting after #MeToo (Levy and Mattsson, 2023) and heightened participation in collective actions (Bursztyn et al., 2021). We depart from the existing work by examining organizational performance, a dimension rarely studied in the context of social movements, and we leverage the healthcare sector as an ideal setting, where performance is observable, quantifiable, and directly linked to life-and-death outcomes.

The remainder of the paper is structured as follows. Section 2 provides background on BLM protests. Section 3 describes the data sources and the construction of key variables. Section 4 outlines the empirical strategy. Section 5 presents new evidence on malleable race-specific provider performance. Section 6 explores the underlying mechanisms for the main results, and Section 7 concludes with a discussion of the findings and their policy implications.

2 Background

Social movements are a powerful means of expressing public dissatisfaction and driving institutional changes (Acemoglu et al., 2018; Dunivin et al., 2022; Gethin and Pons, 2024). We study social protests as an exogenous shock to healthcare providers, building on evidence that such movements could shift individual perceptions and behaviors. More specifically, we leverage the outbreak of Black Lives Matter (BLM) protests. BLM protests are one of the most prominent contemporary social movements in the United States, focusing on racial justice. After George Zimmerman was acquitted following the shooting death of

Trayvon Martin, a Black teenager, in 2013, three activists originated the widespread hashtag #BlackLivesMatter on social media. BLM protests soon followed since 2014, particularly in response to a series of highly publicized police killings of Black Americans. These protests reached global prominence, then, in 2020, following the murder of George Floyd, with an estimated 15 to 26 million participants across the U.S., making it one of the largest protest movements in the nation's history.[4] Despite their scale, over 96% of BLM protests were peaceful, involving no reported injuries or property damage.[5] The non-violent nature of this movement helps to mitigate concerns that healthcare providers' behavior could be influenced by facility damage or safety threats.

Like other social movements, BLM protests have been shown to shift racial attitudes (Mazumder, 2019; Reny and Newman, 2021; Dunivin et al., 2022), and may be even more effective than other movements in doing so (Gethin and Pons, 2024). While BLM protests often center on police violence, they also bring attention to broader issues of racial justice, including the systemic inequality and discrimination that Black Americans face, and they have been documented to elicit responses across a wide range of institutions. For example, Bogan et al. (2021) find that BLM protests after the death of George Floyd led to a 120% increase in the appointment of Black directors on corporate executive boards. Ba et al. (2023) show that policing firms that contracted heavily with the police experienced stock price gains, relative to non-policing firms, after BLM protests. Garcia and Ortega (2024) find that Paycheck Protection Program loan disbursements to Black business owners increased compared to other racial and ethnic groups due to the shift in lenders' racial attitudes following BLM protests.

Given the power of BLM protests to shift racial attitudes and influence decision-making across industries, we examine whether these protests can have far-reaching effects on healthcare providers' racial awareness and their care for Black patients. In particular, providers may become more attentive and deliver higher-quality care to Black patients. Because the BLM movement specifically aims to advance the well-being of Black individuals, we conceptualize it as a race-specific shock that is likely to affect health outcomes of Black patients. Leveraging such a race-specific shock allows us to examine the role of race-specific provider performance in contributing to racial disparities in health outcomes and to generate new insights into potential strategies for mitigating these disparities.

[4] https://www.nytimes.com/interactive/2020/07/03/us/george-floyd-protests-crowd-size.html

[5] https://www.wshu.org/news/2020-10-19/uconn-study-at-least-96-of-black-lives-matter-protests-were-peaceful

3 Data and Measures

3.1 Medicare Claims Data for Heart Attack Patients

We use administrative claims records for a 20% random sample of Medicare beneficiaries spanning from 2010 to 2019. We start by identifying hospital stays with a principal ICD diagnosis code for heart attack from the Medicare inpatient data (the MedPAR file) and link these hospital admissions to the carrier file (which contains records for physician services), using unique beneficiary identifiers and inpatient time ranges.[6] For each patient, the MedPAR file documents the admission and discharge dates (and thus length of stay), discharge destination, DRG code, Medicare payment amount, and other information on the inpatient stay. The carrier file allows us to identify physicians involved in each hospitalization as well as information on procedures and other medical services provided.

We further supplement the above data with Medicare Data on Provider Practice and Specialty (MD-PPAS) and the Doctors and Clinicians national downloadable file from the CMS. This linkage allows us to observe physician characteristics such as full name which we use to predict their races in subsequent analysis. We also merge the above data with the Master Beneficiary Summary File (MBSF) using the beneficiary identifiers. The MBSF provides detailed information on patient demographics and chronic conditions, thereby allowing us to identify patient race and perform risk adjustments based on rich patient characteristics. Importantly, the MBSF file also records patient death dates, enabling us to construct a 30-day mortality indicator for each admission (i.e., death occurring within 30 days of the admission date).[7]

Finally, we exclude patients who experienced a prior hospitalization for heart attack within the preceding year. We then restrict the analytical sample to patients aged 66 to 100 and those with a length of stay no more than 100 days. In some analyses, we also focus on patients who were admitted to the hospital through the ED (i.e., with a positive emergency room charge amount in the MedPAR file), and patients who live outside the protest area (based on their residential zip codes reported in the MBSF file).

3.2 BLM Protest Data

Data on BLM protests from July 2014 through December 2021 were obtained from Elephrame, an independent, open-access archive that documents demonstrations based on online

[6] Specifically, ICD diagnosis codes for heart attack start with "410", "I21", or "I22".

[7] Results are similar when defining 30-day mortality starting from the discharge date instead.

news and social media.[8] This dataset has been used as well in prior research that examines BLM protests (e.g., Dunivin et al., 2022; Campbell, 2024; Garcia and Ortega, 2024). For each protest, we observe its event date, its location at the city level, an estimated number of participants, and a link to at least one media source that reported on the event.

The BLM movement experienced two major waves of protests. The first wave began in the latter half of 2014, following the police killings of Eric Garner in New York City and Michael Brown in Ferguson, Missouri. The second wave emerged in 2020, in response to the murder of George Floyd in Minneapolis, Minnesota. Between 2014 and 2016, there were 1,619 protests across 658 cities. Then 3,410 protests occurred across 1,240 cities between 2020 and 2021. Together, these two waves represent approximately 86% of all BLM protests from 2014 to 2021, as well as a comparable proportion of cities that experienced at least one protest during this period. Because our Medicare data extend only through 2019, the analysis in this paper focuses on the first wave of BLM protests.[9]

We next merge the BLM protest data with the Medicare claims data by the city of hospital. We assume that all hospitals within a city are equally exposed to the focal protest(s). A hospital may be exposed to repeated protests over time, but for the purpose of our analysis, we focus on the first protest that a hospital (more specifically, its city) experiences.

Among hospitals treating heart attack patients in the merged sample, 651, 61, and 111 hospitals experienced their first protest in 2014, 2015, and 2016, respectively. These three cohorts comprise our treated group. In contrast, 480 hospitals experienced their first protest in 2020 or later and are designated as the control group. A total of 79 hospitals with initial protests occurring between 2017 and 2019 are excluded from the analysis, as they constitute a small portion of the sample and lack an adequately long post-treatment observation window for the event study design, given that the Medicare data end in 2019. Figure 1 presents the geographical distribution of the treated and control hospitals included in our final analysis.

[Figure 1 about here]

3.3 Hospital Performance Measures

Our primary outcome of interest is hospital performance, measured by the 30-day risk-adjusted mortality rate. This metric is widely adopted in both the medical and economics literature as a standard measure of hospital quality in the treatment of heart attack pa-

[8] See https://elephrame.com/charts/BLM.

[9] Garcia and Ortega (2024) analyze protests following George Floyd's death and protests earlier in the first wave, finding consistent and comparable effects on Black borrowers' access to credit.

tients (Menees et al., 2013; Myles et al., 2016; Chen, 2021; Mourot, 2025).[10] Following the literature, we allow the risk-adjusted mortality rate to vary by year, capturing underlying quality of a given hospital over time (Kolstad, 2013; Chandra et al., 2016a). Essential to our analysis, we also allow the risk-adjusted mortality rate to vary by racial group. Below, we explain how we construct hospital performance for Black patients. We apply the same approach to White, Asian, and Hispanic patients to calculate group-specific, risk-adjusted mortality rates for each hospital in a given year.

Specifically, we first calculate the predicted mortality rate for each patient using the following logit model:

$$ln\Big(\frac{Pr(D_{ih}=1|\boldsymbol{X_i})}{1-Pr(D_{ih}=1|\boldsymbol{X_i})}\Big) = \alpha + \boldsymbol{X_i}\gamma + \epsilon_{ih}, \tag{1}$$

where D_{ih} is the mortality indicator that equals one if patient i in hospital h died within 30 days of admission. $\boldsymbol{X_i}$ is a vector of the patient's demographics and comorbidities, including age, sex, race, insurance status, disability indicator, and dummies for comorbidities observed at the time of hospital admission.[11] We omit the time subscript for the purpose of clarity but the model estimation and following calculations are done separately for each year.

The fitted values are obtained for each patient in order to form an expected death probability $\hat{p_{ih}}$, which is then used to construct a hospital's risk-adjusted mortality rate (RAMR) following Huckman and Pisano (2006), Ghaferi et al. (2009), and Kolstad (2013). Specifically, we first calculate EMR_h^B, the average expected mortality rate of Black patients treated at hospital h for a given year, and OMR_h^B, the average observed mortality rate of Black patients treated at hospital h in that year:

$$EMR_h^B = \frac{\sum_{i=1}^{N_h^B} \hat{p_{ih}}}{N_h^B}, \tag{2}$$

[10] Following CMS's guidelines, the 30-day time frame is necessary because outcomes within 30 days of admission can be influenced by hospital care, reflecting both inpatient treatment and hospital-led coordination of post-discharge transitions. CMS also notes that using a 30-day window ensures that variation in lengths of stay does not have an undue influence on mortality rates (see Centers for Medicare & Medicaid Services, 2008, 2013).

[11] Age groups are 66-69, 70-74, 75-79, 80-84, 85-89, 90-94, and 95-100. Sex groups are male and female. Race groups are Black, Hispanic, and others. Insurance status indicates whether the patient has dual eligibility for Medicare and Medicaid. We consider the same set of comorbidities as in Chen (2021), which include chronic kidney disease, chronic obstructive pulmonary disease, heart failure, Alzheimer's disease/dementia, diabetes, stroke, end-stage renal disease (ESRD), and cancer (lung/breast/colorectal/endometrial/prostate cancer).

$$OMR_h^B = \frac{\sum_{i=1}^{N_h^B} D_{ih}}{N_h^B}, \tag{3}$$

where N_h^B is the total number of Black patients treated in hospital h for that year. We focus on hospital-year observations with at least two Black heart attack patients.

Then the hospital's Black-specific RAMR is the average observed mortality divided by the average expected mortality for its Black patients, normalized by multiplying the overall average observed mortality rate for Black patients in the sample:

$$RAMR_h^B = \left(\frac{OMR_h^B}{EMR_h^B}\right) \times OMR^B. \tag{4}$$

Intuitively, EMR_h^B is the mortality rate for an average quality hospital with the same Black patient mix as hospital h. $RAMR_h^B$ measures how large or small a hospital's observed Black mortality rate is relative to the average hospital with the same Black patient mix. A hospital is considered to be underperforming for its Black patients, if its observed mortality, OMR_h^B, exceeds the expected mortality given its Black patient mix, EMR_h^B.

4 Empirical Strategy

Our empirical strategy exploits the staggered outbreak of BLM protests across U.S. cities. To account for potential time-varying treatment effects in a staggered adoption setting, we employ a stacked difference-in-differences design.

Specifically, we restructure the data into event-time cohorts based on the year of a hospital's first exposure to a BLM protest, focusing on the 2014, 2015, and 2016 cohorts.[12] For example, in the 2014 cohort, hospitals located in cities that experienced their *first* BLM protests in 2014 are considered the treated hospitals. The control hospitals are later-treated hospitals that did not experience a protest until after 2019, but did so before the end of 2021. We follow the same approach in constructing the treated hospitals for 2015 and 2016 cohorts. We also use the same set of control hospitals for the 2015 and 2016 cohorts to avoid misleading treatment effects created by composition changes.[13] Finally, we append the three cohorts into one dataset.

[12] Our use of yearly cohorts is primarily data-driven, since, as discussed earlier, an annual RAMR offers a reliable measure of a hospital's underlying performance.

[13] In theory, the 2014 (2015) cohort could include as controls the later-treated hospitals that were first exposed to BLM protests in 2018 (2019), though this set is small. Our results remain robust when these additional control hospitals are included.

We then conduct hospital-level analyses to examine the effect of local BLM protests on hospital race-specific performance, measured by a hospital's RAMR for a given racial group. Specifically, we estimate the event-study specification in Equation (5) using the stacked sample separately for Black, White, Asian, and Hispanic patients, and for a pool of non-Black patients.

$$RAMR^r_{htc} = \sum_{k=-4}^{3} \beta_k \times Treated_{hc} \times \mathbf{1}(t = k) + \boldsymbol{Z_{htc}}\phi + \delta_{tc} + \theta_{hc} + \epsilon_{htc}, \tag{5}$$

where $RAMR^r_{htc}$ denotes the hospital h's risk-adjusted mortality rate in event year t and cohort c for patients with race r. The indicator variable $Treated_{hc}$ equals 1 if hospital h experienced a BLM protest in year c. t denotes the cohort-specific relative year. $\boldsymbol{Z_{htc}}$ is a vector of time-varying hospital and county characteristics. Hospital characteristics include hospital bed size (logged), patient admission volume (logged), indicators for teaching hospital status and private not-for-profit hospital status, and the shares of patients discharged through Medicare and Medicaid, respectively. County-level characteristics include median household income (logged), population (logged), percentage of adult population, percentage of non-White population, percentage of the population with a bachelor's degree or higher, and unemployment rate. δ_{tc} denotes cohort-specific event-year fixed effects, and θ_{hc} denotes cohort-specific hospital fixed effects. The year immediately preceding the event ($t = -1$) is omitted as the base period. The coefficients of interest are the β_k; they capture whether there exist any differential pre-trends and identify the treatment effects of BLM protests. We weight each hospital-year observation by the volume of patients in the relevant racial group, in order to reduce the influence of RAMR estimates based on small patient samples. Results from unweighted regressions are similar. Standard errors are clustered at the hospital level.

While our main analysis is primarily conducted at the hospital level, we also estimate the following patient-level regression, Equation (6), to examine changes in patient outcomes and to explore the underlying mechanisms driving these changes:

$$Y_{ihtc} = \sum_{k=-4}^{3} \beta_k \times Treated_{hc} \times \mathbf{1}(t = k) + \boldsymbol{X_i}\gamma + \boldsymbol{Z_{htc}}\phi + \delta_{tc} + \theta_{hc} + \mu^m_t + \mu^d_t + \epsilon_{ihtc}, \tag{6}$$

where all the explanatory variables and fixed effects remain the same as in Equation (5), except that we additionally include two fixed effects, μ^m_t and μ^d_t, for month of year and day of week, based on the date of patient admission into the hospital, respectively. Y_{ihtc} denotes an outcome variable for patient i in hospital h, cohort c, and event year t. To examine changes in health outcomes, we use a patient's 30-day mortality indicator as the outcome variable.

Meanwhile, to explore underlying mechanisms, we consider a range of resource use intensity and productivity measures, with detailed information covered in Section 6.

Our identification strategy relies on the assumption that, absent the occurrence of BLM protests, the treated and control hospitals would have exhibited parallel trends in RAMR between the pre- and post-event periods. Table 1 presents summary statistics for our main analytical sample, i.e., hospital-years that treated more than one Black patient, including RAMR, measures of resource use, hospital characteristics, and county-level characteristics that were used in the regressions, reported separately by treatment status.

5 Main Results

5.1 The Effect of BLM Protests on Patient Mortality

We present our results graphically, using event study figures, which plot estimated β_k along with their 95% confidence intervals. We first study mortality among Black patients. Note that we drop hospital-year observations that have only one or no Black admissions in a given year. The resulting sample for Black patients has a total of 579 treated hospitals and 207 control hospitals, totaling 5,069 hospital-year observations.

Panel (a) of Figure 2 shows that, prior to BLM protests, treated and control hospitals have witnessed parallel trends in their 30-day RAMR for Black patients. However, immediately after the protests (i.e., $t = 0$), hospitals in exposed areas experienced a 4.6 percentage point reduction in $RAMR_h^B$, which represents about one-fifth of the standard deviation of the $RAMR_h^B$. From another perspective, the magnitude of the effect is equivalent to relocating a Black patient from a hospital at the 25th percentile of quality to one at the 32nd percentile of the hospital quality distribution in treating Black patients.[14] The improvement in Black patient outcomes due to a hospital's initial exposure to the protests lasts at most three years, with subsequent repeated exposures generating additional but much smaller effects.[15]

[Figure 2 about here]

To facilitate comparison with the literature, we also conduct a patient-level analysis using Equation (6). The patient-level regression estimates a treatment effect of a 2.8 percentage point reduction in mortality, which is a 26% decline relative to the baseline mortality rate of 10.6% for Black patients (see Appendix Figure A1 for the corresponding event study

[14] We rank hospitals based on their RAMRs such that higher percentiles correspond to better quality.

[15] For example, among the cities first exposed in 2014, 44% (59%) were also exposed again in 2015 (2016). When restricted to hospitals treated *only* in 2014, estimates for the second and third post years are slightly smaller than those when pooling all hospitals treated in 2014.

plot). This magnitude is in a similar ballpark of estimates in the literature. For example, Chan et al. (2023) documents a 4.5 percentage point reduction (or 46% decline) in 28-day mortality for veterans aged 65 and older when treated in a U.S. Department of Veterans Affairs hospital versus a private Medicare-financed hospital. As another example, Doyle Jr et al. (2015) shows that a one–standard-deviation increase in log hospital spending lowers one-year mortality by 3.7 percentage points, or about 10% of the average one-year mortality rate in their sample.[16]

We next assess whether BLM protests affected outcomes for non-Black patients. In contrast to the results observed for Black patients, Panel (b) of Figure 2 shows no discernible change in 30-day risk-adjusted mortality among non-Black patients following BLM protests. These findings have several implications. First, they provide direct evidence of race-specific performance differences within the same providers and indicate that such differences are malleable.

Second, the decline in mortality among Black patients was achieved without an adverse effect on non-Black patients. To assess potential negative spillovers within a hospital, Appendix Figure B1 shows that the result persists even when restricting to treated hospital-years with an above-median share of Black patients, where spillovers would be most likely to arise. Appendix Figure C1 further reports estimates separately for White, Asian, and Hispanic patients; these estimates likewise reveal no detectable effects for any of these groups.

Last and most importantly, these findings reinforce the interpretation that the observed effects were driven by BLM protests aimed at improving the well-being of the Black population. This interpretation is consistent with recent evidence showing that BLM protests meaningfully shift racial attitudes and increase public awareness of racial bias (Reny and Newman, 2021; Dunivin et al., 2022; Gethin and Pons, 2024). It echoes research regarding the impact of BLM protests on other domains, such as studies that show that BLM protests influence the behavior of lenders and the outcome of corporate boards in ways that favor the Black population (Bogan et al., 2021; Garcia and Ortega, 2024).

Robustness Checks Appendix Figure A2 shows that our results remain robust when including state-by-year fixed effects to account for state-level concurrent events, such as Medicaid expansion. Appendix Figure A3 demonstrates that the results are highly consistent when excluding treated hospitals located in cities with above-median populations, thereby

[16]Given that Black patients face 1.5 times the mortality risk of White patients following cardiac surgeries (Khera et al., 2015), a 26% reduction in Black mortality implies that this ratio narrows from 1.5 to 1.1, effectively closing about 80% of the gap. This magnitude of improvement in racial disparities in mortality is large relative to prior work. For example, Alsan et al. (2019) find that racial concordance between a Black patient and a cardiologist in an outpatient setting reduces the Black-White male gap in cardiovascular mortality by 19 percent.

alleviating concerns that not all hospitals in large cities were exposed to the treatment.[17] Appendix Figure A4 further confirms that the estimated treatment effects are comparable when applying the alternative difference-in-differences estimator proposed by Callaway and Sant'Anna (2021) to address the issue of staggered treatment.

Placebo and Permutation Test To further confirm that the observed reduction in mortality among Black patients is indeed driven by BLM protests, we conduct two validation exercises. First, we perform a placebo test, following Buchmueller et al. (2016), by substituting the treated hospitals with control hospitals that closely resemble them in observable characteristics (including both hospital- and county-level covariates specified in Section 4).[18] We then re-estimate Equation (5) as if these "placebo-treated" hospitals had experienced BLM protests. If our findings were driven by concurrent changes in local social or economic conditions, rather than by the protests themselves, we would expect to observe similar effects. However, Appendix Figure A5 shows no significant effects among these "placebo-treated" hospitals, which suggests that the treatment effect is not likely attributable to unobserved market conditions.

Second, we implement a permutation test, following Abadie et al. (2010) and Buchmueller et al. (2016), and in the spirit of Fisher (1935), to assess how likely it would be to observe our results in the absence of BLM protests. Specifically, we randomly assign each BLM protest status and timing from treated hospitals to control hospitals and re-estimate Equation (5) under these randomized assignments. Appendix Figure A6 presents the event-study estimates based on 100 iterations of this procedure. The "true" estimates are at the center of the "permutation" estimates during the pre-treatment period, but the "true" estimates falls below nearly all "permutation" estimates in the post-treatment period. Together, these validation exercises provide strong evidence that the observed decline in mortality among Black patients is highly unlikely to have occurred in the absence of BLM protests.

5.2 Evidence of a Supply-Side Response

It is important to distinguish whether the observed effects are demand-side or supply-side driven. On the demand side, BLM protests may have heightened awareness among Black patients, potentially influencing their hospital choices or prompting more precautionary health behaviors or self-advocacy. However, we consider a demand-side explanation to

[17] Results are robust when excluding cities with more than two or three hospitals, or when omitting treated hospitals that are situated more than five miles from the city center, where protests were most likely to occur.

[18] We match the nearest control hospital to each treated hospital based on the Mahalanobis distance.

be unlikely in this context, given the acute nature of heart attacks and the dominant role of supply-side factors in determining patient outcomes. Furthermore, we provide supporting empirical evidence below that demonstrates that our main findings are, indeed, not driven by demand-side responses.

First, we emphasize that our analysis of mortality outcomes employs risk adjustment based on a rich set of patient demographics and comorbidities. Our results, therefore, are not likely driven by selection on patient observables. If such selection had occurred, we would expect to observe shifts in patient demographics, risk profiles, and/or admission volumes following the protests.

To further evaluate potential patient selection, we compute the average predicted mortality, based on individual characteristics, for all Black patients admitted to a given hospital in each year. This measure provides a comprehensive proxy for patient illness severity, and we estimate its response to BLM protests using Equation (5). As illustrated in Figure 3, we find no evidence that BLM protests affected the severity of cases involving Black patients at a hospital, suggesting stable patient composition over time. Appendix Figure D1 presents pre- and post-event estimates for each individual patient characteristics we control for and shows no systematic changes. Likewise, Appendix Figure D2 confirms that the volume of Black patient admissions remained unchanged.

[Figure 3 about here]

Second, we examine a subsample of Black patients admitted through the emergency department (ED). In such urgent cases, opportunities for patient selection are minimal, as patients and their families exert little influence over hospital choice or treatment decisions. As shown in Figure 4, the results reveal a similarly significant reduction in mortality among Black patients in this subsample, thus further suggesting that the observed effects are not driven by patient selection.

[Figure 4 about here]

Last but not the least, we examine cases in which hospitals were exposed to protests while their Black patients were not. Specifically, we estimate the patient-level regression, Equation (6), restricting the sample to Black patients admitted to treated hospitals before BLM protests occurred in their home cities, if any.[19] Note that these are patients who received care in exposed hospitals but traveled from areas not yet exposed. Focusing on these patients allows us to isolate the provider-side response—if the treatment effect were primarily demand-driven, we would expect a much weaker or null effect for those "non-exposed"

[19] About 75% of the treated hospitals from our main analysis have such "non-exposed" patients.

patients. However, Figure 5 shows a comparable reduction in mortality among those patients, suggesting that the observed effect is not likely driven by patient-side responses to BLM protests.[20]

[Figure 5 about here]

Taken together, these results offer strong support that our findings are unlikely to be driven by demand-side factors. Instead, we interpret the estimated improvements in performance as reflecting provider responses to the onset of BLM protests. In Section 6, we investigate the underlying mechanisms for these improvements on the provider side.

5.3 Heterogeneity

To investigate potential heterogeneity in the treatment effect, we first examine whether the magnitude of the estimated impact varies with the salience of the protests. We proxy protest salience using the total number of participants across protests in the initial exposure year and classify a protest as salient if its participant count exceeds the 75th percentile (approximately 980 participants).[21] We then estimate Equation (5) separately for hospitals exposed to more-salient versus less-salient protests. Panel (a) of Figure 6 shows that hospitals exposed to more-salient protests exhibit larger reductions in mortality, thus lending support to the interpretation that the observed effects are likely driven by the protests themselves.[22]

We next examine heterogeneity in treatment effects based on hospitals' baseline performance in treating Black patients ($RAMR_h^B$). Hospitals with $RAMR_h^B$ (measured as the average across years before the first protest) below the sample median are classified as high-quality, while those above the median are classified as low-quality. We then estimate Equation (5) separately for the high- and low-baseline quality sub-samples. Panel (b) of Figure 6 presents the results. We find that mortality reductions were more pronounced among hospitals with lower baseline quality, which suggests that quality improvements were primarily concentrated in lower-performing hospitals following BLM protests rather than in hospitals that were performing better for Black patients to begin with.

[20] The most comparable figure is Appendix Figure A1, which also presents a patient-level analysis but uses the full sample of Black patients.

[21] Results remain highly consistent when using the average number of participants or normalizing the number of participants by city population.

[22] Using Google search intensity at the Designated Market Area level for the keywords "Black Lives Matter" or "BLM" as a proxy for protest salience, we find that the treatment effect is primarily driven by hospitals located in areas with above-median Google search intensity (Appendix Figure A7). Likewise, when measuring hospital proximity to the city center—where protests most likely occurred—Appendix Figure A8 shows that the effect is concentrated among hospitals closer to the city center (with distance smaller than the median).

We further examine heterogeneity in treatment effects by county-level partisanship and political ideology. County-level voting data from the 2012 presidential election are obtained from the MIT Election Data and Science Lab.[23] The 2012 election, being the most recent election preceding the three BLM protest cohorts (2014, 2015, and 2016) and being unaffected by the protests themselves, serves as an appropriate measure of counties' political leanings for our study.

Following Dahl et al. (2022), we classify a county as Democratic-leaning (Republican-leaning) if its 2012 Democratic (Republican) vote share exceeds 50%.[24] We then estimate Equation (5) separately for hospitals in Democratic and Republican leaning counties. As shown in panel (c) of Figure 6, hospitals in Democratic-leaning counties exhibit significant reductions in mortality, whereas those in Republican-leaning counties display no discernible changes. This heterogeneity is consistent with evidence that BLM protests primarily influenced racial attitudes among politically liberal individuals (Dunivin et al., 2022), and it aligns with the broader understanding that the Democratic Party has historically been more receptive to acknowledging and engaging with issues of racial equity and social justice. Collectively, these findings suggest that the effects of BLM protests are shaped by the surrounding political context.

[Figure 6 about here]

6 Mechanisms

How did hospitals achieve improved health outcomes for Black patients following exposure to BLM protests? One potential mechanism is increased resource utilization, while another involves more efficient use of existing resources, i.e., a productivity improvement.

In this section, we empirically examine both channels. We first demonstrate that the observed reduction in mortality among Black patients primarily reflects a race-specific improvement in productivity, rather than changes in resource utilization. We then investigate two concrete pathways to characterize this improvement in productivity further.

6.1 Resource Utilization

We begin by examining whether improved outcomes for Black patients might have resulted from increased resource utilization or higher care intensity. Specifically, we analyze changes in length of stay, number of exams/tests, whether a surgery was performed,

[23] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/VOQCHQ.

[24] Results remain consistent when using the 2016 presidential vote share data or when applying a stricter threshold for dominant party, such as 60%.

diagnosis-related group (DRG) weights, physician's relative value units (RVUs). We also look at a patient's discharge destination, with discharge to a skilled nursing or rehabilitation facility being considered as more intense post-discharge care, compared to discharge home. We conduct this analysis at the patient level following Equation (6), with the relative year indicators replaced by a single post-period indicator. The results, presented in Figure 7, show no statistically significant changes across all measures of resource utilization among Black patients. These findings suggest that the observed reductions in mortality are unlikely to be driven by increased resource use.

[Figure 7 about here]

6.2 Productivity

To explore the productivity channel, we first measure a hospital's total factor productivity (TFP), following the methodology used by Chandra et al. (2016a,b). Specifically, we consider a patient-level log health production function:

$$ln(S_{iht}) = ln(A_{ht}) + \boldsymbol{X_i}\gamma + \theta \cdot ln(Input_{iht}) + \epsilon_{ih}, \tag{7}$$

where S_{iht} is the number of days that patient i survives within 365 days following admission to hospital h in year t. $\boldsymbol{X_i}$ include the same set of patient demographics and comorbidities as in Equation (1).

We measure input as the sum of DRG weights during the index stay, which captures the expected resources needed to treat a patient based on their medical conditions and procedures. In an alternative specification, we use the total Medicare payments to proxy input and obtain similar results. Because both DRG weights and Medicare payments capture expected rather than actual resource use, we also consider total length of stay and number of tests as proxies for realized input. The results are robust across all specifications.

We estimate Equation (7) using the sample of Black heart attack patients. A hospital's TFP is captured by $ln(A_{ht})$, the hospital-year fixed effect, which is essentially the risk- and input-adjusted patient survival rate.[25] This hospital-year measure captures a hospital's efficiency in converting inputs into health outcomes for Black patients (i.e., race-specific hospital productivity). We then test whether exposure to a BLM protest led to productivity improvement using Equation (5). Figure 8 shows a significant 16% increase in Black-specific productivity, lasting three years after the first exposure to BLM protests.

[25]The TFP may be estimated with error for some hospital-years with a small number of Black patients. To address this, we follow Chandra et al. (2016a) by applying an empirical Bayes shrinkage procedure to adjust the estimated $ln(A_{ht})$ and find similar results.

[Figure 8 about here]

6.3 Two Pathways

In this subsection, we examine two possible pathways to explore the drivers of productivity improvements. The first is through a Black patient being treated by a physician who has demonstrated high productivity specifically in treating Black patients. Previous literature has found evidence of large heterogeneity in physician quality (Currie and MacLeod, 2017; Gowrisankaran et al., 2023; Mourot, 2025). If BLM protests led to a better matching of high-productivity physicians with Black patients, this could help explain the observed reduction in mortality despite there having been no significant change in a hospital's resource use. The second pathway is through racial concordance. Recent studies, such as Alsan et al. (2019), have found evidence that racial concordance leads to improved patient outcomes among Black patients. A higher productivity can therefore also be driven by a Black patient being more likely assigned a Black physician.

Treated by High-Productivity Physicians To explore the first pathway, we construct an indicator for whether a Black patient was treated by a high-productivity physician. For each patient, we identify a main physician, who provides the largest share of in-hospital care (in terms of allowable charge). To define a high-productivity physician, for each Black patients treated before BLM protests, we first calculate a residual mortality rate as the difference between the observed mortality indicator and the expected mortality predicted by patient characteristics and care input (measured by DRG weights). We then aggregate these patient-level residual mortality rates to the physician-by-hospital level. Finally, within each hospital, we define high-productivity physicians as those with a residual mortality rate below the 75th percentile. Note that this definition of high-productivity physicians are specific to Black patients and a given hospital. The result is similar when we define physician productivity based on their patients of all racial groups.

Panel (a) of Figure 9 shows the patient-level event study results using an indicator for being treated by a high-productivity physician as outcome. Following BLM protests, Black patients are 5.8% more likely to be treated by a high-productivity physician. This effect is non-trivial in magnitude, given that prior to the protests, 64% of Black patients were treated by high-productivity physicians. It is worth noting that these results do not necessarily imply prior discriminatory intent by providers because Black and non-Black patients were treated by high-productivity physicians at similar rates prior to the protests (64% vs. 66%, $p = 0.53$).

[Figure 9 about here]

To quantify how much this pathway contributes to productivity gains, we estimate the pre-post version of Equation (6), with 30-day mortality indicator as outcome and an indicator for being treated by a high-productivity physician as an additional control. We then compare the estimated treatment effect, β', to the baseline estimate, β, which does not control for the high-productivity physician indicator. The resulting change in the treatment effect, $\beta' - \beta$, represents the portion of the mortality reduction that can be explained by improved matching of Black patients to high-productivity physicians.[26] Based on this method, we estimate that improved patient-physician matching accounts for 1.0 percentage points ($= -0.018 - (-0.028)$), or approximately one-third of the overall reduction in patient mortality after BLM protests.

A natural question is whether the probability of a non-Black patient being treated by a high-productivity physician declined as Black patients became more likely to be treated by high-productivity physicians. Appendix Figure E1 shows that, overall, non-Black patients were not assigned to lower-productivity physicians, regardless of whether physician productivity is defined based on performance with Black or non-Black patients. Appendix Figure E2 further shows that in hospital-years with a high share of Black patients, non-Black patients experienced a modest decline in the probability of being treated by a high-productivity physician but only in period $t = 0$.

Together, these results suggest that the higher probability of Black patients being treated by high-productivity physicians does not appear to have pushed high-productivity physicians to the limits of their capacity. This is plausible, given that Black patients constitute only about 10% of total patient volume. Moreover, we find that health outcomes for non-Black patients did not deteriorate, even in hospitals with a high share of Black patients. This seems to suggest that prior allocation of high-productivity physicians might have exceeded what was necessary to sustain favorable outcomes for non-Black patients.

Racial Concordance Even with comparable resource use, racially concordant physicians may achieve better outcomes through improved communication, which can lead to clinical decisions that are more appropriate, though similarly intensive, and to greater adherence to medical advice. Therefore, we construct an indicator of racial concordance if a Black patient was assigned to a Black physician.

[26] Mechanically, the mortality reduction attributable to better patient–physician matching, $(\beta' - \beta)$, is equivalent to the product of the protest's effect on the likelihood of being treated by a high-productivity physician and the mortality impact of being treated by such a physician.

We can observe patients' race in the Medicare claims data, but not physicians' race and ethnicity. To address this missing information, we use a name-based machine learning algorithm that infers a physician's race based on their first and last names.[27] The algorithm returns race-specific probabilities for each name. We then define a physician as being Black if their Black probability is above a calibrated cutoff which aligns the percentage of Black physicians in our sample with that reported by the American Medical Association (AMA) for physicians specializing in cardiovascular disease.[28]

The event study results are shown in panel (b) of Figure 9, where we find no evidence of an increase in racial concordance between patients and physicians following BLM protests. This might be due to limited capacity and scarcity of Black physicians, who, according to the AMA, only account for 3% of the labor force for the specialty of cardiology.

7 Conclusion

This paper leverages the staggered onset of BLM protests across U.S. cities to examine the role of race-specific provider performance in shaping racial disparities in healthcare. We hypothesize that if provider performance varies by patient race, exposure to BLM protests—which center on the well-being of the Black population—could raise providers' racial awareness and societal accountability, thereby leading to improved quality of care for Black patients. Consistent with this hypothesis, we find that hospitals improve survival outcomes only for Black patients following local BLM protests, which suggests that provider performance is race-specific, malleable, and potentially an important lever for reducing racial disparities in healthcare. We also show that these gains are driven by enhanced provider productivity in treating Black patients, rather than increased resource use. A meaningful share of this productivity gain arises from Black patients being more likely to be treated by physicians who are particularly effective at treating Black patients.

Our findings carry important policy implications. First, by showing that hospitals improved survival outcomes for Black patients without compromising care for non-Black patients, our results highlight the potential of public discourse and provider education as scalable policy tools for reducing racial disparities in healthcare. Chandra et al. (2024) propose reallocating patients to higher-quality hospitals and increasing resources for hospitals that serve large Black populations. While these suggestions offer important insights, they may, in practice, be met with logistical and financial constraints. Likewise, while the Institute of

[27] This algorithm is built on a recurrent neural network architecture and trained using Florida's voter registration data. See Xie (2022) for details.

[28] https://www.aamc.org/data-reports/workforce/data/table-13-practice-specialty-males-race/ethnicity-2018

Medicine has advocated increasing the number of Black physicians to promote racial concordance (Nelson, 2002), only about 5% of active physicians are Black, a fact that constrains the scope of this approach.[29] In contrast, initiatives that improve provider performance through public engagement or physician education can leverage the existing, predominantly White workforce and do not depend on patient reallocation or racial concordance.

Second, our findings suggest that improving race-specific provider productivity offers an alternative approach to existing policies aimed at reducing racial gaps in healthcare. For instance, prior research and related policy discussions have often emphasized disparities in treatment intensity, including less frequent stroke testing for Black patients (Philip and Ozkaya, 2024), higher rates of unnecessary C-sections among low-risk Black mothers (Corredor-Waldron et al., 2024), longer hospital wait times for Black patients (Singh and Venkataramani, 2022), and lower rates of aggressive interventions for Black heart attack patients (Chandra and Staiger, 2010). In contrast, our evidence points to productivity as the key mechanism driving improvements in Black patients' health outcomes. One promising pathway for addressing health disparities is by improving Black patients' access to physicians who demonstrate high productivity in treating them.

[29] https://www.aamc.org/data-reports/workforce/data/figure-18-percentage-all-active-physicians-race/ethnicity-2018

References

Abadie, A., A. Diamond, and J. Hainmueller (2010). Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American statistical Association 105*(490), 493–505.

Acemoglu, D., T. A. Hassan, and A. Tahoun (2018). The power of the street: Evidence from egypt's arab spring. *The Review of Financial Studies 31*(1), 1–42.

Alsan, M., O. Garrick, and G. Graziani (2019). Does diversity matter for health? experimental evidence from oakland. *American Economic Review 109*(12), 4071–4111.

Ba, B. A., R. Rivera, and A. Whitefield (2023). Market response to racial uprisings. Technical report, National Bureau of Economic Research.

Bishu, K. G., A. Lekoubou, E. Kirkland, S. O. Schumann, A. Schreiner, M. Heincelman, W. P. Moran, and P. D. Mauldin (2020). Estimating the economic burden of acute myocardial infarction in the us: 12 year national data. *The American journal of the medical sciences 359*(5), 257–265.

Bogan, V. L., E. Potemkina, and S. E. Yonker (2021). What drives racial diversity on us corporate boards. *Available at SSRN 3952897*.

Bor, J., A. S. Venkataramani, D. R. Williams, and A. C. Tsai (2018). Police killings and their spillover effects on the mental health of black americans: a population-based, quasi-experimental study. *The Lancet 392*(10144), 302–310.

Buchmueller, T., S. Miller, and M. Vujicic (2016). How do providers respond to changes in public health insurance coverage? evidence from adult medicaid dental benefits. *American Economic Journal: Economic Policy 8*(4), 70–102.

Bursztyn, L., D. Cantoni, D. Y. Yang, N. Yuchtman, and Y. J. Zhang (2021). Persistent political engagement: Social interactions and the dynamics of protest movements. *American Economic Review: Insights 3*(2), 233–250.

Cai, X., S. Chen, Z. Cheng, and E. E. Nix (2025). Gender-based violence and judge responses. Technical report, National Bureau of Economic Research.

Callaway, B. and P. H. Sant'Anna (2021). Difference-in-differences with multiple time periods. *Journal of econometrics 225*(2), 200–230.

Campbell, T. (2024). Black lives matter's effect on police lethal use of force. *Journal of Urban Economics 141*, 103587.

Centers for Medicare & Medicaid Services (2008). 30-day risk-standardized mortality measures: Acute myocardial infarction (ami) and heart failure (hf). https://www.cms.gov/medicare/quality-initiatives-patient-assessment-instruments/hospitalqualityinits/downloads/hospitalmortalityaboutami_hf.pdf.

Centers for Medicare & Medicaid Services (2013). Updates to the hospital 30-day mortality measures for ami, hf, and pneumonia. https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/Mortality_AMI-HF-PN_Measures_Updates_Report_FINAL_06-13-2013.pdf.

Chan, D. C., D. Card, and L. Taylor (2023). Is there a va advantage? evidence from dually eligible veterans. *American Economic Review 113*(11), 3003–3043.

Chandra, A., A. Finkelstein, A. Sacarny, and C. Syverson (2016a). Health care exceptionalism? performance and allocation in the us health care sector. *American Economic Review 106*(8), 2110–2144.

Chandra, A., A. Finkelstein, A. Sacarny, and C. Syverson (2016b). Productivity dispersion in medicine and manufacturing. *American Economic Review 106*(5), 99–103.

Chandra, A., P. Kakani, and A. Sacarny (2024). Hospital allocation and racial disparities in health care. *Review of Economics and Statistics 106*(4), 924–937.

Chandra, A. and D. O. Staiger (2010). Identifying provider prejudice in healthcare. Technical report, National Bureau of Economic Research.

Chen, Y. (2021). Team-specific human capital and team performance: evidence from doctors. *American economic review 111*(12), 3923–3962.

Corredor-Waldron, A., J. Currie, and M. Schnell (2024). Drivers of racial differences in c-sections. Technical report, National Bureau of Economic Research.

Currie, J. and W. B. MacLeod (2017). Diagnosing expertise: Human capital, decision making, and performance among physicians. *Journal of labor economics 35*(1), 1–43.

Cutler, D., A. Deaton, and A. Lleras-Muney (2006). The determinants of mortality. *Journal of economic perspectives 20*(3), 97–120.

Dahl, G. B., R. Lu, and W. Mullins (2022). Partisan fertility and presidential elections. *American Economic Review: Insights 4*(4), 473–490.

Doyle, J., J. Graves, and J. Gruber (2019). Evaluating measures of hospital quality: Evidence from ambulance referral patterns. *Review of Economics and Statistics 101*(5), 841–852.

Doyle Jr, J. J., J. A. Graves, J. Gruber, and S. A. Kleiner (2015). Measuring returns to hospital care: Evidence from ambulance referral patterns. *Journal of Political Economy 123*(1), 170–214.

Dunivin, Z. O., H. Y. Yan, J. Ince, and F. Rojas (2022). Black lives matter protests shift public discourse. *Proceedings of the National Academy of Sciences 119*(10), e2117320119.

Fisher, R. A. (1935). The design of experiments. oliver and boyd. *London 4th Ed. 125p*.

Garcia, R. E. and A. Ortega (2024). Racial protests and credit access. Technical report, National Bureau of Economic Research.

Gertsberg, M. (2022). The unintended consequences of# metoo: Evidence from research collaborations. *Available at SSRN 4105976*.

Gethin, A. and V. Pons (2024). Social movements and public opinion in the united states. Technical report, National Bureau of Economic Research.

Ghaferi, A. A., J. D. Birkmeyer, and J. B. Dimick (2009). Variation in hospital mortality associated with inpatient surgery. *New England Journal of Medicine 361*(14), 1368–1375.

Gowrisankaran, G., K. Joiner, and P. T. Léger (2023). Physician practice style and healthcare costs: Evidence from emergency departments. *Management Science 69*(6), 3202–3219.

Huckman, R. S. and G. P. Pisano (2006). The firm specificity of individual performance: Evidence from cardiac surgery. *Management science 52*(4), 473–488.

Khera, R., M. Vaughan-Sarrazin, G. E. Rosenthal, and S. Girotra (2015). Racial disparities in outcomes after cardiac surgery: the role of hospital quality. *Current cardiology reports 17*, 1–8.

Kochanek, K. D., S. L. Murphy, J. Xu, and E. Arias (2023). Deaths: Final data for 2020.

Kolstad, J. T. (2013). Information and quality when motivation is intrinsic: Evidence from surgeon report cards. *American Economic Review 103*(7), 2875–2910.

Levy, R. and M. Mattsson (2023). The effects of social movements: Evidence from# metoo. *Available at SSRN 3496903*.

Lins, K. V., L. Roth, H. Servaes, and A. Tamayo (2024). Sexism, culture, and firm value: evidence from the harvey weinstein scandal and the# metoo movement. *Journal of Accounting Research 62*(5), 1989–2035.

Luo, H. and L. Zhang (2022). Scandal, social movement, and change: Evidence from# metoo in hollywood. *Management Science 68*(2), 1278–1296.

Madestam, A., D. Shoag, S. Veuger, and D. Yanagizawa-Drott (2013). Do political protests matter? evidence from the tea party movement. *The Quarterly Journal of Economics 128*(4), 1633–1685.

Marx, M., Q. Wang, and E. Yimfor (2025). Minimum viable signal: Venture funding, social movements, and race. *Management Science*.

Mazumder, S. (2019). Black lives matter for whites' racial prejudice: assessing the role of social movements in shaping racial attitudes in the united states.

Menees, D. S., E. D. Peterson, Y. Wang, J. P. Curtis, J. C. Messenger, J. S. Rumsfeld, and H. S. Gurm (2013). Door-to-balloon time and mortality among patients undergoing primary pci. *New England Journal of Medicine 369*(10), 901–909.

Mourot, P. (2025). Should top surgeons practice at top hospitals? sorting and complementarities in healthcare. *University of Chicago, mimeo*.

Myles, P. S., J. A. Smith, A. Forbes, B. Silbert, M. Jayarajah, T. Painter, D. J. Cooper, S. Marasco, J. McNeil, J. S. Bussières, et al. (2016). Stopping vs. continuing aspirin before coronary artery surgery. *New England Journal of Medicine 374*(8), 728–737.

Nelson, A. (2002). Unequal treatment: confronting racial and ethnic disparities in health care. *Journal of the national medical association 94*(8), 666.

Philip, M. and O. Ozkaya (2024). Disparate treatment and outcomes in emergency departments: Evidence from florida.

Reny, T. T. and B. J. Newman (2021). The opinion-mobilizing effect of social protest against police violence: Evidence from the 2020 george floyd protests. *American political science review 115*(4), 1499–1507.

Singh, M. and A. Venkataramani (2022). Rationing by race. Technical report, National Bureau of Economic Research.

Soule, S. A. (2018). Social movements and their impact on business and management. In *Oxford research encyclopedia of business and management*.

Wasow, O. (2020). Agenda seeding: How 1960s black protests moved elites, public opinion and voting. *American Political Science Review 114*(3), 638–659.

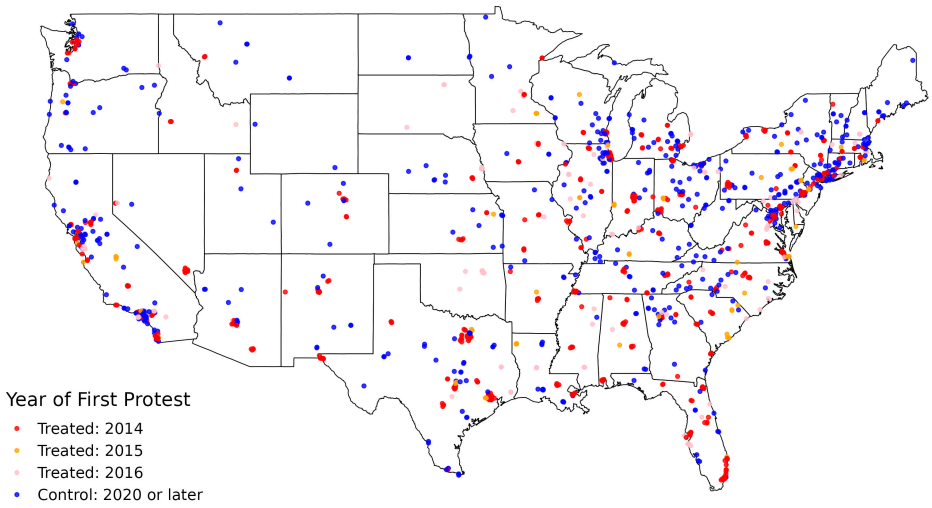
Xie, F. (2022). rethnicity: An r package for predicting ethnicity from names. *SoftwareX 17*, 100965.

Ye, H. and J. Yi (2023). Patient-physician race concordance, physician decisions, and patient outcomes. *Review of Economics and Statistics 105*(4), 766–779.

Yearby, R. (2011). Racial inequities in mortality and access to health care: The untold peril of rationing health care in the united states. *The Journal of legal medicine 32*(1), 77–91.

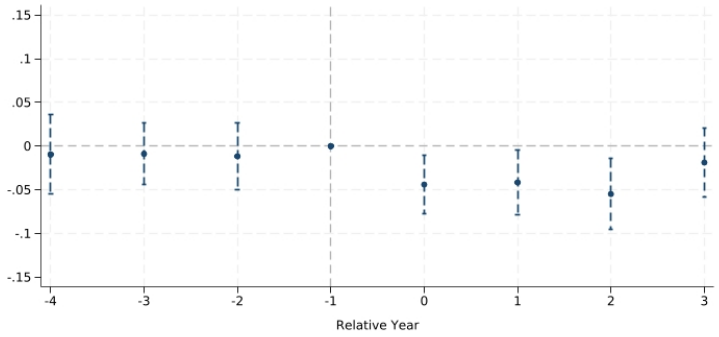
Figures

Figure 1: Hospitals Exposed to BLM Protests

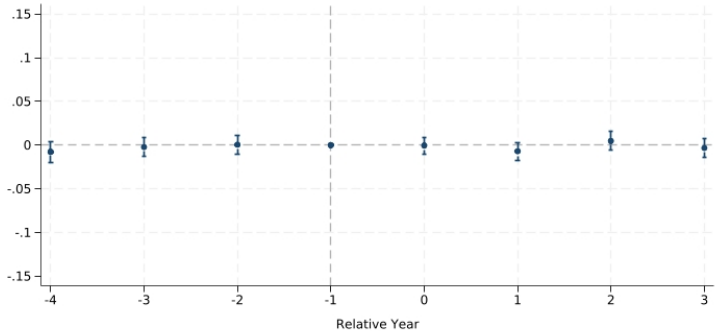


Notes: Each dot in the map represents a hospital. Hospitals that experienced their first BLM protest in 2014, 2015, or 2016 are assigned to the treated group in the corresponding cohort and are shown as red, yellow, and pink dots, respectively. Blue dots indicate control hospitals that did not experience a protest until 2020 but eventually did by 2021.

Figure 2: Effect of BLM Protests on Hospital RAMR



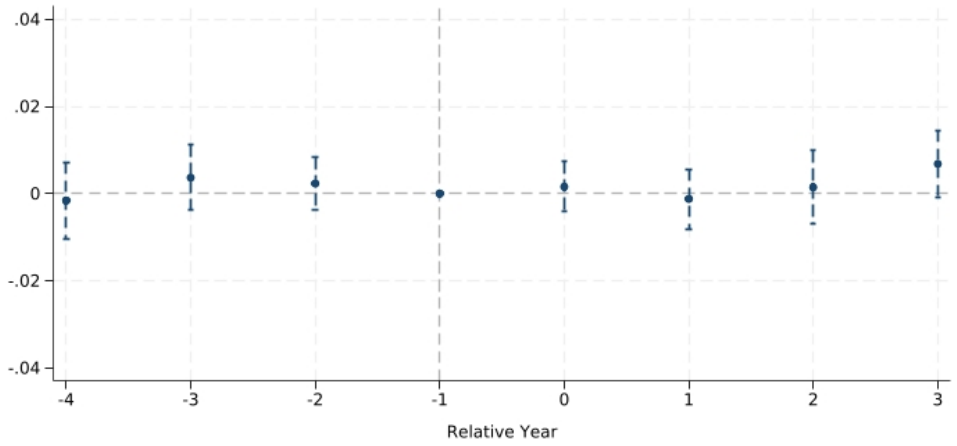
(a) Black Patients



(b) Non-Black Patients

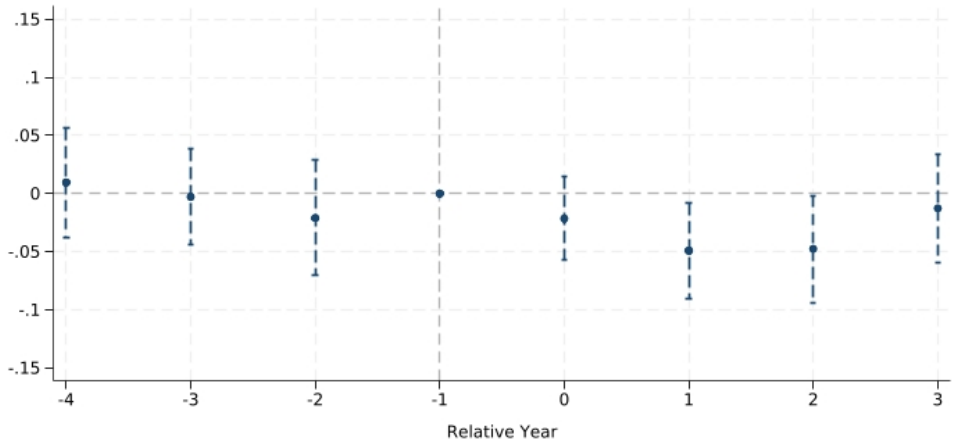
Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black (Panel (a)) and Non-Black (Panel (b)) heart attack patients, based on Equation (5), with 95 percent confidence intervals. Effects are normalized to the year prior to the protests. Standard errors are clustered at the hospital level.

Figure 3: Effect of BLM Protests on Hospital-Level Black Patient Severity



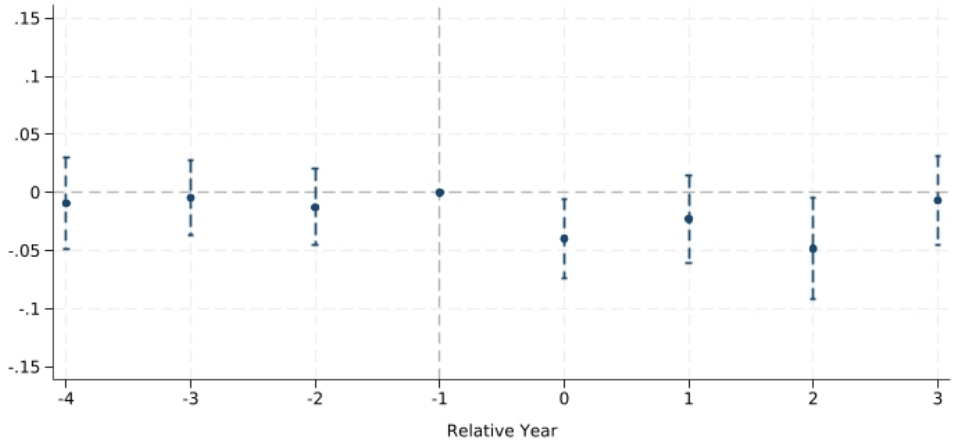
Notes: The figure plots the estimated treatment effects of BLM protests on a hospital's expected mortality rate for Black patients (EMR^{B}_{htc} as defined in Equation (2)), which serves as a measure of overall patient severity in a hospital, based on Equation (5), with 95 percent confidence intervals. Standard errors are clustered at the hospital level.

Figure 4: Effect of BLM Protests on Hospital RAMR for ED Black Patients



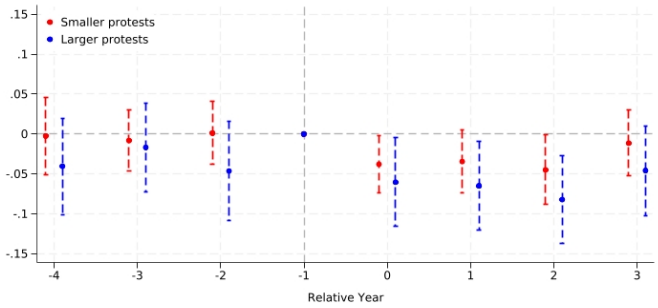
Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black patients admitted through the Emergency Department, based on Equation (5), with 95 percent confidence intervals. Standard errors are clustered at the hospital level.

Figure 5: Effect of BLM Protests on Patient-level Mortality of Non-exposed Black Patients

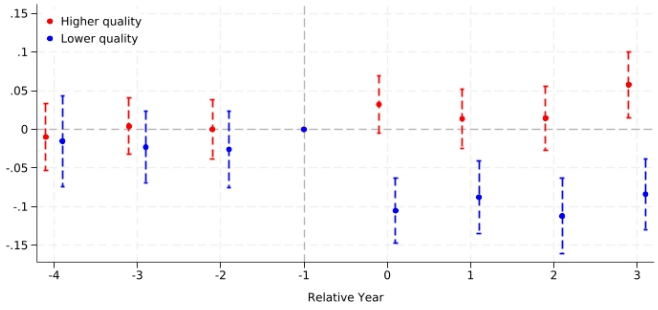


Notes: The figure plots the estimated treatment effects of BLM protests on patient level risk-adjusted mortality rates for Black patients who were admitted to the exposed hospitals *before* any protests occurred in their home cities, based on Equation (6), with 95 percent confidence intervals. Standard errors are clustered at the hospital level.

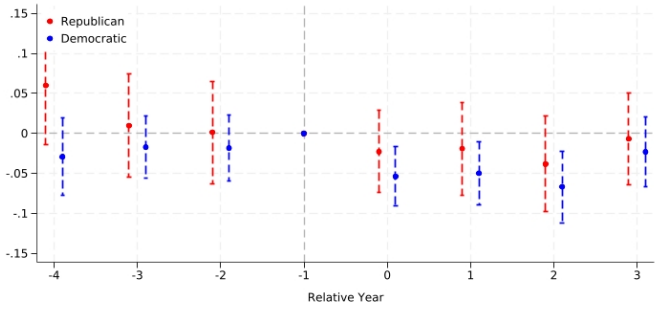
Figure 6: Heterogeneous Effects of BLM Protests on Black Patients' RAMR



(a) By Protest Size



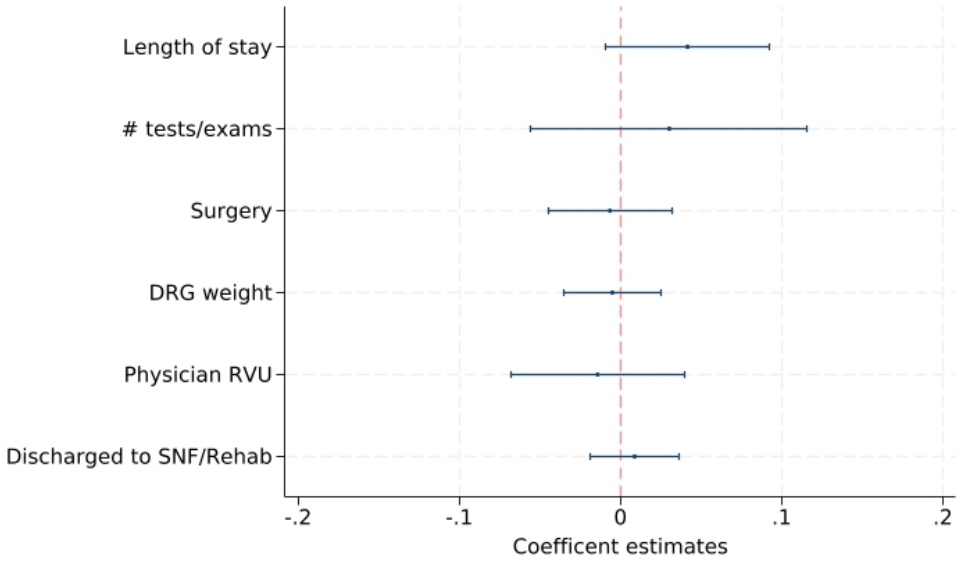
(b) By Hospital Ex-ante Quality



(c) By Political Ideology

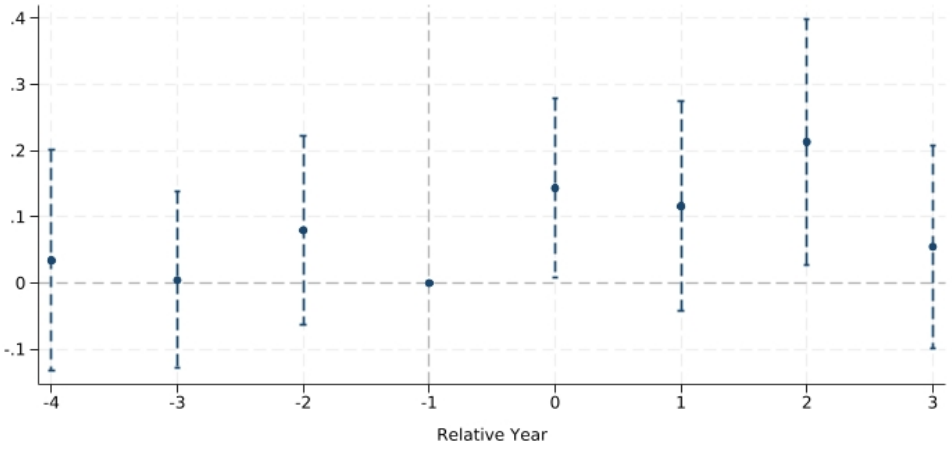
Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black heart attack patients by protest size (panel (a)), hospital ex-ante quality for Black patients (panel (b)), and county political ideology (panel (c)), based on Equation (5), with 95 percent confidence intervals. The control groupsa are the same across all sub-samples: hospitals exposed to protests only in 2020 or later. Standard errors are clustered at the hospital level.

Figure 7: Changes in Care Resource Utilization for Black Patients



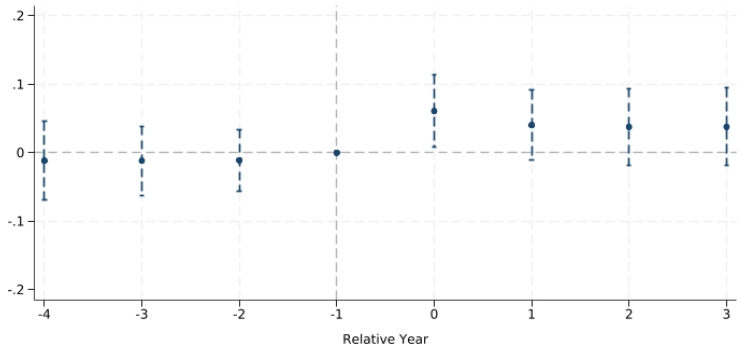
Notes: The figure plots the estimated treatment effects of BLM protests on measures of individual Black patients' care intensity and resource use, based on a pre-post version of Equation (6), with 95 percent confidence intervals. Specifically, the relative year dummies in Equation (6) are replaced with a single post-period indicator. Standard errors are clustered at the hospital level.

Figure 8: Changes in Hospitals' Total Factor Productivity for Black Patients

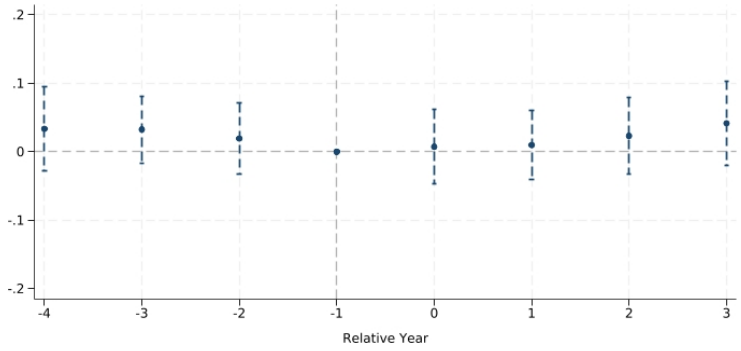


Notes: The figure plots the estimated treatment effects of BLM protests on hospitals' Black-specific TFP, based on Equation (5), with 95 percent confidence intervals. Hospital TFP is estimated using a patient-level log health production function as specified in Equation (7), following the methodology of Chandra et al. (2016a,b). Standard errors are clustered at the hospital level.

Figure 9: Effect of BLM Protests on Patient-Physician Matching



(a) Prob. of Being Treated By a High-Productivity Physician



(b) Prob. of Being Treated By a Black Physician

Notes: The figure plots the estimated treatment effects of BLM protests on a Black patient's likelihood of being matched with a high-productivity physician (panel (a)) and with a Black physician (panel (b)), based on Equation (6), with 95 percent confidence intervals. Effects are normalized to the year prior to the protests, and standard errors are clustered at the hospital level.

Tables

Table 1: Summary Statistics by Hospital Treatment Status

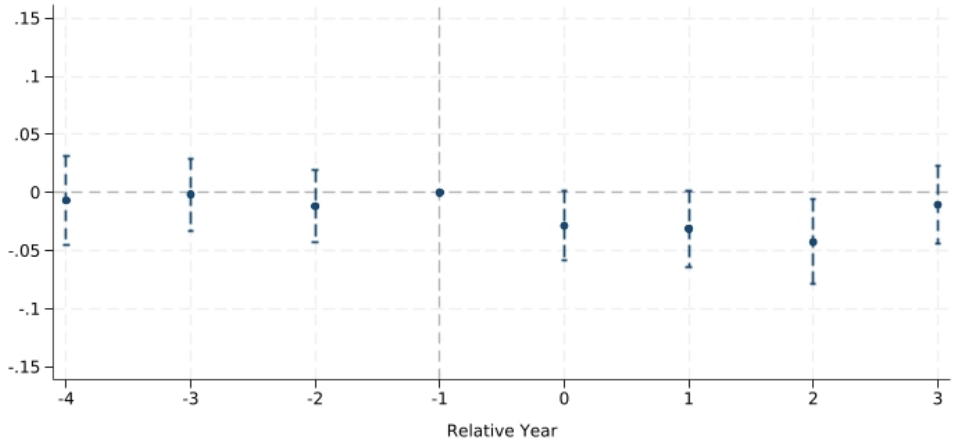
	All Hospitals	Treated Hospitals	Control Hospitals
Health Outcome			
30-day RAMR	0.10	0.10	0.09
	(0.17)	(0.17)	(0.17)
Care Utilization			
Length of stay	5.49	5.63	5.31
	(3.26)	(3.24)	(3.28)
Number of tests/exams	5.08	5.16	4.98
	(3.91)	(3.92)	(3.90)
Surgery rate	0.43	0.42	0.44
	(0.29)	(0.28)	(0.30)
DRG weights	2.24	2.31	2.15
	(1.07)	(1.07)	(1.05)
Relative value unit	5.45	5.32	5.62
	(4.74)	(4.66)	(4.83)
Hospital Characteristics			
Log(available bed)	5.80	5.95	5.61
	(0.58)	(0.60)	(0.50)
Log(total admission)	10.37	10.48	10.24
	(0.57)	(0.59)	(0.51)
Teaching hospital	0.67	0.78	0.53
	(0.47)	(0.42)	(0.50)
Private non-profit hospital	0.73	0.71	0.74
	(0.45)	(0.45)	(0.44)
Medicaid patient ratio	0.12	0.13	0.10
	(0.10)	(0.11)	(0.09)
Medicare patient ratio	0.32	0.29	0.34
	(0.10)	(0.11)	(0.10)
County Characteristics			
Log(median household income)	10.90	10.85	10.96
	(0.25)	(0.21)	(0.28)
Log(population)	13.31	13.58	12.96
	(1.20)	(1.15)	(1.16)
Unemployment rate	0.07	0.07	0.06
	(0.02)	(0.02)	(0.02)
Ratio: adult population	0.69	0.70	0.67
	(0.10)	(0.12)	(0.08)
Ratio: non-White population	0.31	0.35	0.26
	(0.14)	(0.14)	(0.12)
Ratio: with bachelor degree or above	0.31	0.33	0.30
	(0.10)	(0.09)	(0.11)
Observations	5,069	2,860	2,209

Notes: This table reports the summary statistics of the stacked regression sample. Only hospital-year observations with more than one Black patient are included. Means are reported with standard errors in parentheses.

Supplemental Appendix

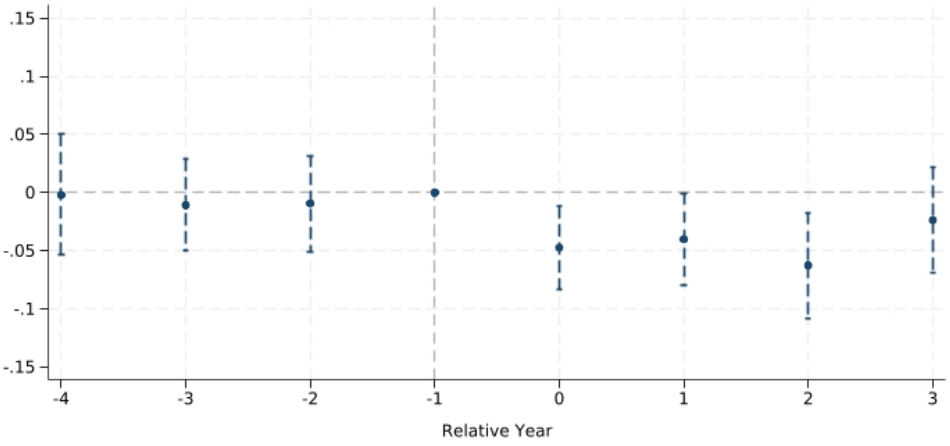
A Robustness Checks on Mortality Reductions for Black Patients

Figure A1: Effect of BLM Protests on Patient-Level Mortality for Black Patients



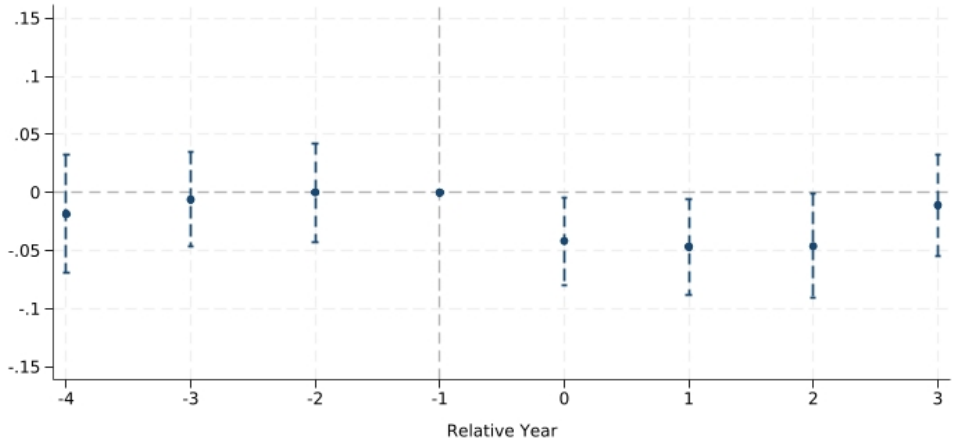
Notes: The figure plots the estimated treatment effects of BLM protests on patient level mortality for Black heart attack patients, based on Equation (6). Effects are normalized to the year prior to the protests. Standard errors are clustered at the hospital level.

Figure A2: Effect of BLM Protests on Hospital RAMR for Black Patients: Including State-by-year FE



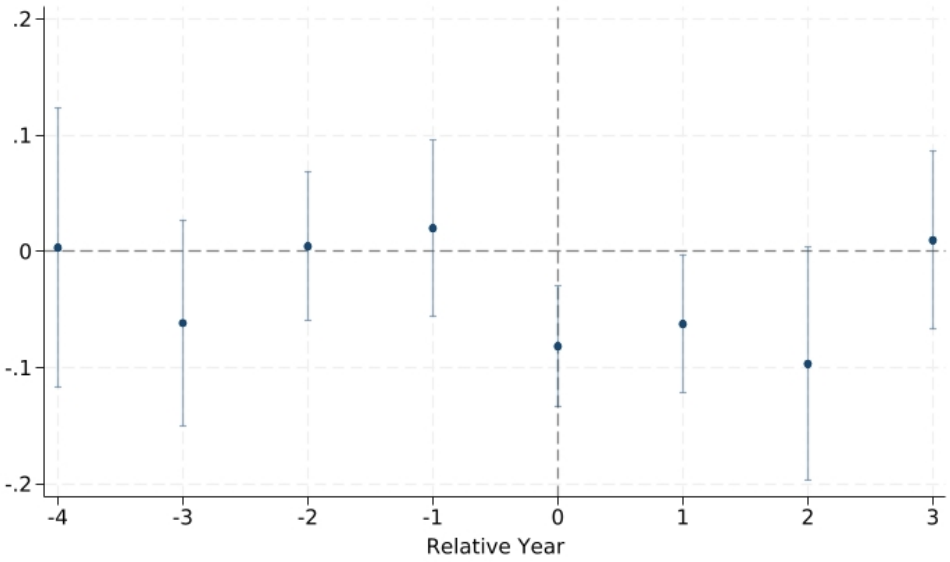
Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black heart attack patients, based on Equation (5) plus state-by-year fixed effects. Effects are normalized to the year prior to the protests. Standard errors are clustered at the hospital level.

Figure A3: Effect of BLM Protests on Hospital RAMR for Black Patients: Dropping Large Cities



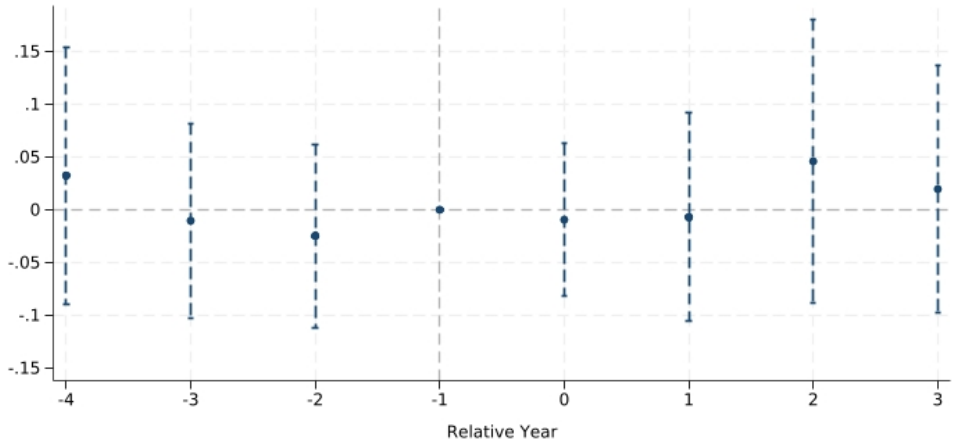
Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black heart attack patients, based on Equation (5), excluding cities with above-median population. Effects are normalized to the year prior to the protests. Standard errors are clustered at the hospital level.

Figure A4: Effect of BLM Protests on Hospital RAMR for Black Patients: CSDID



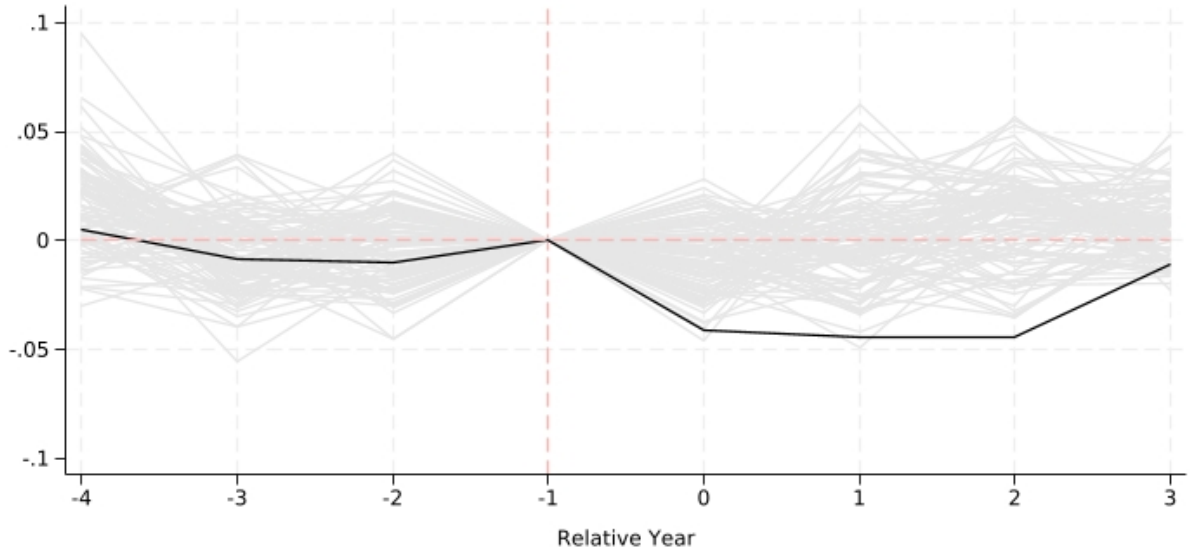
Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black heart attack patients using the alternative estimator proposed by Callaway and Sant'Anna (2021).

Figure A5: Placebo Treatment Effect on Hospital RAMR for Black Patients



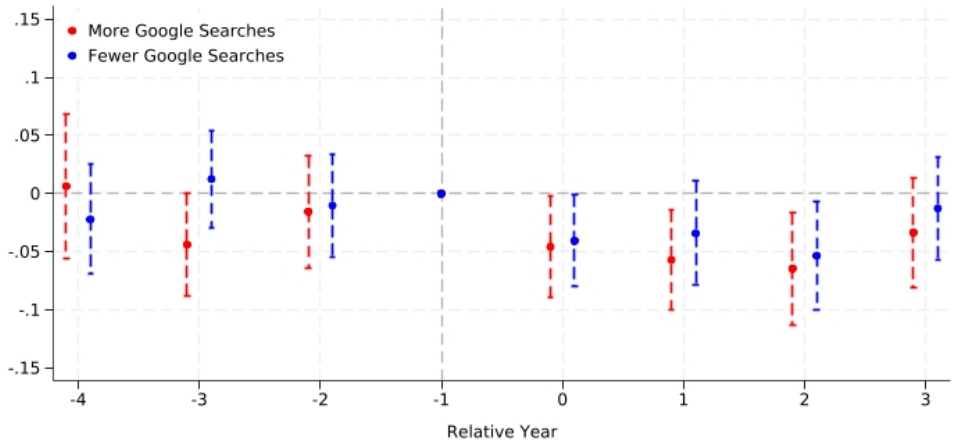
Notes: The figure plots the placebo treatment effects on hospital risk-adjusted mortality rates for Black heart attack patients, estimated from Equation (5) using placebo-treated hospitals.

Figure A6: Placebo Treatment Effects from the Permutation Test



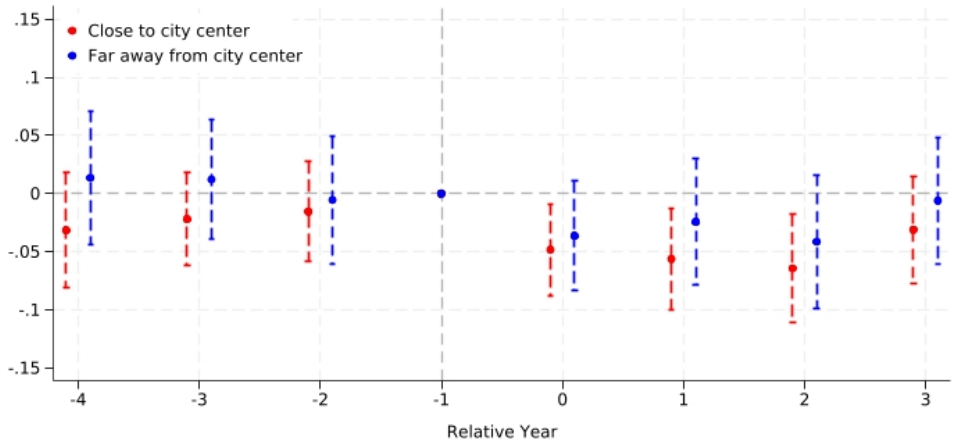
Notes: This figure plots the permutation treatment effects and the "true" treatment effect based on Equation (5). The gray lines indicate the permutation treatment effects; the black solid line indicating the "true" treatment effect.

Figure A7: Heterogeneous Effects on Black Patients' RAMR by Google Search Trend



Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black heart attack patients, split by Designated Market Area level Google search intensity for "Black Lives Matter" or "BLM," using the median intensity as the cutoff.

Figure A8: Heterogeneous Effects on Black Patients' RAMR by Distance to City Center

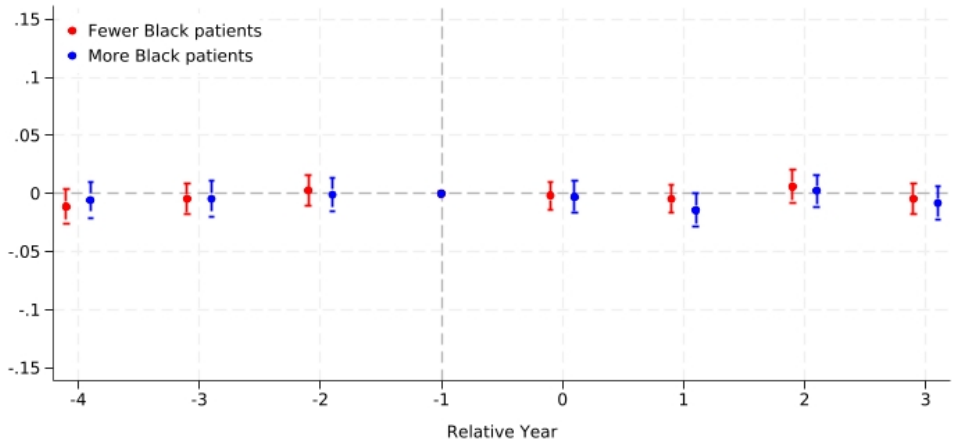


Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black heart attack patients, split by hospitals' distance from the city center, where protests most likely occurred, using the median distance as the cutoff.

B The Effect of BLM Protests on Non-Black Patients by Hospital-Year's Share of Black Patients

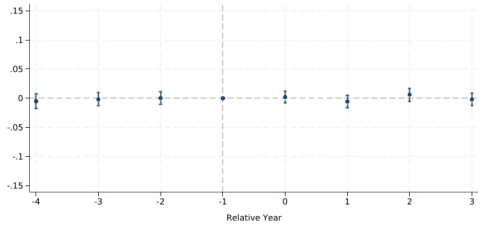
To define hospital-years with a high share of Black patients, we use data from all treated hospitals in 2013 and earlier to construct the distribution of hospital-level Black patient shares and set the threshold at the pre-2014 median. Treated hospital-year observations with a Black patient share above this threshold are classified as high-share. The control group is the same as the main analysis. We take this approach instead of classifying hospitals permanently into high or low share group because a hospital's racial composition may vary from year to year, and what matters for our analysis is whether, in a given year, the hospital had a relatively high share of Black patients, and how that may influence outcomes for Non-Black patients.

Figure B1: Effect of BLM protests on Hospital RAMR for Non-Black Patients

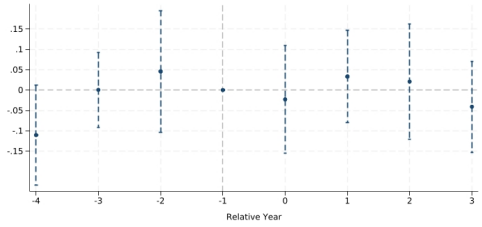


C The Effect of BLM Protests on White, Asian, and Hispanic Patients

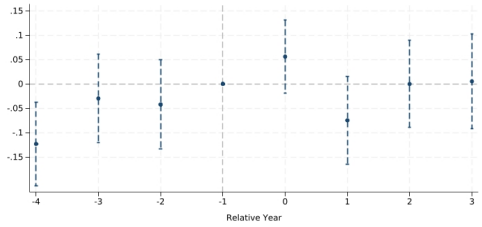
Figure C1: Effect of BLM Protests on Hospital RAMR



(a) White Patients



(b) Asian Patients



(c) Hispanic Patients

Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for White (panel (a)), Asian (panel (b)), and Hispanic (panel (c)) heart attack patients, based on Equation (5), with 95 percent confidence intervals. Standard errors are clustered at the hospital level.

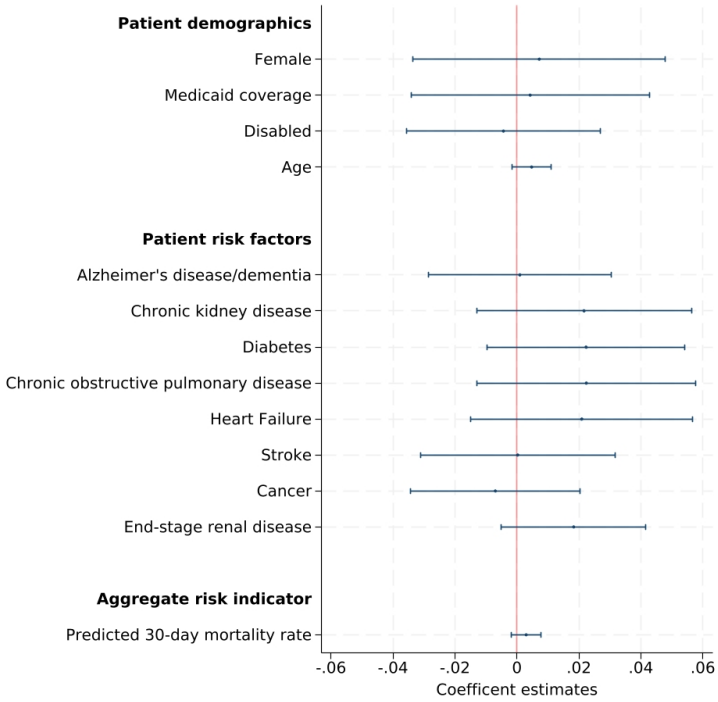
D Patient Selection

We present a pre-post patient-level event study examining whether observed patient characteristics respond to BLM protests. Had patient selection occurred, we would expect shifts in patient demographics and risk factors following BLM protests.

$$Y_{ihtc} = \beta \times Treated_{hc} \times \mathbf{1}(t \geq 0) + \delta_{tc} + \theta_{hc} + \epsilon_{ihtc}. \tag{D1}$$

We estimate Equation (D1) using patient characteristics as outcomes, restricting the sample to Black patients. As shown in Figure D1, these characteristics remain balanced after protests, providing no evidence of selection on observables.

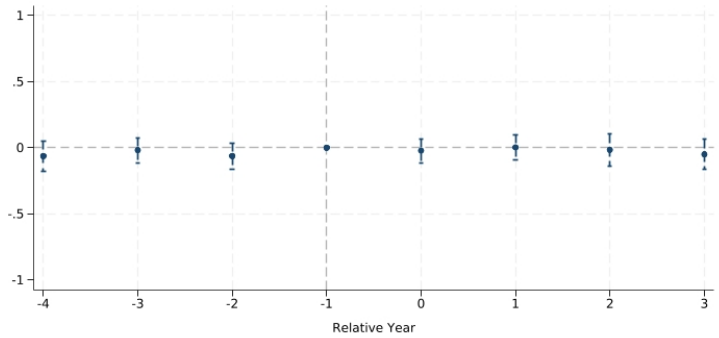
Figure D1: Balance Check on Patient Characteristics



Notes: The figure plots the estimated treatment effects of BLM protests on various Black patients' demographics and risk factors, based on Equation (D1), with 95 percent confidence intervals. The predicted 30-day mortality rate is the fitted value from Equation (1), denoted as $\hat{p}_{ih}$. Standard errors are clustered at the hospital level.

We also examine whether the volume of Black patients changed following BLM protests. We estimate a Poisson pseudo–maximum likelihood model; results are similar under a linear specification.

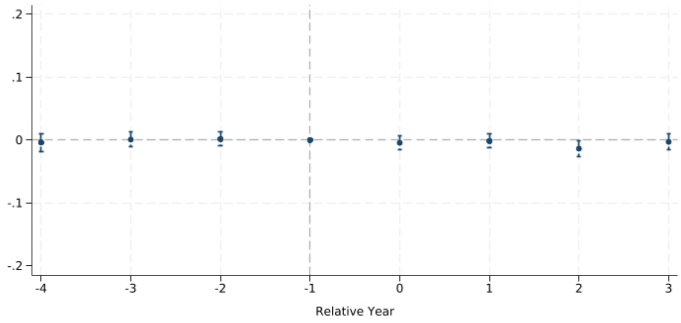
Figure D2: Treatment Effect on Black Patient Volume



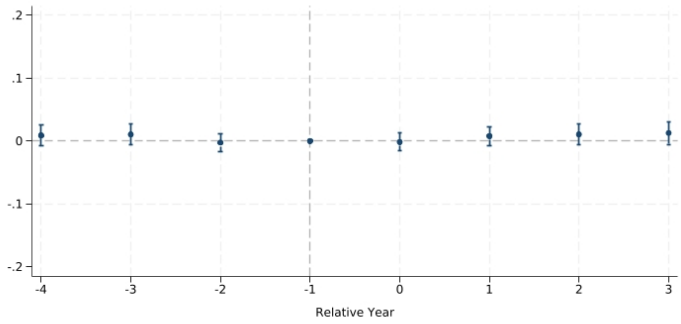
Notes: The figure plots the estimated treatment effects of BLM protests on Black patient volume, based on Poisson pseudo–maximum likelihood. Standard errors are clustered at the hospital level.

E Matching Between Non-Black Patients and High-Productivity Physicians

Figure E1: Prob. of Non-Black Patients Being Treated By High-Productivity Physicians



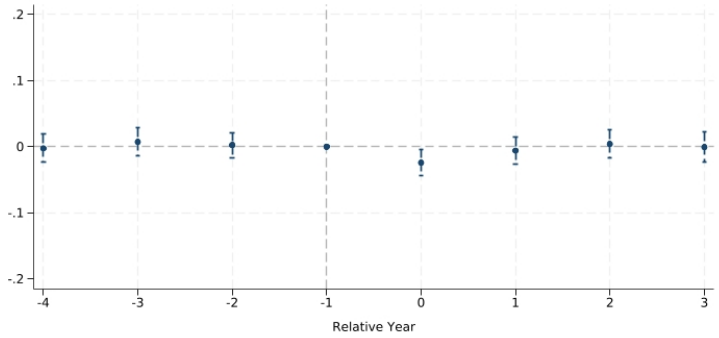
(a) Defining High-Productivity Physicians Based On Performance With Black Patients



(b) Defining High-Productivity Physicians Based On Performance With Non-Black Patients

Notes: The figure plots the estimated treatment effects of BLM protests on a non-Black patient's likelihood of being treated by a high-productivity physician, based on Equation (6), with 95 percent confidence intervals. Panel (a) defines physician productivity based on performance with Black patients, while Panel (b) uses performance with non-Black patients. Effects are normalized to the year prior to the protests, and standard errors are clustered at the hospital level.

Figure E2: Prob. of Non-Black Patients Being Treated By High-Productivity Physicians: High Black-Share Hospitals



Notes: The figure plots the estimated treatment effects of BLM protests on a non-Black patient's likelihood of being matched with a high-productivity physician, focusing on hospital-years with an above-median share of Black patients. Physician productivity is measured based on performance with non-Black patients. Effects are normalized to the year prior to the protests, and standard errors are clustered at the hospital level.