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

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October, 2025

Abstract

This paper examines the role of provider performance in shaping racial disparities in healthcare outcomes. We leverage the outbreak of local Black Lives Matter (BLM) protests as an external shock to providers' racial awareness and societal pressure. We find that hospitals exposed to BLM protests experienced significant reductions in 30-day risk-adjusted mortality among Black patients admitted for acute myocardial infarction, with no detectable changes observed for non-Black patients. These mortality improvements are more pronounced following protests with more involved participants, and are concentrated in hospitals with lower baseline performance treating Black patients and those located in Democratic-leaning counties. Furthermore, the effects persist among emergency admissions and among "non-exposed" patients treated in exposed hospitals prior to any BLM activity in their home cities, suggesting that the observed mortality decline is primarily driven by changes on the supply side rather than patient selection or demand-side factors.

Our results do not necessarily indicate prior discriminatory intent among providers. Rather, salient social events may have heightened providers' attentiveness, leading to improved outcomes for Black patients. In examining the underlying mechanisms, we observe no significant changes in overall resource utilization but find strong evidence of increased productivity. Notably, enhanced matching between Black patients and higher-productivity attending physicians accounts for approximately one-third of the observed productivity gains, while racial concordance between patients and providers remains unchanged. These results highlight the potential of improving race-specific productivity as a complementary pathway for reducing racial disparities in healthcare delivery.

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

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1 Introduction

Racial disparities in heath remain a persistent issue in the U.S., with Black population experiencing an age-adjusted mortality rate that is 30% higher than that of their White counterpart (Kochanek et al., 2023). Racial disparities have also existed across a wide range of healthcare services, from basic care to the most advanced diagnostic and therapeutic interventions (Nelson, 2002). The literature has identified serval contributing factors, including disparities in socioeconomic status (Cutler et al., 2006), barriers to accessing high-quality hospitals (Chandra et al., 2024), greater communication challenges with White providers (Alsan et al., 2019), and provider discretion (Singh and Venkataramani, 2022; Corredor-Waldron et al., 2024). In this paper, we examine the role of race-specific provider performance in shaping racial disparities in healthcare and present new evidence that, even within the same hospital, improving performance for Black patients can serve as an additional force to reduce racial disparities.

Isolating the role of race-specific provider performance remains an empirical challenge. Even when observationally identical Black and White patients receive care at the same hospital, differences in health outcomes could reflect not only hospital side factors such as variations in resource allocation, but also demand side factors including unobserved differences in medical risk or patient preferences. As a result, comparing seemingly similar Black and White patients does not fully isolate race-specific provider performance.

We leverage the outbreak of social events as an external shock to 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. We hypothesize that BLM protests influence provider performance toward Black patients.[1] BLM protests are typically sparked by police killings of unarmed African Americans. These protests brought substantial attention to racial justice issues, shifting public attitudes and increasing awareness of racial bias (Reny and Newman, 2021; Dunivin et al., 2022; Gethin and Pons, 2024). Previous evidence shows that BLM protests can directly affect decision-making across various industries in ways that benefit the Black population (Bogan et al., 2021; Garcia and Ortega, 2024). Building upon this literature, we posit that exposure to BLM protests could enhance provider racial awareness and amplify societal pressures due to public scrutiny, media attention, and societal expectations, all of which could change how providers engage with Black patients and therefore improve health outcomes among Black patients, in the presence of race-specific provider performance.

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

We focus on patients admitted to hospitals with Acute Myocardial Infarction (AMI), or heart attack. There are several reasons for choosing this setting. First, AMI is an acute condition that always requires hospitalization and timely medical intervention, highlighting the role of providers rather than patient preferences, in determining patient outcomes (Chandra and Staiger, 2010). Second, AMI is a leading cause of death and imposes a substantial financial burden, with annual costs estimated at $84.9 billion in 2016 dollars (Bishu et al., 2020). Third, AMI care exhibits stark racial disparities. For example, Black patients face up to 1.5 times the mortality risk of White patients after cardiac surgeries (Khera et al., 2015). Finally, hospital performance measures for AMI, such as 30-day risk-adjusted mortality, have been extensively validated in the literature (Doyle et al., 2019), which allows us to offer compelling analyses regarding provider performance.

We link comprehensive data on BLM protests from 2014 to 2021 to Medicare claims to study how social movements affect patient outcomes. Our empirical strategy leverages the staggered rollout of local BLM protests across U.S. cities between 2014 and 2016. During this period, approximately 700 cities experienced their first BLM protest, which defines our set of treated hospitals. Specifically, we construct three event-time cohorts based on the year of initial exposure (2014, 2015, or 2016) and use as controls those hospitals that did not experience a protest until after 2019 but 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 the exposed and non-exposed hospitals. Our identification strategy relies on the assumption that, absent BLM protests, the treated and control hospitals would have exhibited parallel trends in their underlying risk-adjusted mortality rates.

We find that hospitals exposed to BLM protests experienced a significant 4.6 percentage point reduction in the 30-day risk-adjusted mortality rate among 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 to one at the 32nd percentile of the quality distribution. Moreover, the improvement in patient outcomes persists for up to three years following the initial exposure.

In contrast, we find no detectable changes in health outcomes for White, Asian, or Non-Black Hispanic (hereafter Hispanic) patients. These results offer direct evidence that hospital performance is race-specific and that improvements in outcomes for Black patients can be achieved without adversely affecting non-Black patients. Moreover, the absence of spillover effects strengthens the causal interpretation of our main findings, suggesting that the observed mortality reduction among Black patients is plausibly driven by the BLM protests' emphasis on the well-being the Black population.

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 replace the treated hospitals with matched control hospitals and find no significant effects for these placebo-treated counterparts. In the permutation test, we randomly assign protest timings to control hospitals and repeat the estimation multiple times. The estimated effect from the true treated hospitals lies at the extreme tail of the placebo distribution, indicating that the observed effect is highly unlikely to have arisen 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).

Additional heterogeneity analyses reveal several noteworthy patterns. We find that mortality reductions are more pronounced following protests with more involved participants. These effects are also concentrated in hospitals with lower baseline performance in treating Black patients and in those located in Democratic-leaning counties.

We next present evidence that the observed improvements in health outcomes are primarily driven by supply-side responses. First, we show that demand side observables, including patient demographics, risk factors, predicted mortality based on patient characteristics, and the volume of Black patients, remain stable following BLM protests. This finding mitigates concerns that the observed effects are attributable to shifts in the underlying health of Black patients or to patient selection into higher-quality hospitals in response to the protests.[2] Second, we observe comparable reductions in mortality among Black patients admitted through emergency departments, where patients and families exert minimal influence over over hospital choice or treatment decisions. Finally, we analyze a subsample of "non-exposed" patients who were treated at exposed hospitals prior to any BLM protests occurred in their home cities. Because these patients could not have been affected by demand-side behavioral responses, finding largely consistent results further corroborate that the mortality reductions are largely supply-side driven.

It is important to note that these findings do not necessarily indicate prior discriminatory intent among providers. Rather, salient external events appear to have prompted greater provider attentiveness, potentially through improved physician–patient matching and more engaged communication, resulting in better outcomes for Black patients. To further understand how hospitals achieve better outcomes for Black patients after BLM protests, we examine two potential mechanisms: increased resource utilization or enhanced productiv-

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

ity with existing resources. We find no significant changes in key indicators of resource use, including length of stay, number of diagnostic tests, surgery rates, Diagnosis-Related Group (DRG) weights, attending physicians' relative value units (RVUs), or discharge destination (e.g., transfer to skilled nursing or rehabilitation facilities). These results suggest the observed improvements primarily reflect improved productivity in the treatment of 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). Further analysis reveals that improved matching between Black patients and higher-productivity attending physicians accounts for approximately one-third of the overall productivity gains. Importantly, matching quality for non-Black patients remains unchanged, indicating that physicians were not operating at capacity constraints given the relatively small proportion of Black patients.[3] Finally, we find no evidence of increased racial concordance between Black patients and their attending physicians.

Our study contributes to the literature examining the underlying causes of racial disparities in healthcare. Such disparities stem from a variety of factors, including social determinants of health (Cutler et al., 2006; Town, 2024), 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 aligned with work demonstrating how provider discretion leads to differential treatment decisions and health outcomes for Black patients (Singh and Venkataramani, 2022; Corredor-Waldron et al., 2024; Philip and Ozkaya, 2024). While Singh and Venkataramani (2022) and Corredor-Waldron et al. (2024) exploit variation in hospital capacity to examine the role of providers in resource allocation and unnecessary procedures, we leverage BLM protests as a race-specific external shock to assess whether provider performance along racial lines contributes to healthcare disparities. We extend this literature by demonstrating that, beyond differences in resource utilization, providers' productivity itself varies by patient race, and that improving race-specific performance represents a distinct and complementary mechanism for mitigating racial disparities in healthcare delivery. This productivity-based approach may offer an additional and potentially more actionable avenue for addressing racial disparities in healthcare. Efforts aimed at improving the socioeconomic conditions of Black patients often progress slowly, while strategies that redirect patients to higher-quality hospitals face substantial geographic and

[3]Prior to the protests, the quality of physician–patient matching was comparable between Black and non-Black patients, providing no evidence of preexisting discriminatory assignment.

logistical constraints, particularly in emergency settings. Similarly, initiatives to promote racial concordance are limited by the relatively small number of Black physicians in the workforce.

Lastly, our paper contributes to the literature on social movements by examining their impact on the performance of organizations that are not connected to those movements. Prior research shows that social movements can heighten public awareness, shift public sentiment, and affect the targeted institutions (Madestam et al., 2013; Soule, 2018; Wasow, 2020; Dunivin et al., 2022). More recent work further reveals the spillover effects of social movements on domains connected with the immediate target of those movements (Acemoglu et al., 2018; Ba et al., 2023; Luo and Zhang, 2022; Lins et al., 2024). For example, Acemoglu et al. (2018) find that, Egypt's Arab Spring protests -intended to challenge political regimes, led to declines in the stock valuations of politically connected firms. Our study extends this line of work by exploring how social movements influence *non-connected* institutions. In this vein, our paper is similar to studies documenting the broader effect of social movements on corporate board diversity (Bogan et al., 2021), lending practices (Garcia and Ortega, 2024), 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, such as increased crime reporting after #MeToo (Levy and Mattsson, 2023) and heightened participation in collective actions (Bursztyn et al., 2021). Our study departs from the existing work by examining organizational performance, a dimension rarely examined in the context of social movements. We leverage the healthcare sector as an ideal setting, where performance is observable, quantifiable, and has life-or-death consequences.

The remainder of the paper is structured as follows. Section 2 provides background on the 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 race-specific provider performance through the lens of the BLM protests. Section 6 explores the underlying mechanisms, 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 (Dunivin et al., 2022; Gethin and Pons, 2024; Acemoglu et al., 2018). Notably, the influence of social movements often extends beyond their immediate targets. For example, Acemoglu et al. (2018) show that Egypt's Arab Spring protests, primarily focused

on political regime change, led to lower stock market valuations for politically connected firms. Similarly, Luo and Zhang (2022) find that the #MeToo movement, while focused on addressing sexual misconduct, spurred broader changes in the entertainment industry, including increased collaboration between producers and female writers on new projects. However, there is limited evidence on the ripple effects of social movements on the broader society.

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 protest is 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 African-American teenager Trayvon Martin 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 African Americans. These protests reached global prominence 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] This non-violence nature helps 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 African Americans face, and elicit responses across a wide range of institutions. 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

[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

across industries, we hypothesize that 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, which is likely to affect health outcomes of Black patients. Leveraging such a race-specific shock allows us to examine the role of provider race-specific performance in shaping racial disparities in care quality and to evaluate whether a social movement can improve hospital performance for Black patients and help reduce racial disparities in health outcomes.

3 Data and Measures

3.1 Medicare Claims Data for Heart Attack Patients

We use administrative claim records (MedPAR files) for a 20% random sample of Medicare beneficiaries from 2010 to 2019. We restrict the sample to patients aged 66 to 100, with a principal ICD diagnosis code for AMI, or heart attack.[6]. We also exclude patients who were directly admitted to nursing homes or who had a prior heart attack hospitalization within the past year.

We then link these admissions to the Carrier files (claims billed for physician services) by unique beneficiary identifiers and inpatient time ranges. This allows us to identify physicians involved in each admission and define resource use measures, including: (1) length of stay; (2) number of tests; (3) whether surgery was performed; (4) DRG weights; (5) physician RVUs; and (6) whether the patient was discharged to a skilled nursing or rehabilitation facility.

We merge the admissions with the Master Beneficiary Summary File (MBSF) using the beneficiary identifiers. The MBSF file provides patient demographics and chronic conditions, allowing us to identify patient race and perform risk adjustments based on rich patient characteristics. We construct a 30-day mortality indicator for each admission (i.e., death within 30 days of the admission date) using the death date reported in the MBSF. Results are similar when defining 30-day mortality based on the discharge date instead.

3.2 BLM Protests Data

Data for a comprehensive record of BLM protests from July 2014 through December 2021 were scraped from Elephrame, an independent, open-access archive that records demonstra-

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

tions based on online news and social media.[7] This same data source has been used in the literature studying BLM protests (e.g., Dunivin et al., 2022; Campbell, 2024; Garcia and Ortega, 2024). For each protest, we observe its event date, the location at the city level, an estimate of the number of participants, and a link to at least one media source that reported on the event. For most of the protests, Elephrame also documents the primary subject being protested, typically incidents involving violent law enforcement actions against African Americans.

There have been two major waves of BLM protests. The first wave began in the second half of 2014, initially triggered by the police killings of Eric Garner in New York City and Michael Brown in Ferguson, Missouri. The second wave occurred in 2020, following the murder of George Floyd in Minneapolis, Minnesota. Both waves sparked nationwide protests. There were 1,619 protests across 658 cities from 2014 to 2016, and 3,410 protests across 1,240 cities from 2020 to 2021. These two waves account for about 86% of all BLM protests between 2014 and 2021, as well as a similar share of cities that ever experienced a protest during this period. Given that our Medicare data end in 2019, this paper focuses on the effects of the first wave of BLM protests.[8]

We next merge the BLM protest data with the Medicare claims data by city. 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; for the purpose of our analysis, we focus on the timing of the first protest a hospital experiences.

Among hospitals with heart attack patients in the merged sample, 651, 61, and 111 hospitals had their first protest in 2014, 2015, and 2016, respectively. These three cohorts constitute our treated group. 480 hospitals experienced their first protests in 2020 or later and serve as the control group. We exclude hospitals with first protests in 2017-2019, as they represent a small share of the sample and lack a sufficiently long post-treatment period for our event study analysis, given that our Medicare data ends in 2019.[9] The geographical distribution of the treated and control hospitals used in our final analysis is presented in Figure 1.

[Figure 1 about here]

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

[8] Garcia and Ortega (2024) examines both the protests sparked by George Floyd's death and those that occurred earlier, finding consistent and comparable impacts on Black borrowers' credit access.

[9] Only 79 hospitals are excluded due to their first protest occurring between 2017 and 2019.

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 patients (Menees et al., 2013; Myles et al., 2016; Chen, 2021; Mourot, 2025).[10] Essential to our analysis, we allow hospital performance to vary by year and by racial group. Below we explain how we construct hospital performance for Black patients. The same approach is applied to White, Asian, and Hispanic patients to calculate group-specific risk-adjusted mortality rates for each hospital in a given year.

In constructing our hospital performance measure, we first calculate the predicted mortality rate for each patient using the following logit model:

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

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 demographics and comorbidities of the patient, including age, sex, race (Black, White, and others), insurance status (whether dual eligible for Medicaid), disability indicator, and diagnoses dummies for any of the 23 conditions.[11]

This model is estimated separately for each year. The fitted values are obtained for each patient to form an expected death probability $\hat{p_{ih}}$, which is 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 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 not male. The 23 comorbidity conditions are: unstable angina, chronic atherosclerosis, respiratory failure, hypertensive heart disease or heart failure, valvular heart disease, arrhythmia, hypertension, stroke, cerebrovascular disease, renal failure disease, dialysis, COPD, pneumonia, diabetes, protein calorie malnutrition, dementia, paralysis and disability, peripheral vascular disease, metastatic cancer, trauma, substance abuse, major psychiatric disorder, and chronic liver disease.

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

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 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 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. 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 located in cities outside of the treated ones, which did not experience a protest until after 2019 but before the end of 2021. We keep four years before and three years after the event year, defining years -4 to –1 as the pre-period, 0 as the event year, and 1 to 3 as the post-event period.

We follow the same approach in constructing the 2015 and 2016 cohorts. The control hospitals for the 2015 and 2016 cohorts are the same as those for the 2014 cohort.[12] Finally,

[12]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 append the three cohorts into one dataset. When analyzing outcomes for Black patients, we drop hospital-year observations with only one or no Black admissions in that year. The resulting sample for Black patients has 579 treated hospitals and 207 control hospitals during event years -4 to 3, totaling 5,069 hospital-year observations. We apply the same restriction when constructing samples for White, Asian, and Hispanic patients.

To proceed, we first 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 non-Black pool combining White, Asian, and Hispanic patients.

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

where $RAMR^{r}_{htc}$ denotes the risk-adjusted mortality rate of patients with race r for hospital h in event year t and cohort c. The indicator variable $Treated_{hc}$ equals 1 if hospital h in cohort c is treated. 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 hospitals, and the shares of patients discharged through Medicare and Medicaid. 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.

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 risk-adjusted mortality rates between the pre- and post-event periods.

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:

$$Y_{ihtc} = \sum_{k=-4}^{3} \beta_k \times Treated_{hc} \times \mathbf{1}(t = k) + \boldsymbol{\gamma} \boldsymbol{X_{it}} + \delta_{tc} + \theta_{hc} + \phi_t^m + \phi_t^d + \epsilon_{ihtc}, \tag{6}$$

where 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. To explore underlying mechanisms, we consider a range of resource use intensity and productivity measures, including logged values of length of stay, number of tests, DRG weight, physician RVUs, an indicator for whether the patient underwent surgery, an indicator for whether the patient was discharged to a skilled nursing or rehabilitation facility, an indicator for whether a Black patient was matched with a high-productivity attending physician, and an indicator for racial concordance between the patient and physician. $\boldsymbol{X_{it}}$ is the vector of patient characteristics defined in Equation (1). ϕ_t^m and ϕ_t^d are fixed effects for the calendar month and day of week, respectively.

Table 1 presents summary statistics for our main analytical sample, i.e., hospitals that treated more than one Black patient, including risk-adjusted mortality rates, measures of resource use, hospital characteristics, and county-level characteristics 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. Panel (a) of Figure 2 shows that, prior to BLM protests, treated and control hospitals have witnessed parallel trends in their 30-day risk-adjusted mortality rates 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.

[Figure 2 about here]

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

event study plot. The magnitude of the estimated effect is smaller than the 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 documented in Chan et al. (2023). To some extent, Our estimated effect is more comparable to the findings of Doyle Jr et al. (2015), who show that hospitals with one standard deviation higher log spending reduce 1-year mortality by 3.7 percentage points, or about 10% of average 1-year mortality in their sample.[13]

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.[14] Our findings suggest diminishing marginal returns to repeated exposure, as the effect in the fourth year after initial exposure was nearly zero.

We next examine whether BLM protests have affected non-Black patients. Contrary to the results for Black patients, Panel (b) of Figure 2 shows no detectable change in 30-day risk adjusted mortality for Non-black patients following BLM protests. These results have several implications. First, they offer direct evidence of race-specific performance differences within the same provider and demonstrate that these differences are subject to change.

Second, the reduction in mortality among Black patients was achieved without adversely affecting non-Black patients. To assess potential negative spillovers, Appendix Figure B1 shows the result persists even when restricting to treated hospital-years with an above-median share of Black patients, where spillovers would be most likely. Furthermore, Appendix Figure C1 reports estimates separately for White, Asian, and Hispanic patients and finds no detectable effects for any group.

Last and more importantly, these results reinforce the interpretation that the observed effects were driven by BLM protests aimed at improving the well-being of the Black population. Our finding aligns with recent evidence that BLM protests significantly shift racial attitudes and increase awareness of racial bias (Reny and Newman, 2021; Dunivin et al., 2022; Gethin and Pons, 2024). It is also consistent with studies showing that BLM protests influence the behavior of lenders and corporate boards in ways that favor the Black population (Bogan et al., 2021; Garcia and Ortega, 2024).

[13] 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.

[14] The effect from restricting the sample to hospitals treated only in 2014 also persists for three years, although the effects in the second and third post years are slightly smaller than when pooling all hospitals, including those with repeated treatment in 2015 and 2016. Among the cities first exposed in 2014, 44% (59%) were also exposed again in 2015 (2016).

Robustness Check 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 similar when dropping treated hospitals in cities with above-median population, alleviating concerns that not all hospitals in large cities were treated.[15] Appendix Figure A4 presents similar treatment effects when we apply the alternative difference-in-differences estimator of Callaway and Sant'Anna (2021).

Placebo and Permutation Test To further confirm that the observed mortality reduction for Black patients is driven by BLM protests, we conduct two validation exercises. First, we perform a placebo test by replacing the treated hospitals with control hospitals that are most similar in terms of observable characteristics, including both hospital and county level covariates from Equation (5) in Section 4.[16] We then estimate Equation (5) as if these matched controls had experienced BLM protests. If our findings were driven by concurrent changes in local social or economic conditions, we would expect to observe similar effects for these placebo-treated controls. However, Appendix Figure A5 shows no significant effect for the placebo-treated controls, suggesting that the treatment effect is not attributable to local economic conditions.

Second, we conduct a permutation test following Buchmueller et al. (2016) and Cooper et al. (2020), 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 date to control hospitals and estimate Equation (5) as if these hospitals had been exposed to protests. Appendix Figure A6 presents the event-study estimates based on 100 repetitions of the procedure using Equation (5). In all pre-periods, placebo and "true" estimates are nearly identical, but in every post-period the "true" effect lies below almost all placebo estimates, representing the lower bound of the placebo estimates. Together, these results strongly indicate that the observed effect is highly unlikely to have occurred in the absence of BLM protests.

5.2 Heterogeneity

The estimated treatment effect varies across different hospitals. We first hypothesize that if the estimated effects are truly driven by BLM protests, we should expect a larger effect when the protest shock is more salient. To test this, we use the total number of participants

[15] When we exclude cities with more than two or three hospitals, or drop treated hospitals located more than five miles from the city center, where protests most likely occurred, the results remain highly similar.

[16] Hospitals are matched using Mahalanobis distance, and the closest control hospital is selected.

across protests in the initial exposure year as a proxy for its intensity or salience.[17] More specifically, we define a protest as salient if its number of participants exceeds the 75th percentile (roughly 980 participants). We then estimate Equation (5) separately for hospitals exposed to more salient versus less salient protests, using a common control group, i.e., hospitals exposed to protests only in 2020 or later. Panel (a) of Figure 3 shows that hospitals exposed to more salient protests exhibit larger reductions in mortality, lending support that the effects are likely driven by the protests themselves.[18]

We then conduct a heterogeneous analysis by hospitals' baseline level of performance for Black patients ($RAMR_h^B$). We hypothesize that hospitals with lower baseline quality in treating Black patients would exhibit greater improvements following BLM protests. To test this, we classify hospitals with $RAMR_h^B$ (measured as the average across years before the first protest) below the median as high-quality, and those above the median as low-quality. We estimate Equation (5) separately for the high- and low-baseline quality subsamples. Panel (b) of Figure 3 presents the results. As expected, mortality reductions were larger among hospitals with lower baseline quality, suggesting that quality improvements were primarily concentrated in lower-performing hospitals following BLM protests.

We next explore the heterogeneous effects of BLM protests on patient outcomes by county-level partisanship and political ideology. We use county-level voting results from the 2012 presidential election, obtained from the MIT Election Data and Science Lab.[19] The 2012 election is the most recent election prior to the three event cohorts of BLM protests (in 2014, 2015, and 2016) and is unaffected by the protests, making it the most appropriate proxy for 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%.[20] We estimate Equation (5) separately for hospitals in Democratic and Republican leaning counties. As shown in panel (c) of Figure 3, hospitals in Democratic-leaning counties exhibit significant improvements, whereas those in Republican-leaning counties show no meaningful changes. This heterogeneity is consistent with evidence that BLM protests primarily influenced racial attitudes among politically liberal individuals (Dunivin et al., 2022), and aligns with the broader view that the Democratic Party has

[17] The results remain highly consistent when using the average number of participants or when normalizing the absolute count by city population.

[18] 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). Similarly, when measuring proximity to the city center where protests most likely occurred, Appendix Figure A8 shows that the effect is concentrated among hospitals closer to the center (with the median distance as the cutoff).

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

[20] Results are consistent when using 2016 presidential vote share data or when applying a stricter threshold, such as classifying a county based on a vote share exceeding 60%.

historically been more receptive to acknowledging and engaging in public discourse on issues of racial equity and social justice. These findings not only lend additional support to our identification but also suggest that the impact of BLM protests may depend on the local political context.

[Figure 3 about here]

5.3 Evidence of a Supply-Side Response

It is important to distinguish whether the observed effect is demand or supply side driven. On the demand side, BLM protests could lead to increased awareness among Black patients themselves, which could encourage them to select better-performing hospitals or to take more precautionary actions. We suspect that demand-side response is unlikely to drive our results, given the acute nature of heart attack and the major role that supply side plays in determining patient outcomes in our setting. Moreover, we provide supporting empirical evidence below to show that our main findings are not driven by a demand-side response.

First, we note that our study of mortality rates is risk adjusted using a rich set of patient demographics and comorbidities. Our results therefore are not likely subject to selection on patient observables. In addition, we directly test whether BLM protests affected Black patients' hospital choices. Had patient selection occurred, we would expect shifts in patient demographics, risk factors, and/or patient volume following BLM protests. We therefore calculate the average predicted mortality based on individual characteristics for all Black patients admitted to the hospital in a given year. This measure serves as a comprehensive metric of patient severity and we estimate whether it responds to BLM protests using Equation (5). As shown in Figure 4, we find BLM protests have no impact on a hospital's Black patient severity, confirming that patient composition remained stable. Appendix Figure D1 provides a pre-post event study for each patient characteristics, suggesting that observed patient characteristics did not respond to BLM protests. Moreover, Appendix Figure D2 shows that the volume of Black patients did not change.

[Figure 4 about here]

Second, we focus on a subsample of Black patients admitted through the emergency department (ED). In these urgent cases, patient selection is even more limited, and patients and families have minimal influence over hospital choice or treatment decisions. Figure 5 shows the results, revealing a similar reduction in mortality for Black patients.

[Figure 5 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 any protests occurred in their home cities. Such restriction allows us to keep about 75% of the treated hospitals from our main analysis.

Note that these patients received care in exposed hospitals but traveled from areas not yet exposed, allowing 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" patients. However, Figure 6 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.[21]

[Figure 6 about here]

Taken together, all of these results offer support that our findings are unlikely to be driven by demand side factors. Instead, we interpret the estimated improvements in performance as a provider response to the outbreak of BLM protests. In the following section, we explore the underlying mechanisms on the provider side.

6 Mechanisms

How could hospitals achieve better health outcomes for Black patients after being exposed to the BLM protests? One possible channel is through increasing resource utilization; and the other is through using the same level of existing resources more efficiently to deliver better results, namely a productivity improvement.

In this section, we examine both channels empirically. We first show that the observed reduction in patient mortality reflects a Black-specific productivity improvement rather than changes in resource utilization. We then explore two tangible measures in uncovering such an improvement in productivity.

6.1 Resource Utilization

We first explore the channel of increased resource utilization or higher care intensity by directly examining length of stay, number of tests, whether a surgery was performed, DRG weights, attending-physician RVUs, and discharge destination. Discharge to a skilled nursing or rehabilitation facility is considered more intense post-discharge care relative to discharge

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

home. We conduct this analysis at the patient level by following Equation (6). The results are plotted in Figure 7 where the relative year dummies in Equation (6) are replaced with a single post-period indicator.

Overall, we detect no significant changes in any of these resource utilization measures among Black patients. These results suggest that the observed reductions in mortality among Black patients are not likely to be explained 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 in the literature (Chandra et al., 2016a,b). Specifically, we consider a patient-level log health production function:

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

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

Following Chandra et al. (2016a,b), 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 and obtain similar results. Because both Medicare payments and DRG weights capture expected rather than actual resource use, we also consider total length of stay and the number of tests as proxies for realized input. The results are robust across all specifications.[22]

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

[22] Additionally, due to the small number of Black patients in some hospitals, the TFP may be estimated with error. To address this, we also apply an empirical Bayes shrinkage procedure to adjust the estimated $ln(A_{ht})$ for the measurement error following Chandra et al. (2016a). The results are robust across all specifications.

[Figure 8 about here]

6.3 Two Pathways

A hospital's TFP reflects all elements that contribute to its efficiency in producing patient health. To explore the drivers of productivity improvements, we examine two possible pathways that capture efficiency gains conditional on a given level of care intensity, using the patient-level regression specified in Equation (6).

The first is through matching a Black patient with 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 lead to a better matching of high-productivity physicians with Black patients, this could help explain the observed reduction in mortality despite no change in resource use. The second pathway is through racial concordance, in which a Black patient was assigned a Black physician. Some recent studies, such as Alsan et al. (2019), have found evidence that racial concordance leads to improved patient outcomes among Black patients.

Matching. To explore the first pathway, we construct an indicator for whether a Black patient was matched with a high-productivity attending physician. We focus on attending physicians because they make the key clinical decisions and are ultimately responsible for patient outcomes.[23] We define a Black-specific high-productivity physician based on their average risk- and input-adjusted mortality for Black patients in the years prior to any BLM protests. Specifically, we calculate a risk- and input-adjusted mortality rate for each Black patient admitted before 2013, defined as the difference between the observed mortality indicator and the expected mortality given patient characteristics and care input (measured by DRG weights). We then aggregate these patient-level adjusted mortality rates to the physician level. High-productivity physicians are defined as those whose Black-specific, ex-ante risk- and input-adjusted mortality rates fall below the hospital-specific 75th percentile.

First, as shown in panel (a) of Figure 9, we find that following BLM protests, Black patients are 5.8% more likely to be assigned to a Black-specific high-productivity attending physician. Such an improved matching is non-trivial given a baseline matching rate of 64%. When physician productivity is defined based on overall performance across all racial groups, we still find a significant improvement in the matching of Black patients to uniformly high-performing physicians. These results do not necessarily imply prior discriminatory intent by

[23] We choose attending physician instead of surgeon because not all heart attack patients receive care from a surgeon unless a procedure is performed.

providers: the quality of physician–patient matching was similar for Black and non-Black patients (64% vs. 66%; p-value = 0.53).

[Figure 9 about here]

To quantify the contribution of this pathway to productivity gains, we estimate the pre-post version of Equation (6), including an indicator for matches with a high-productivity attending physician. We then compare the estimated treatment effect β' with that from the baseline specification without controlling for the high-productivity physician indicator, β. The resulting change in the treatment effect, $\beta' - \beta$, represents the portion of the mortality reduction explained by improved patient-physician matching.[24] Based on this calculation, we conclude that improved matching between Black patients and physicians with high productivity in treating Black patients accounts for 1.0 percentage points ($= -0.018 - (-0.028)$), or approximately one third of the estimated reduction in patient mortality.

A natural question is whether the matching quality for non-Black heart attack patients declined following the improvement in Black patients' physician assignment. Appendix Figure E1 shows that, overall, non-Black patients were not assigned to lower-productivity attending 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, the probability of assigning a non-Black patient to a high-productivity physician decreased modestly only in the event year (year 0). The results are similar when we examine White, Hispanic, and Asian patients separately.

Because non-Black patients' matching patterns were stable and health outcomes did not deteriorate, the improvements in matching for Black patients appear not to have pushed physicians to their capacity limits. This is plausible given that Black patients constitute less than 20% of total volume. Moreover, the lack of significant mortality changes among non-Black racial groups, despite slight declines in matching with high-productivity physicians in high Black share hospitals, suggests that prior allocation of high-productivity physicians may 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 more appropriate, though similarly intensive, clinical decisions and greater adherence to medical advice. We construct an indicator of racial concordance if a Black patient is assigned to a Black physician.

[24] 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 matched with a high-productivity physician and the mortality impact of being treated by such a physician.

Although we directly observe patients' race in the Medicare claims data, physicians' race and ethnicity are not recorded. To address this, we use a name-based algorithm that infers a physician's race from their first and last names.[25] The algorithm returns race-specific probabilities for each name, and we apply cutoffs calibrated so that the overall racial distribution aligns with that reported by the American Medical Association (AMA) for physicians specializing in Cardiovascular Disease.[26]

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

7 Conclusion

This paper leverages the staggered outbreak of BLM protests across U.S. cities to examine the role of race-specific provider performance in explaining racial disparities in healthcare. We hypothesize that if provider performance varies by patient race, exposure to BLM protests, which focus on the well-being of the Black population, could raise providers' racial awareness and societal pressure, leading to improved quality of care for Black patients. We find that hospitals improve survival outcomes only for Black patients in response to BLM protests, supporting the hypothesis that provider performance is race-specific and that targeted improvement in provider performance for Black patients can help reduce racial disparity in healthcare. We further find that the improvement in health outcomes is driven by increased productivity in treating Black patients, rather than greater resource use. A non-trivial portion of this productivity gain comes from assigning Black patients to attending physicians who are particularly effective at treating Black patients.

Our findings carry important policy implications. That hospitals can improve survival outcomes for Black patients without compromising care for non-Black patients, in response to greater racial awareness and societal pressure, highlights the potential of public discourse and provider education as effective policy tools for addressing racial disparities in healthcare.

Targeting performance improvements specifically for Black patients within hospitals may offer a more actionable and scalable policy approach than those commonly implied in the literature. For example, Chandra et al. (2024) propose both reallocating patients to higher-quality hospitals and increasing resources for hospitals in markets with a high share of

[25] We adopt a machine learning algorithm built on a recurrent neural network architecture and trained using Florida's voter registration data. See Xie (2022) for details.

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

Black patients. While these strategies offer important insights, they may face logistical or financial constraints and may not extend to hospitals serving smaller but still significant Black populations. Our findings suggest that efforts to improve performance within existing facilities, without requiring patient reallocation or market-level targeting, could reach a broader set of hospitals that serve Black patients. Similarly, while the Institute of Medicine has advocated for increasing the number of Black physicians to enhance racial concordance (Nelson, 2002), only 5% of active physicians identify as Black,[27] limiting the potential impact of this strategy. By contrast, improving provider performance through public discourse or physician education can engage the predominantly White physician workforce and does not depend on racial concordance.

Improving race-specific provider productivity offers an alternative yet complementary strategy to efforts focused on reducing racial gaps in healthcare resource use. Policy efforts and prior research have often focused on disparities in treatment intensity, for example, 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 particular, we find a promising mechanism to improve hospitals' productivity: by better matching Black patients with physicians who have high productivity in treating them, hospitals can improve survival outcomes for Black patients without compromising care for non-Black patients.

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

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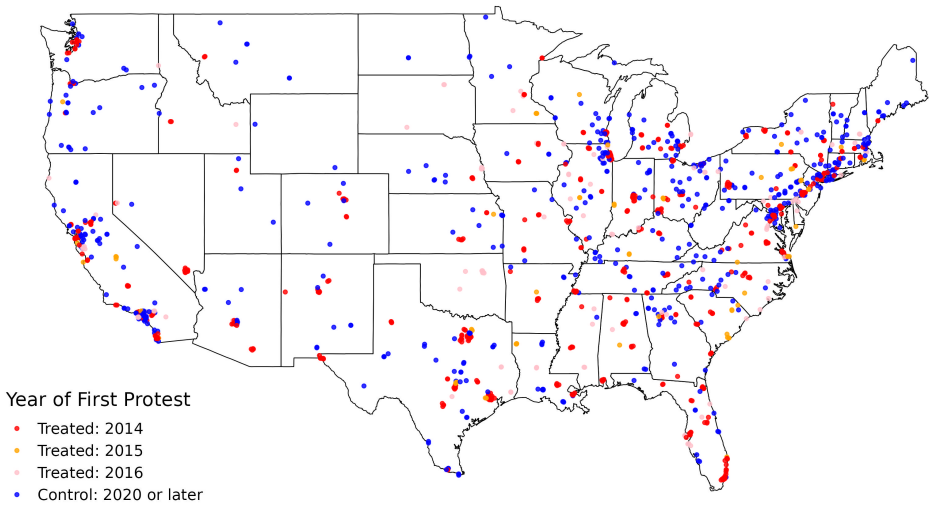
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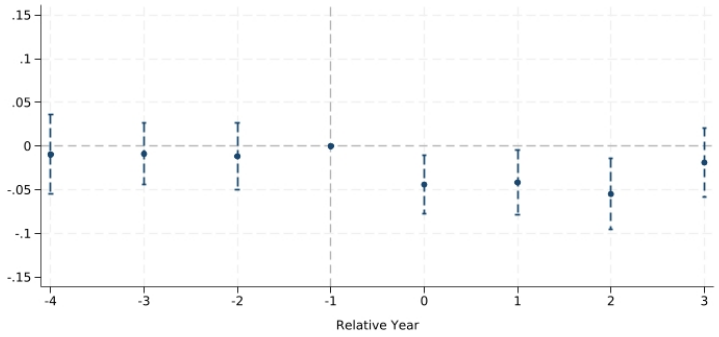
Figures

Figure 1: Hospitals Exposed to BLM Protests

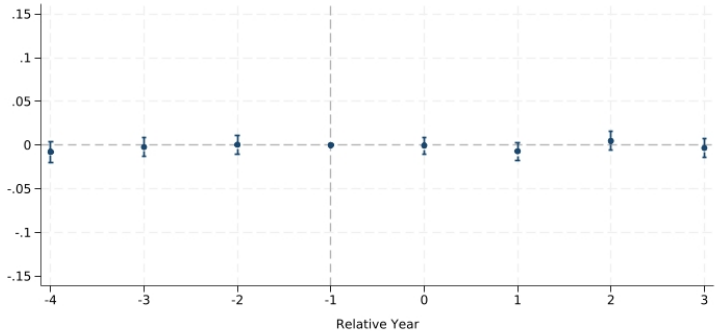


Notes: Each dot in the map represents a hospital. Hospitals that experienced their first BLM protest in 2014, 2015, or 2016 are assigned to the treated group in the corresponding cohort and are shown as red, yellow, and pink dots, respectively. Blue dots indicate hospitals that did not experience a protest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

Figure 2: Effect of BLM Protests on Hospital RAMR



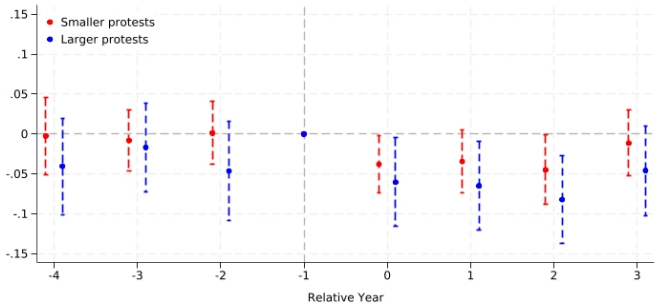
(a) Black Patients



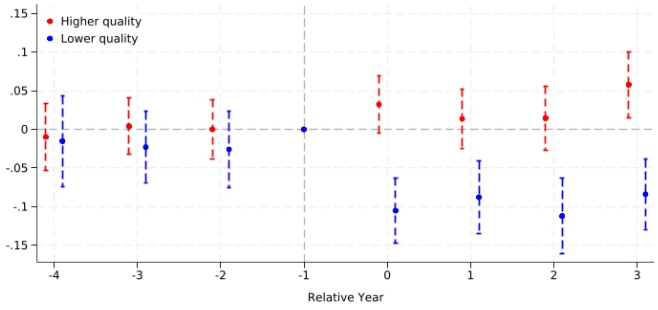
(b) Non-Black Patients

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.

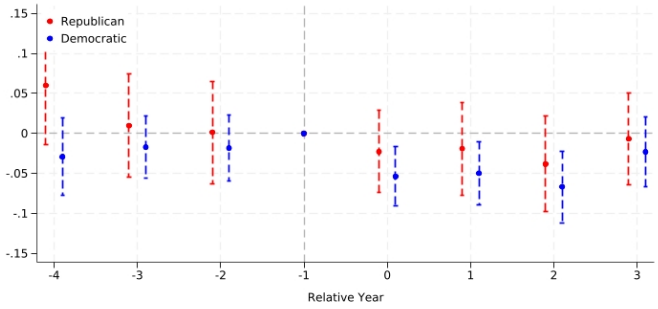
Figure 3: Heterogeneous Effects of BLM Protests on Black Patients' RAMR



(a) By Protest Size



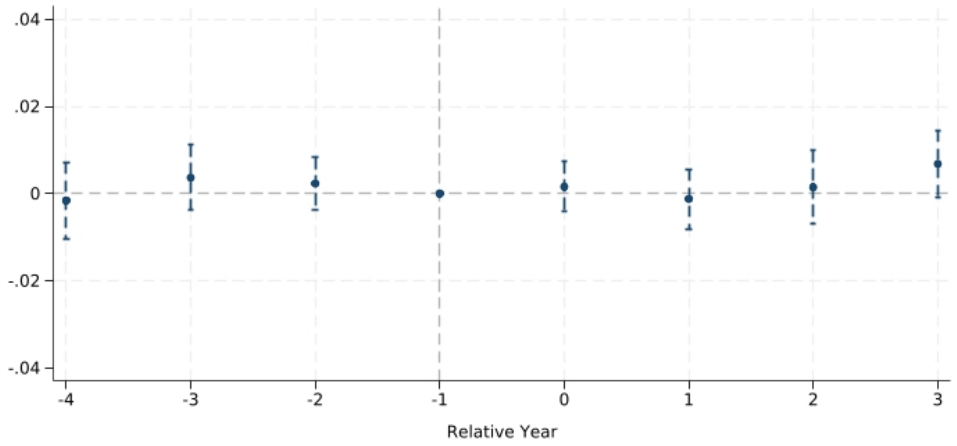
(b) By Hospital Ex-ante Quality



(c) By Political Ideology

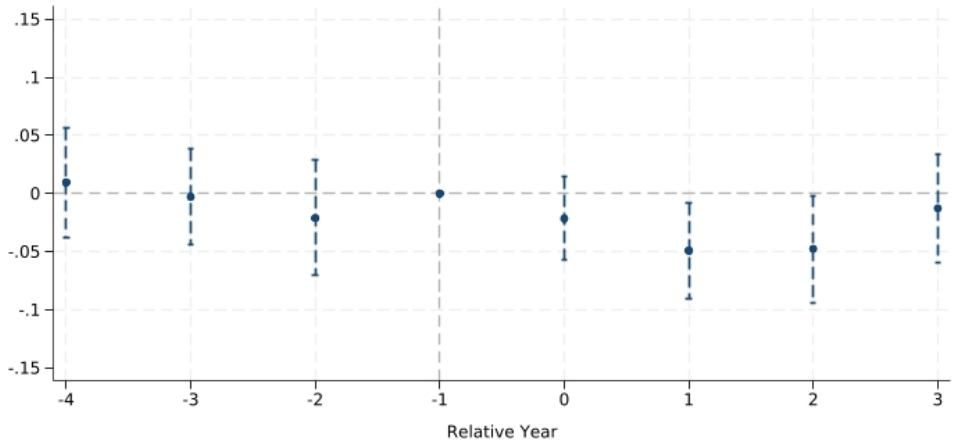
Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black heart attack patients by protest size (panel (a)), hospital ex-ante quality for Black patients (panel (b)), and county political ideology (panel (c)), based on Equation (5), with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

Figure 4: Effect of BLM Protests on Hospital-Level Black Patient Severity



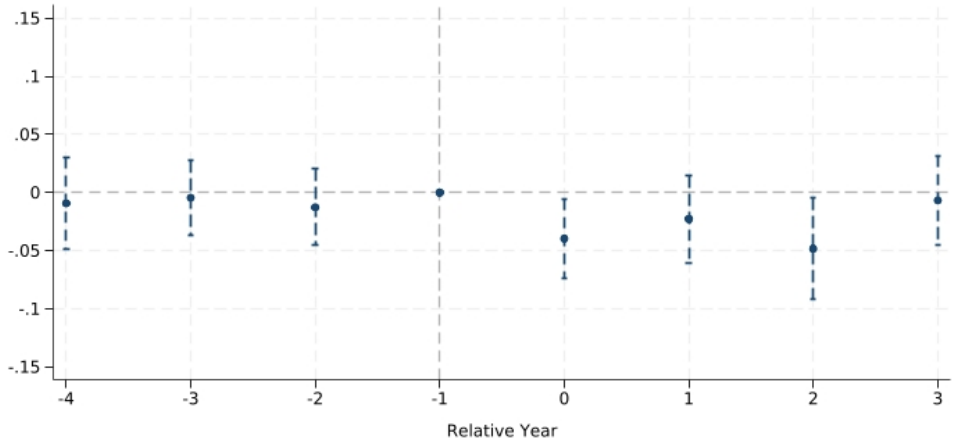
Notes: The figure plots the estimated treatment effects of BLM protests on a hospital's expected mortality rate for Black patients (EMR^{B}_{htc} as defined in Equation (2)), which serves as a measure of overall patient severity in a hospital, based on Equation (5), with 95 percent confidence intervals.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

Figure 5: Effect of BLM Protests on Hospital RAMR for ED Black Patients



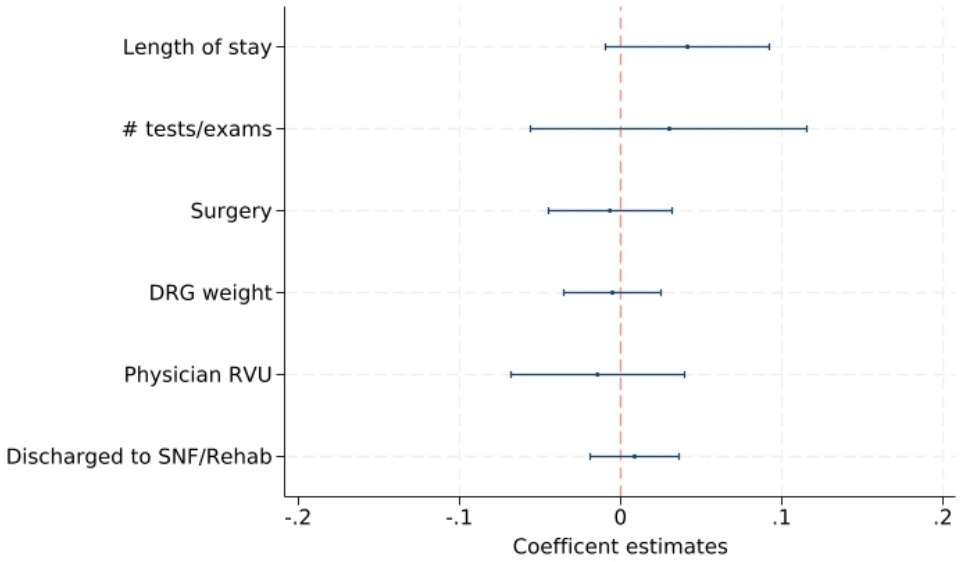
Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black patients admitted through the Emergency Department, based on Equation (5), with 95 percent confidence intervals. Standard errors are clustered at the hospital level.

Figure 6: Effect of BLM Protests on Patient-level Mortality of Non-exposed Black Patients



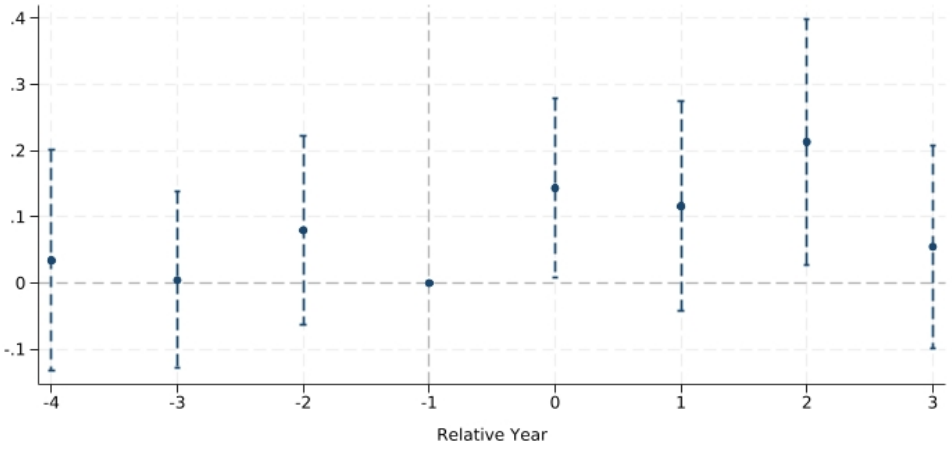
Notes: The figure plots the estimated treatment effects of BLM protests on patient level risk-adjusted mortality rates for Black patients who were admitted to the exposed hospitals *before* any protests occurred in their home cities, based on Equation (6), with 95 percent confidence intervals. Standard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

Figure 7: Changes in Care Resource Utilization for Black Patients



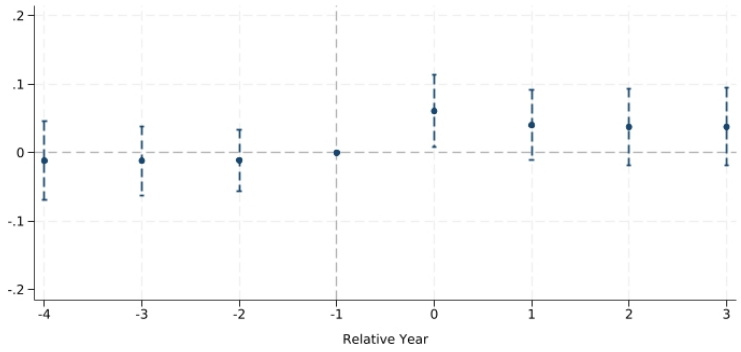
Notes: The figure plots the estimated treatment effects of BLM protests on measures of individual Black patients' care intensity and resource use, based on a pre-post version of Equation (6), with 95 percent confidence intervals. Specifically, the relative year dummies in Equation (6) are replaced with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

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

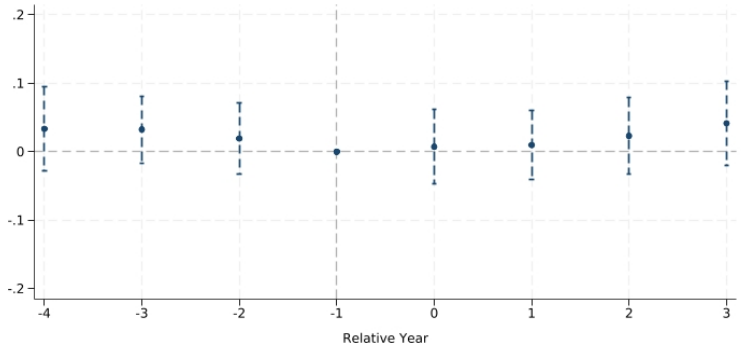


Notes: The figure plots the estimated treatment effects of BLM protests on hospitals' Black-specific TFP, based on Equation (5), with 95 percent confidence intervals. Hospital TFP is estimated using a patient-level health production function as specified in Equation (7), following the methodology of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

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



(a) Assigning Black Patients to High-Productivity Physicians



(b) Assigning Black Patients to Black Physicians

Notes: The figure plots the estimated treatment effects of BLM protests on a Black patient's likelihood of being matched with a Black-specific 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

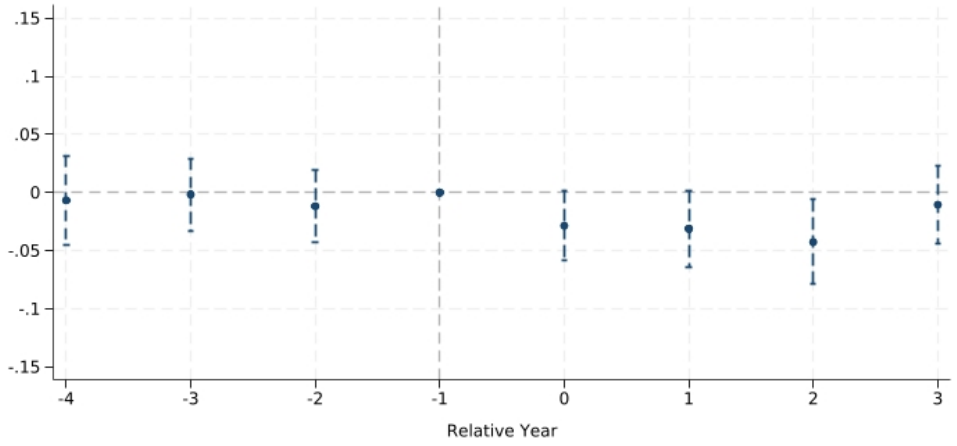
	All Hospitals Treating Black Patients	Treated Hospitals	Control Hospitals
Health Outcome			
30-day RAMR	0.10	0.10	0.09
	(0.17)	(0.17)	(0.17)
Care Utilization			
Length of stay	5.49	5.63	5.31
	(3.26)	(3.24)	(3.28)
Number of tests/exams	5.08	5.16	4.98
	(3.91)	(3.92)	(3.90)
Surgery rate	0.43	0.42	0.44
	(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	0.14	0.13	0.15
	(0.16)	(0.16)	(0.16)
Observations	5,069	2,860	2,209

Notes: Means are reported with standard errors in parentheses. The unit of observation is hospital-years with more than one Black patient.

Appendix

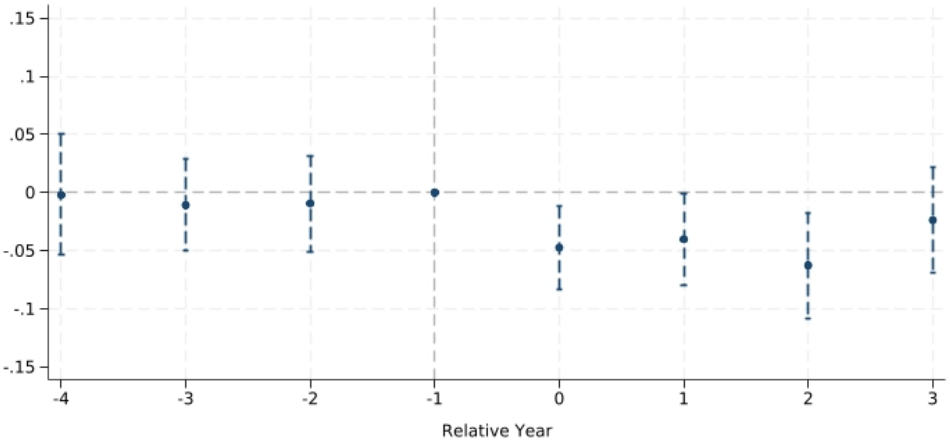
A Robustness Checks on Mortality Reductions for Black Patients

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



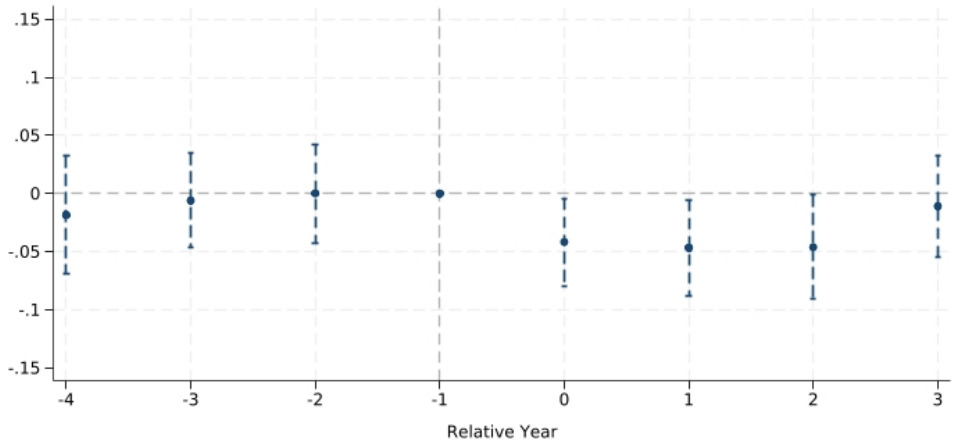
Notes: The figure plots the estimated treatment effects of BLM protests on patient level mortality for Black heart attack patients, based on Equation (6). Effects are normalized to the year prior to the protests. Standard errors are clustered at the hospital level.

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



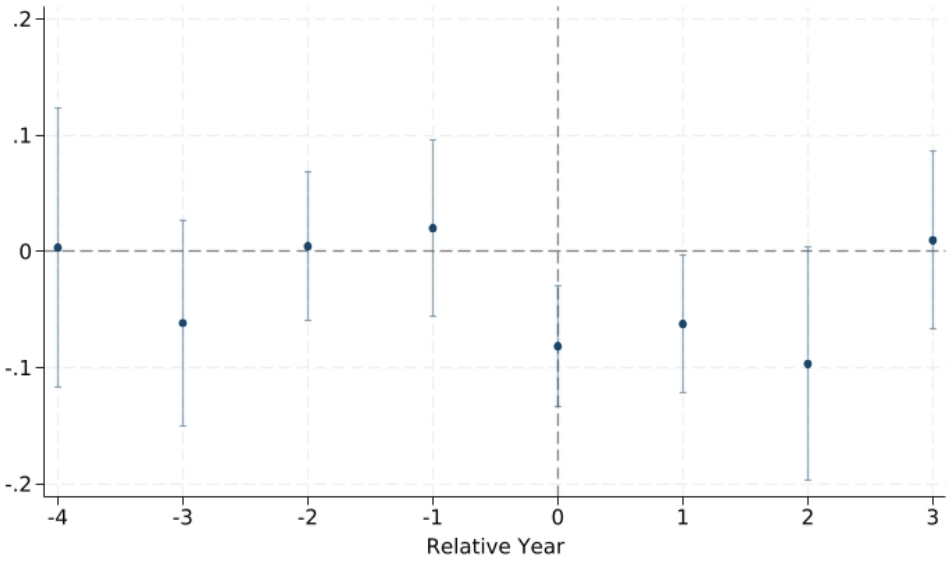
Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black heart attack patients, based on Equation (5) plus state-by-year fixed effects. Effects are normalized to the year prior to the protests. Standard errors are clustered at the hospital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

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



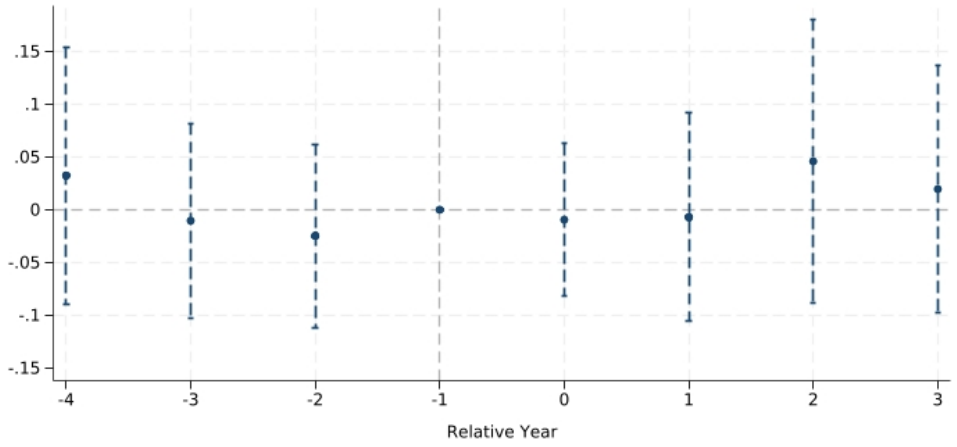
Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black heart attack patients, based on Equation (5), excluding samples located in cities with above-median population. Effects are normalized to the year prior to the protests. Standard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

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



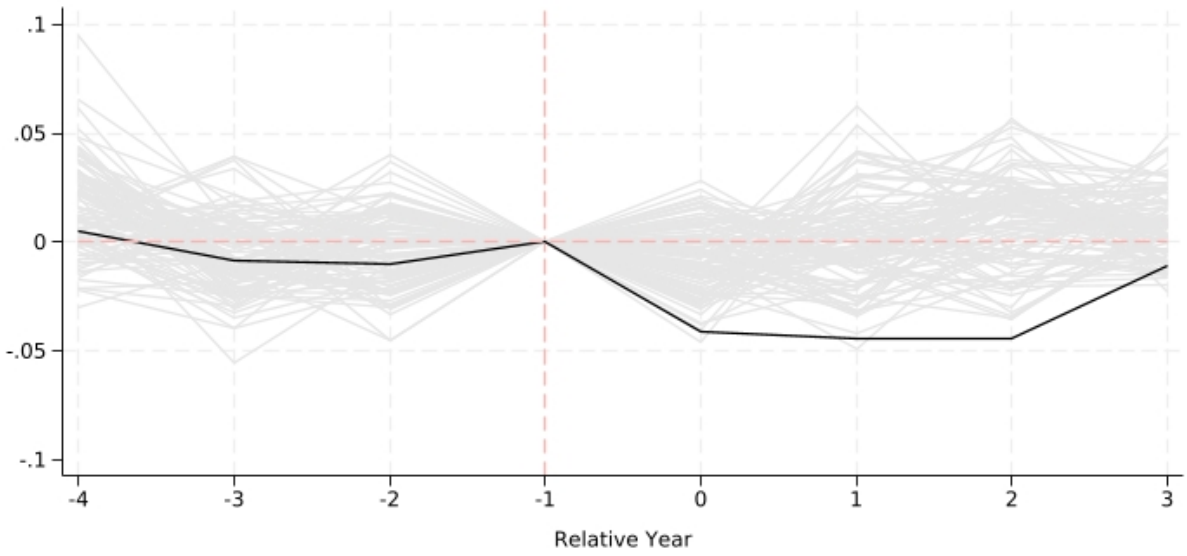
Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black heart attack patients using the alternative estimator proposed by Callaway and Sant'Anna (2021).

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



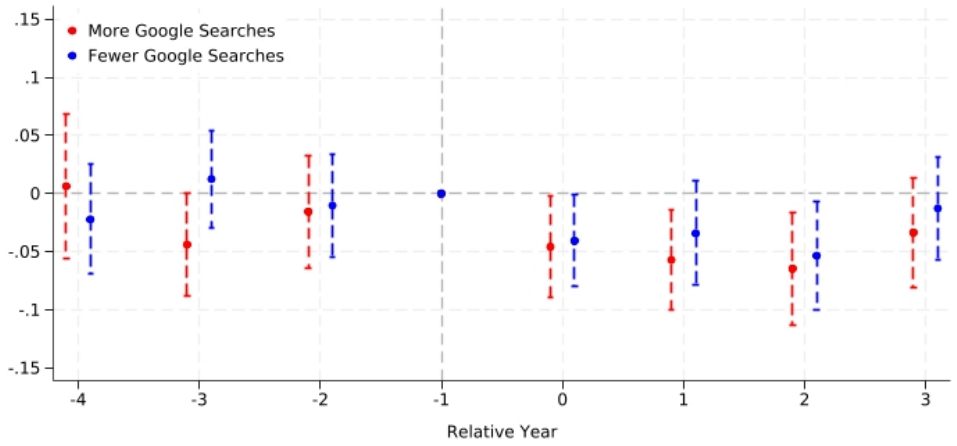
Notes: The figure plots the placebo treatment effects on hospital risk-adjusted mortality rates for Black heart attack patients, estimated from Equation (5) using matched placebo-treated control hospitals.

Figure A6: Placebo Treatment Effects from the Permutation Test



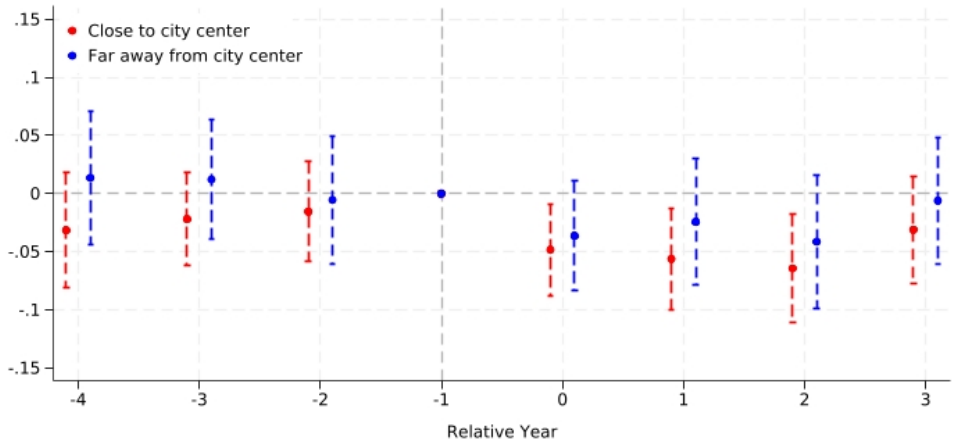
Notes: This figure plots the event-study placebo treatment effects based on Equation (5), with the black solid line indicating the "true" treatment effect.

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

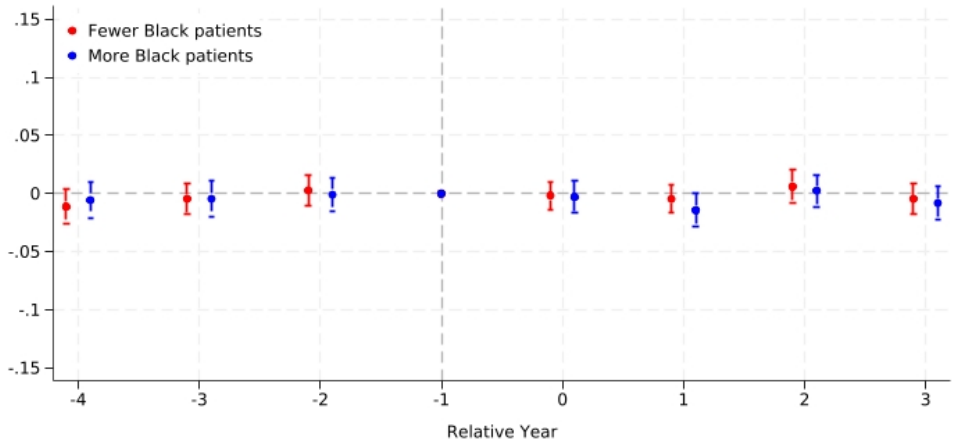


Notes: The figure plots the estimated treatment effects of BLM protests on hospital risk-adjusted mortality rates for Black heart attack patients, split by hospitals' distance from the city center, where protests most likely occurred, using the median distance as the cutoff.

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

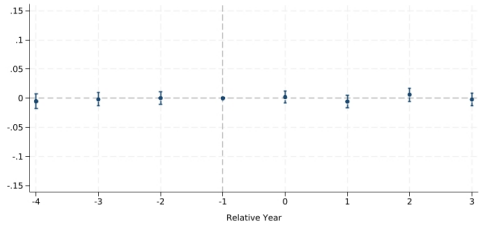
To define hospital-years with a high share of Black patients, we use data from all treated hospitals in 2013 and earlier to construct the distribution of hospital-level Black patient shares and set the threshold at the pre-2014 median. Treated hospital-year observations with a Black patient share above 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

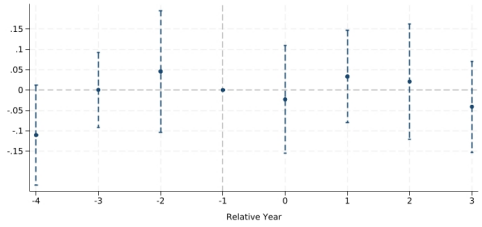


C The Effect of BLM Protests on White, Asian, and Hispanic Patients

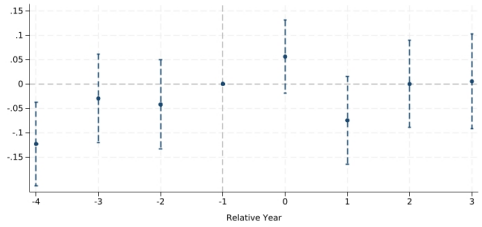
Figure C1: Effect of BLM Protests on Hospital RAMR



(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.

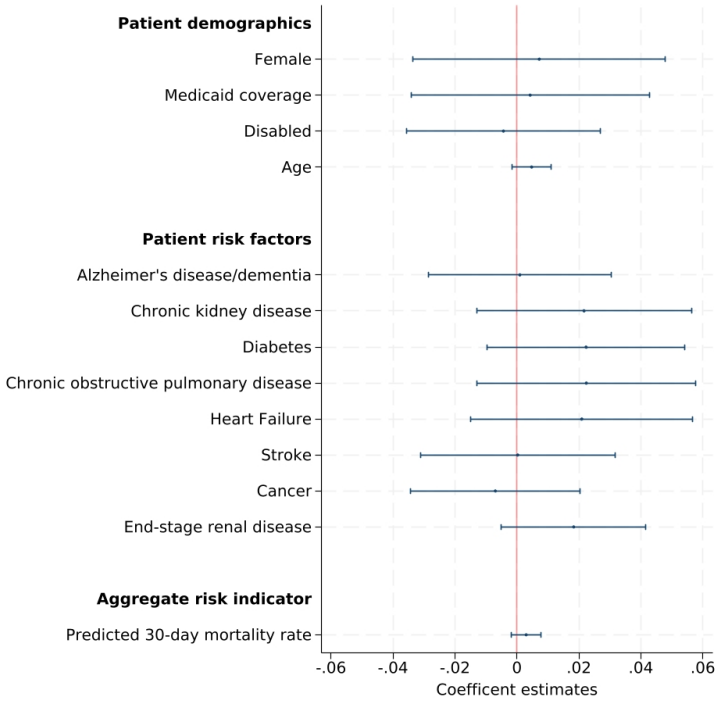
D Patient Selection

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.

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

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.

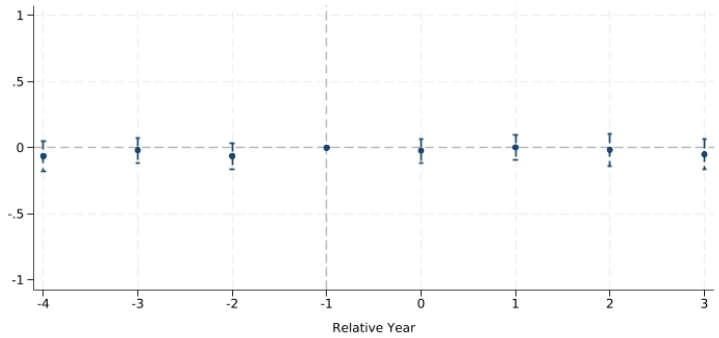
Figure D1: Balance Check on Patient Characteristics



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.

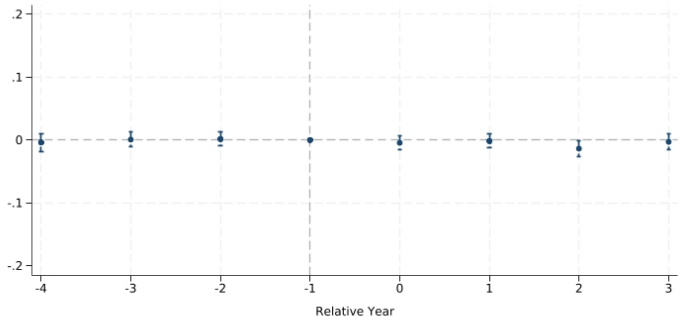
Figure D2: Treatment Effect on Black Patient Volume



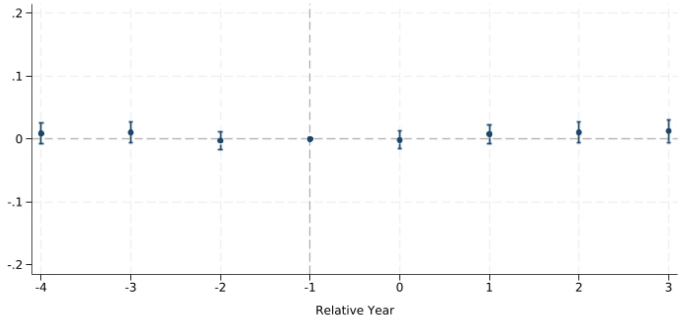
Notes: The figure plots the estimated treatment effects of BLM protests on Black patient volume, based on Poisson pseudo–maximum likelihood. Standard errors are clustered at the hospital level.

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

Figure E1: Assigning Non-Black Patients to High-Productivity Physicians



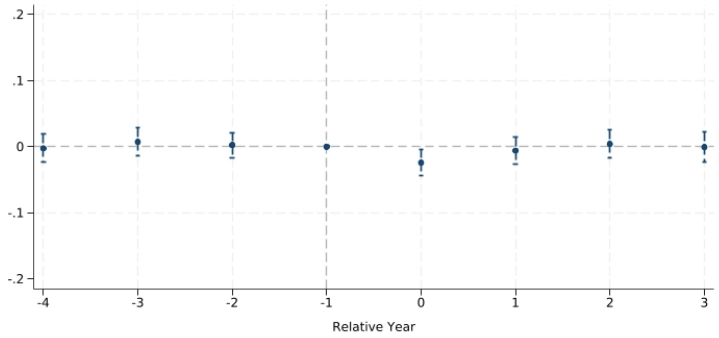
(a) High-Productivity Physicians in Treating Black Patients



(b) High-Productivity Physicians in Treating Non-Black Patients

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, 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: Assigning Non-Black Patients to High-Productivity Physicians in 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.