Can Social Movements Reduce Racial Disparities? Evidence from Medical Crowdfunding During the Black Lives Matter

Kaixin Liu[†] Jiwei Zhou[‡] Junda Wang[±]

August 2024

Online Complete Version

Abstract

Using high-frequency donation records from a major medical crowdfunding platform and careful difference-in-difference analysis, we demonstrate that the 2020 BLM surge decreased the fundraising gap between Black and non-Black beneficiaries by around 50%. We show that the effect is not a notion of ethnic nepotism, nor protesting act, but a piqued sentiment of empathy and awareness of racism. The effect is delivered across wide geographics through the *information enchancement* role of social media. However, the spillover is not targeting to the regions with previously long-standing racial discrimination, suggesting the existence of *echo chambers*.

Keywords: Social Movement; Black Lives Matter; Racial Disparity; Medical Crowdfunding; Health Disparity; Social Media; Social Safety Net

JEL Classification Numbers: D74; I14; J15; P32

We wish to thank David Autor, Hanmin Fang, Shuaizhang Feng, Narayana Kocherlakota, Cong Liu, David Ong, Ande Shen and participants in the Applied Reading Group and Graduate Student Seminar at the University of Rochester, for their suggestions for this paper. We are especially thankful to our advisors Travis Baseler, Lisa Kahn, and Ronni Pavan for their fantastic guidance on this project. We especially thank Junda Wang for his generous help

1 Introduction

Beyond garnering ideological support and attitude reform, what tangible impact does a social movement have on social and economic outcomes? From #BlackLivesMatter in U.S, to #ClimateStrike worldwide, and to #NotoWar in Ukraine, citizens have witnessed the momentous impact of large-scale movements on shaping public opinions and societal norms (Bosi, Giugni, and Uba (2016); Meyer (2021)). These movements have utilized digital networks to amplify their messages and mobilize emotional support rapidly (Castells (2015)). While the intangible effects—such as changing discourse and raising awareness—are critical and have been widely studied in the social movement literature, little empirical evidence exists about whether these movements lead to substantial material changes. The #BlackLivesMatter movement, for instance, has grown from a hashtag into a global network advocating against systemic racism, changing many people's beliefs. However, does this translate into reduced discrimination and tangible improvements for the Black community? This question is critical both academically and politically. The same logic applies to #ClimateStrike, #NotoWar, as well as other social movements: do we observe actual environmental protection behaviors and reduced global conflicts? In general, can social movements transcend online activism and beliefs into concrete actions, economic outcomes, and social resource shifts?

Moreover, a second key aspect in gauging the success of social movements is whether the concepts permeate beyond the activists to influence the general public. This in-

in data access and technical support.

† Institute for Economic and Social Research, Jinan University, email: kaixinliu@jnu.edu.cn or liukaixin888@gmail.com
‡ Department of Economics, University of Rochester, email: jiwei.zhou@rochester.edu
± Department of Computer Science, UMass Amherst, email: jundawang@umass.edu

volves assessing if the movements' ideologies and calls-to-action are confined to political acts or expressions of dissatisfaction by their partisans. Or do social movements, through the lens of social media, motivate the broader public to think critically, enhance their awareness of democracy and social justice, and spur them to act? The digital age has introduced a new dynamic where social media serves as both a platform for activism and a battleground for competing narratives, making it essential to distinguish "*information enhancement*" (Zhuravskaya, Petrova, and Enikolopov (2020)) from "*political echo chambers*" (Cinelli et al. (2021); Gentzkow and Shapiro (2011)). Social media platforms like Twitter and Facebook can either reinforce preexisting beliefs, create polarization or facilitate cohesion by disseminating information and mobilizing support (Boxell, Gentzkow, and Shapiro (2017),Di Tella, Gálvez, and Schargrodsky (2021),Törnberg (2022)). This phenomenon raises critical questions about the actual impact of social movements: Are these movements fostering genuine understanding and empathy, or are they merely preaching to the choir?

This paper aims to understand these critical questions by examining the impact of the Black Lives Matter (BLM) movement on racial disparities present on a leading medical crowdfunding platform[1] . By analyzing high-frequency donation records across the entire U.S, we investigate how the movement changes individuals' propensity to donate to the medical crowdfunding projects of Black beneficiaries compared to those of non-Black beneficiaries. Medical crowdfunding is a purely philanthropic activity that reflects individual donors' altruistic and empathetic concerns for the adverse health conditions of others. The crowdfunding system represents an important source of the supplementary social safety net, helping to address the under-insurance problem and health disparities in the U.S.[2]

[1]GoFundME, which controls 90% of the US donation-based crowdfunding market.

[2]We would like to recall sayings from Angus Deaton in his book *Economics in America: An Immi-*

The institutional structure of medical crowdfunding has three unique advantages to meet our research objective. First, individual charitable giving is prevalent on the platform and can be distinctly identified from institutional charity. This minimizes the risk of donations being seen as politically motivated acts. Second, access to detailed information about both the crowdfunding posts and the donations allows us to distinguish between demand behavior and supply behavior. Lastly, the high-frequency daily-level data provides keen observations on donation dynamics during the BLM movements and enables precise causal identification. Additionally, the donation records across the whole breadth of the U.S. provide us with rich geographical variation to exploit the mechanisms behind these effects.

We adopt a careful difference-in-differences (DID) framework to show that the surge of the BLM movement leads to an increase in altrusim behavior to projects organized by Black individuals. We find that the BLM movement reduces the racial disparity in the final raised funds by approximately half, from an initial baseline gap of 20% down to 10%. This rise is not due to an increased demand for financial support from Black individuals. Using precise daily-level donation records, we provide strong causal evidence showing that immediately following the onset of BLM, the daily number of donors to Black beneficiaries increased by 10 percent (from 4.0 to 4.4). While the dollar amount of each donation did not change significantly. The immediate increase in donations to Black beneficiaries lasted only for 3 months; however, it influenced almost half of the Black beneficiaries' projects in 2020.

We explore the mechanisms behind the effect of BLM movements, aiming to under-

grant Economist Explores the Land of Inequality to highlight how important this issue is. In page 116 of Chapter 6, "*None of these racial inequalities inspires more discomfort than differences in health and longevity between Black people and white people.*"

Moreover, given the coincidence of the murder of George Floyd and COVID period, systemic racism was finally classified by many as *a public health crisis.* (Washington Post) stand whether they genuinely reduce racial disparity and long-term discrimination. We obtain the following novel findings. First, we show that the effect is not due to *ethnic nepotism* but rather cross-race altruism. By inferring donor race from their names, we find that non-Black donors primarily (95%) contribute to this donation surge. Second, by exploring the geographical variation in on-street demonstrations, we show that the effect does not align with donating as a way of protest expression. Contrary to traditional thought, we don't find any monotonic pattern showing that Black beneficiaries in counties with more (or fewer) occurrences of demonstrations are receiving more donations. This means that the influenced altruistic behavior is not confined to activists and not a self-referential way of protesting. Third, we investigate the role of social media in broadcasting the reach of protests. We construct a local measure of exposure to outside protest events through social media connectivity, following Bailey et al. (2020). We find that counties with higher exposure to global protests through social media, witness a larger donation act in crowdfunding. This indicates the strong role of social media in transmitting the concepts of anti-racism across geographics. Fourth, we show that the public's donation behavior in response to the movement is due to the enhanced awareness of racism and empathy. However, it is not tailored to address inequality and discrimination issues. We find that counties with greater long-term racial inequality and racial prejudice receive less donation help. This finding suggests that the effect to some extent is an echo chamber.

The structure of the paper is as follows: In section 2, we discuss the related literature and our contribution. Section 3 provides background information and data; Section 4 delivers a descriptive analysis of the racial fundraising gap, highlighting systemic racial disparity. We focus specifically on the time frames around the surge of the BLM movement and the COVID pandemic. Section 5 exploits daily-level donation records to assess the causal impact of the BLM movement on mitigating the fundraising gap. Section 6 scrutinizes alternative mechanisms behind the effect of BLM, arguing in favor of enhanced empathy and anti-racism attitudes through the vehicle of social media. Section 7 concludes the paper. We present additional discussions in Online Appendix A and additional Figures and Tables in Online Appendix B.

2 Related Literature

This paper contributes to four strands of existing literature.

First, our paper expands on the economic impact of social movements. Previous research has primarily focused on political or ideological outcomes, leaving the exploration of social movements' influence on individual economic behavior relatively unaddressed.[3] For BLM research, most existing research largely focuses on the political and ideological outcomes of BLM movements such as demand for books with anti-racism themes in schools (Agarwal and Sen (2022)), racial attitudes (Reny and Newman (2021)), voter registration (Engist and Schafmeister (2022)), and the public discourses&awareness (Dunivin et al. (2022)). Besides the academic inquiry, the question of whether social movements lead to better economic lives of minorities is particularly politically emergent. Ongoing public discourse debates whether the resources raised by BLM organizations are truely directed towards the causes of fighting racial injustice. Our study demonstrates how the BLM movement can not only enhance people's awareness of racial inequality but also yield tangible economic benefits, which alleviate adverse health, insurance, or financial conditions for Black individuals.

Second, perhaps our paper addresses the challenge of identifying the causal effect of so-

[3]See these papers: Andrews, Beyerlein, and Tucker Farnum (2016); Van Dyke and Taylor (2018); Levy and Mattsson (2023); Luo and Zhang (2022)

cial movements and contributes to the literature methodologically (Giugni, McAdam, and Tilly (1999); Bosi, Giugni, and Uba (2016)). We rise to this challenge by advocating for the use of high-frequency panel data to establish a persuasive causal effect of social movements. The simultaneous occurrence of the COVID-19 pandemic and associated policy responses could confound the identification of all BLM-related research, a problem that would not be solved by monthly or even weekly data in the current literature. By leveraging daily-level outcomes, we effectively distinguish the BLM's effect from potential confounders such as the COVID-related policy shocks in a careful difference-in-difference framework.

Thirdly, our paper is also related to the literature on racial disparities and social segregation in informal health insurance. Studies show that the health status and life expectancy of Black individuals are generally poorer compared to other racial groups (Yearby (2018); Carratala and Maxwell (2020); Orsi, Margellos-Anast, and Whitman (2010)). Many studies (Lillie-Blanton and Hoffman (2005); Nelson (2002); Buchmueller et al. (2016)) have identified the underlying cause of this issue as the disproportionately limited access that Black individuals have to health care and health insurance.[4] We extend this broad literature by shedding light on the medical crowdfunding platform, a type of informal health insurance and social safety net.

Last and most importantly, our paper lies at the intersection of the literature on social movement, social media, and social segregation. This three-way interaction is the key novelty of our research. On the one hand, we add to the existing literature on the role of social media in facilitating collective protests, which centers around either the channel of *strategic complementarity*[5] or the channel of *information en-*

[4]In 2013, 25.8% of Black individuals were uninsured. Black individuals are 1.5 times less likely than white individuals to be covered by any health insurance.

[5]This term refers to the notion that individuals are more likely to participate when many others participate, as it reduces personal costs to political activism. See Enikolopov, Makarin, and Petrova

hancement[6](Zhuravskaya, Petrova, and Enikolopov (2020)). Since our work does not examine the causes of the BLM protests but focuses on the subsequent economic impact, it naturally aligns with the *information enhancement* channel. Related works include Casanueva et al. (2022), who show that increased social media usage during the Covid turns to mobilize the occurrence of BLM protests and Manacorda and Tesei (2020), which demonstrate that the expansion of digital technology encourages information exchanges and boosts political movements in Africa. We highlight in our paper how social media disseminates information about the concept of BLM protest theme, i.e., systemic discrimination and social empathy.

However, given the segregated and polarized nature of the U.S. political environment, we cast doubts on the solo role of *information enhancement* and turn to scrutinize the possibility of *echo chambers* (Gentzkow and Shapiro (2011)). Therefore, we contribute to the literature on how political echo chambers cause and sustain social segregation (Levy and Razin (2019),González-Bailón and Lelkes (2023)). Our analysis reveals that while social media significantly broadens the reach of BLM's message and fosters empathy beyond protestors and across different geographic regions, it does not necessarily dismantle deep-rooted racism or correct entrenched beliefs about racial inequality. This dual role of social media, where it can both enhance information and create echo chambers, implies that social segregation could be either increased or decreased. Thus, our work adds to the debate on whether social media increases polarization (Boxell, Gentzkow, and Shapiro (2017),Di Tella, Gálvez, and Schargrodsky (2021),Törnberg (2022))[7]

(2020) Cantoni et al. (2019) and Qin, Strömberg, and Wu (2021) for empirical works.

[6]The role of social media in disseminating more information about the reasons for protests and grievances, along with its broader political goal.

[7]The opinions here can be divided into three: Boxell, Gentzkow, and Shapiro (2017) finds that polarization has increased the most among the demographic groups least likely to use the Internet. Törnberg (2022) and Lelkes, Sood, and Iyengar (2017) show that access to internet can lead to

Altogether, our work makes contributions by examining the complex interactions between social movements, social media, and social segregation. It highlights how social media can both amplify a movement's message and create echo chambers that limit its broader impact. These, as we view them, are two principles for assessing the efficacy of social movements: First, gauging the impact of social movements on actual social segregation; and second, understanding how social media directs the information of movements to specific audiences and regions, and whether it leads to genuine information learning or merely reinforces existing beliefs.

3 Background and Data

3.1 Black Lives Matter movement and George Floyd protest

The Black Lives Matter (BLM) movement is rooted in the long history of social activism and the struggle against racial injustice in the U.S. The movement began in earnest in 2013 after the acquittal of George Zimmerman, the neighborhood watch volunteer who fatally shot Trayvon Martin, an unarmed African-American teenager. The hashtag *#BlackLivesMatter* was created in response to the verdict, and quickly became a rallying cry for people protesting against systemic racism and police brutality against Black individuals. Over the years, the BLM gained prominence as a decentralized movement addressing a wide range of issues related to racial inequality.

In this paper, we focus on the outburst of the Floyd protests. On May 25, 2020, in Minneapolis, Minnesota, George Floyd, a 46-year-old Black man, was killed during an arrest when a police officer knelt on his neck for over nine minutes. Floyd repeatedly

more polarization. Levy (2021) and Di Tella, Gálvez, and Schargrodsky (2021) show a middle ground: it depends on the online materials and the social group people are exposed to. Exposure to counter-attitudinal opinions decreases negative attitudes toward the opposing political party. However, the selective nature of the social media algorithms makes such exposure rare and causes long-term polarization.

told the officers that he could not breathe, but his pleas were ignored. The incident was captured on video by a bystander and quickly went viral on social media, sparking widespread outrage and protests.

More importantly, the Floyd protests represent a more pivotal point in the BLM campaign in the U.S. than any preceding events. The protests soon became the largest social movement in the history of the U.S. since the 1960s. An estimated 15 to 26 million people participated in the 2020 BLM protests (Buchanan, Bui, and Patel (2020)). Further, the protests attracted a wide range of participants, including people from diverse racial, ethnic, and socio-economic backgrounds.

***Protest Data*:** We use the Crowd Counting Consortium[8] to collect the protest data. The data set contains records on political crowds reported in the U.S. obtained from newspapers and Twitter, including the date, claim, and location of the protest/demonstration. We select BLM-related records. As shown in Figure I, there is a small number of BLM protests before the circulation of the video, but immediately after May 25, 2020, the protests surge at the national level. We also present the dynamics of newspaper reports and Google search index related to "BLM" and broader racism topics. We can observe that Google search intensity follows a close catch-up with protests. While newspaper reports follow quite a different pattern and spike at the mid of June.

3.2 Medical Crowdfunding Records

We obtained official access to the medical crowdfunding project records on GoFundMe. It is the largest crowdfunding platform for personal fundraising, especially for medical fundraising. More than $15 billion have been raised since its launch in

[8]Find the resources at https://github.com/nonviolent-action-lab/crowd-counting-consortium.

2010.

A typical medical crowdfunding project on GoFundMe adheres to the following process. First, the fundraiser must set up a project on the platform (crowdfunding posting). The donors then have access to the project title, text description, profile photos of the beneficiary(es), and the goal (target amount to be raised). Figure B.1 from Online Appendix B shows an example of what a donor will see when accessing a medical crowdfunding project post. After seeing this information, the donors decide whether to give money and, if so, how much they wish to donate.

We observe the following information for each fundraising project: title; start date of the project; text description (usually a paragraph describing why they need the money); beneficiary(es)'s name; zip code where the beneficiary(es) live; photo of the beneficiary(es); goal($); amount of money($) so far raised; total number of donations(#) so far received.

More importantly, under each project, we have visibility into each donation record, capturing up to the most recent 100 donations. The information on a donation record includes the donor's name, the amount of the donation, and the timing of the donation on the day. These records enable us to track the donation process on a high-frequency basis and identify the impact of medical crowdfunding in a granular time setting.

For projects that have received more than 100 donations throughout their life-cycle, although we lose track of the earlier donations beyond the most recent 100, we can impute the average daily flow for those records given we know its launch date and the total number of donors giving money to the project. For projects with more than 100 donations, the imputation is to allocate the invisible donation to dates between the project launch date and the date when the earliest 100th donation appears.[9] We

[9]As an illustrative example, consider a project that was launched on May 29, 2020, and has received

assume that the weight used to allocate the unobserved donation records follows the donation flow distribution of the fundraising projects that have aggregate donations of the entire life cycle less than 100 donations. We test the robustness of our main results to alternative choice of weighting strategy in Online Appendix A.2

Our original data consists of around 550,000 medical crowdfunding projects worldwide from January 1, 2019, to July 31, 2021. Our data provide a complete snapshot of all medical crowdfunding projects on July 31, 2021. Namely, at the end of July 2021, we observed the status of all crowdfunding projects launched from January 1, 2019, to July 31, 2021. We focus on projects launched in the U.S. and started before March 31, 2021 (we then exclude the ongoing projects that were receiving money by the end of July 2021, since the average life-cycle of the project is about three months). About 316,767 medical records remain. Table I summarizes the characterizing variables of these projects. Additionally, we zoom into the donation records between April 1 and September 1 to identify the causal effect of the BLM. 71,364 projects actively received money during this period. Panel A of Table II summarizes the characteristics of these projects.

Racial Information Inference: We determine the beneficiary's race based on the uploaded photo in the project. Specifically, we utilize the third-party facial reorganization APIs, which identifies racial information (the number of faces and their races) from faces in the images. This approach is remarkably accurate when distinguishing the faces of Black and non-Black people (Serengil and Ozpinar (2020); Yang et al. (2021)). Panel B of Table II reports the projects' racial information. On

a total of 150 donations. The most recent donation was made on July 1, 2020, and the 100th most recent donation was made on June 20, 2020. Our observed data consists of donations made between June 20 and July 1, capturing the latest 100 donations. To complete the dataset, we would then need to allocate the remaining 50 earlier donations to the time period spanning from May 29 to June 19.

average, each project is associated with a photo having two faces. Around 10 percent of projects have photos including Black face(s), and we identify those projects with at least one Black face as projects raised by Black people.

Other Fundraising Characteristics: Previous literature shows that the text description on the project's profile may influence the outcomes of crowdfunding projects (Gorbatai and Nelson (2015)). Following Younkin and Kuppuswamy (2018), we utilize text-analysis software *LIWC* (Pennebaker et al. (2015)) to measure the key attributes of the text description in the crowdfunding records. Panel C of Table II reports these attributes. On average, the description of these projects comprises around 1600 words. Among all the words, twenty of them show authenticity, about four of them deliver positive attitudes/emotions, and two of them express negative attitudes. On average, all project descriptions have around two male- and female-related words.

3.3 Other Data Sources

Twitter Posts Data: We complement our study with 10,000 randomly selected Twitter posts from the period of April 2020 to September 2020. We use the API portal to select Twitter posts that contain at least the keyword "GoFundMe".

Facebook Connectivity: We utilize Facebook connectivity measures at the county-to-county level, sourced from Bailey et al. (2018). This measure calculates the probability of a Facebook user in one county being linked with any user in another county.

Covid-19 Data and Policies Our data on COVID-19 infections by race, state, and calendar week comes from an online public project—the *COVID Tracking Project* at The Atlantic. The COVID policies and regulations are sourced from federal government notices and state government websites.

News Bank Data: We extract circulation volumes on the topic of "Black Lives

Matter" at the state level, based on News Bank data created by NewsLibrary.com.

Implicit Attitude Test: We utilize all Implicit Attitude Test datasets, originating from Project Implicit created by Harvard University (Xu, Nosek, and Greenwald (2014)). This data contains rich opinions and unconscious attitudes towards different races at the yearly level. We calculate the level of discrimination towards Black people at the county level, based on data from the years 2008-2019.

Nationscape Date by the Democracy Fund and UCLA: The NS is a large-scale weekly survey (N = 6,250 per week) that began in July 2019. The survey questions are designed to elicit a variety of political opinions, beliefs, and attitudes (Tausanovitch et al. (2019)). The NS was conducted daily in the field, averaging about 900 respondents per day, providing information with daily variations.

3.4 The Nature of GoFundMe as a Political Tool

Before diving into the main part of this paper, we briefly articulate why we focus on individual medical crowdfunding on GoFundMe: the individual fundraising acts here are not a form of political activism but are most likely altruistic behaviors.

Individuals may express their donations to earn a warm-glow or engage in political acting; organizations and corporations may make monetary offerings to the racial equality cause as a form of political acclamation, aiming for better profit in the future. Both theories suggest that the donation response does not necessarily indicate an actual reduction motive in racial inequality.

We verify these theories by analyzing a randomly selected sample of 10,000 Twitter posts during the studied period that contain "GoFundMe'" as a keyword. We use ChatGPT to conduct a topic analysis and show the evolution of the salience of these topics over time, with the importance rating calculated by the total number of retweets.

Figure II presents the importance rating of three major topics: (1) Donating to help BLM, anti-discrimination causes, or explicitly helping black people or organizations. (2) Donation to certain larger organizational fundraisers. (3) Donating or help sharing to help some families and individuals.

Our finding is that the first and second topics, which are suspected to be more related to political activism, experienced a significant importance spike around July 15, coinciding with the peak of social media coverage on the BLM movement and protest intensity, as shown in Figure II. The dynamics of these two topics are highly consistent with the theory of political activism. The first one focuses on the potential movement activists themselves, while the other involves large corporations' political actions. In contrast, the third topic only seems to experience a slight surge, if any, around the beginning of May 25.

Notably, a further contextual analysis shows that only 3.8% of the first topic tweets are related to medical crowdfunding. The second topic is never about individual fundraising. The third topic is purely about helping fundraisers through donations or sharing links, without mentioning any racial information. And a significant 18% of the third topic involves medical crowdfunding.

This phenomenon, in contrast with previous findings, suggests that medical crowdfunding on GoFundMe is less likely a battleground for displaying political stances related to helping Black people. We view this as a distinctive institutional feature of medical crowdfunding that facilitates our research study.

4 Racial Disparities in Medical Crowdfunding

This section demonstrates the racial gap in fundraising outcomes between Black and non-Black beneficiaries' projects. In particular, we are interested in documenting the evolution of the fundraising gap from two angles — money raised and total number of donors.

Figure III plots the money raised against the project launch time for Black and non-Black beneficiaries. The x-axis represents the launch date of the fundraising project. Regarding the total money eventually raised, we find a significant fundraising gap between Black and non-Black beneficiaries. Overall, Black beneficiaries raise 12% less money (an average of $3,274) than non-Black beneficiaries (an average of $3,683). More significantly, before February 2020, when the pandemic and the BLM movement have not emerged, there was a larger 20% gap . The gap remains robust, conditional on projects' observed characteristics, and resilient in the long run. Given that the Black-white income disparity is 15%, the gap of 20% indicates a huge disparity persisted in the informal insurance safety net of the U.S.

Summary statistics in Tables I and II also document racial disparities along five other dimensions: the number of donors, the average amount of donations, the fraction of the goal achieved, whether the goal is achieved, and whether the number of donations exceeds 100. These figures jointly support the existence of racial disparity on crowdfunding platforms and its severity across different aspects.

However, there was also a significant decrease in this persistent gap for projects launched after February 2020, as shown in FigureIII. Table III uses a DID framework and identifies a significant $186 to $293 increase in the money raised for Black beneficiaries after February 2020. This amounts to about a 50% reduction in the racial gap before February 2020, making it an unprecedented change in crowdfunding history. Columns (2) and (3) of Table III show that controlling project goal, characteristics variables for text descriptions and profile pictures, or state/date fixed effects, barely changes our conclusion.

We decompose this disparity reduction into an extensive margin and an intensive margin. First, for the extensive margin, we focus on the gap reduction in the total number of donors for each project. Figure IV (a) presents the total number of donors over the project launch time for Black and non-Black beneficiaries. Regarding the total number of donors, we observe a slight initial gap between Black and non-Black beneficiaries for projects launched before February 2020. Overall, Black beneficiaries receive 5% fewer donors (an average of 40) than non-Black beneficiaries (an average of 42). This gap begins to significantly decrease for projects launched after February 2020. During this period, Black beneficiaries' projects collected more donors than those of non-Black beneficiaries. This reverse gap in the eventual number of donors remains stable in the following months.

One novel observation from FiguresIII and IV (a) is that although the convergence in racial gap starts in February, it reaches its peak (the gap itself reaches its minimum level) exactly around May 26^{th}, which marks the start of the nationwide BLM movement/Floyd protests. This motivates a question on whether the significant disparity reduction since February 2020 could be attributed to the role of the BLM movement.

We also examine the intensive margin of donation, i.e.,the average dollar amount of donation. We define the average dollar amount of donation to a project as the total money raised in that project divided by the total number of donors. Figure IV (b) plots the average donation for Black and non-Black beneficiaries over the project launch dates. The average dollar amount of donations for Black beneficiaries ($70) remains 17% smaller than that of non-Black beneficiaries ($82). Unlike the number of donors or the total amount of money raised, the gap in the average amount of donations remains stable. Table IV reports the DID estimations of the changes in the gaps in the total number of donors (Panel A) and the average dollar amount of donation (Panel B) across project launching dates.

Finally, we examine the dynamics of the donation gap for other critical dimensions that reflect racial disparities in the quality of crowdfunding. These dimensions include (1) the ratio between funds raised and the project goal, (2) whether the goal has been achieved, (3) whether the number of donations exceeds 100, and (4) funds raised in the first two weeks since the project's launch. We leave the detailed discussion to the Online Appendix, including the results in Figure B.3 and Table B.1.

In summary, this section reveals three key findings: first, large racial disparities exist on the crowdfunding platform across various dimensions. Second, the fundraising gap between Black and non-Black beneficiaries begins to decrease after February 2020, possibly due to the pandemic or the BLM movement. Lastly, the reduction is primarily driven by the extensive margin–the number of donations–rather than the intensive margin of donation quality

5 The Overall Causal Impact of the BLM Movements

The BLM movement could potentially drive the convergence in the fundraising gap. On average, a project lasts approximately three months. Thus, a project launched in February 2020 could experience the potential impact of the BLM on public's charitable giving behavior before the end of its life cycle. Namely, projects launched between February and May 26, 2020, would be partially impacted by BLM protests. The closer a project's launch date is to the start of the nationwide BLM movement, the greater the impact on the project.

However, it remains challenging to establish the causal effect of the BLM surge. On the one hand, it is necessary to determine the exact timing of when a project was influenced by the BLM movement. On the other hand, many other confounders, such as the pandemic and related policies, may also contribute to this racial convergence.

5.1 Identification Strategy

To solve the identification challenge, we leverage the daily-level donation inflow records of each project and develop a difference-in-differences strategy. Section 4 shows that the reduction in the fundraising gap is due to the closing gap of the number of donors in each racial group. Thus, we focus on the daily number of donations received by one project.[10]

The detailed daily cash flow panel data for each project provides two critical advantages in identifying the causal impact of BLM movements. First, tracking the daily level flows across each project's life cycle enables us to identify whether or not a project is affected by the surge of the BLM movement at a precise time. Within one project, we can pinpoint the exact date when the project was impacted by the surge of BLM movements. Solely relying on the project-level ultimate outcomes fails to identify whether and to what extent the project is affected by the BLM event, especially for those projects launched before late May 2020. Second, this daily data provides a rich measurement that immediately responds to the social movement. The high-frequency cash inflows enable us to trace instantaneous donation behaviors (if

[10] We also examine whether the amount of donation ($) is affected by the BLM movement. Our results show that there is zero impact. See Figure B.4 from Online Appendix B for evidence.

any) on fundraising platforms back to changes in the BLM movement.

5.1.1 The Identification Assumption and Difference-in-differences (DID) Regression

We first provide intuitive evidence. Figure V (a) non-parametrically illustrates the DID estimation of the effects of the Floyd protests on the number of daily donations received by a project. We use the projects of non-Black individuals as the control group and those of Black individuals as the treatment group. Each data point represents the daily average number of donations received across all active projects within the racial group on that day.

It can be observed that before the nationwide George Floyd protests on May 26, there was no significant gap between Black and non-Black individuals' projects in terms of daily donation numbers. On average, every project received around 3.8 donations per day. During the surge of the Floyd protests, there was a dramatic increase in the number of donations supporting projects of Black beneficiaries: approximately a 90% surge within a week, and a 20% surge over two months. Meanwhile, the number of donors for non-Black beneficiaries remained stable after the event, revealing no crowding-out effect associated with the increase in donations for Black beneficiaries. This impact is unprecedented in history: Figure VI from the Online Appendix zooms out and shows donation evolution around police injustice killings in history since the very beginning of our data.

Regression specification

To formally quantify the impact of the BLM movements, we employ the following

DID regression by utilizing the timing discontinuity around the George Floyd event.

$$y_{j,t} = \gamma_0 Black_j \times \mathbf{1}(t > t_{May26}) + \gamma_1 Black_j + X_{jt}\Gamma + \tau_t + \mu_{State} + \varepsilon_{jt} \tag{1}$$

Project j is active (i.e.,be available for donors) at date t, within the range of April 1 to September 1, 2020. $y_{j,t}$ denotes the number of donations that fundraising project j receives on date t. $Black_j$ indicates whether or not the beneficiary of project j is identified as a Black person. $\mathbf{1}(t > t_{May26})$ denotes the indicator for whether the donation happens after May 26, 2020. $X_{j,t}$ represents a set of control variables at the project level, including the goal of the project, and project description variables (e.g., length, emotions, language use), project creation date, an indicator of whether affected by the pandemic, and etc. τ_t is the time fixed effect for date t, which absorbs the nationwide common trend in donations. μ_{State} is the state fixed effect of where the beneficiaries live. We also optionally control for project ID fixed effects, which absorb all the project-level unobserved heterogeneities. γ_0 represents our estimated effect of BLM on the donation.

The causality of the regression 1 hinges upon two identification assumptions: (i) If there is no surge of BLM, the numbers of daily donation provided to projects of Black and non-Black individuals should continue to share the parallel time trend after May 26, 2020; (ii) No other shocks can have a heterogeneous influence across races during our treatment period. From Figure V (a), we learn that before the Floyd protests, there was no significant difference in time pattern across Black and non-Black people. This observation suggests that assumption (i) is plausible. Regarding assumption (ii), other shocks in the spring and summer 2020, such as the pandemic, the start of the stay-at-home order (SAH), the end of the stay-at-home order, and so on pose threats. We develop a careful framework to rule out these possible threats based on our daily level records in Section 5.3.2.

5.2 Main empirical results

Table V presents our main estimates using Equation (1) across seven specifications. Column (1) is the baseline regression, which includes no extra control variables beyond the Black indicator $Black_j$ and the post-BLM indicator $\mathbf{1}(t > t_{May26})$. Column (2) includes the log value of the goal of the project. Column (3) adds more observed characteristics of the projects profile (the text description and the photo),[11]. Column (4) includes more fixed effects. Since the majority of the donations come from the fundraisers' network, the fixed effect of the state where the fundraisers live absorb the state-level time-invariant factors that affect donations. The date-fixed effect absorbs the common time trend. The fixed effect of the project's launch date adjusts for the project's tenure, since naturally a project would receive fewer donations as time goes by. Column (5) and Column (6) address the potential threats from the pandemic in two different aspects. In Column (5) we include the interaction between Black beneficiaries and the fixed effect of the post period of the COVID-19 Stay-at-Home Orders in each state, as these policies disproportionately affect Black individuals, who are more likely to work in in-person jobs. Column (6) includes the control of whether the project asks for help due to the COVID, which is indicated by their text descriptions. Column (7) is unique in that it focuses on projects that have experienced the BLM movement and controls for the project's fixed effects, which absorb all project-level time-invariant confounders.

Our results from Columns (1) to (7) show that the surge of the BLM causally initiates

[11] The characteristics of the text description include the length of the description, the emotion index of the description, the gender tendency index, and the authenticity index. The characteristics of the photo include the number of faces, the ratio of male faces, the beauty index of the photo.

an average increase in donations to Black people's projects of 0.334 to 0.434 donations per day significantly. Compared to the mean value of the non-Black control group before the treatment period, this represents a robust 7.8% to 11% increase in the daily donation number. Adding more control variables slightly inflates the estimate of BLM effect, though the increase is not statistically significant.

To diagnose the dynamics of the effect, we also estimate the event study following Miller (2023). Panel (b) of Figure V presents the results from a weekly event study framework. It is evident that before the treatment period, there was no significant pre-trend for projects organized by Black individuals. However, in the immediate aftermath of the start of the treatment period, these projects experienced a significant positive impact compared to those of non-Black individuals. This pattern suggests that without the surge of BLM, the projects of Black and non-Black beneficiaries would likely have followed a parallel trend in the number of daily donations.

The second observation from the event study is that despite both the statistical and economic significance observed, the effect of the surge of BLM on Black individuals is short-lived. During the first five weeks of the BLM movement, Black people received about one more donation per day compared with non-Black people, which is about a 30% increase compared to the pre-treatment period. However, this effect lasts for at most twelve weeks and then shrinks to negligible levels in the following weeks.

In addition, we also examine the intensive margin of the dollar amount of each donation. Figure B.4 and Table B.2 show that the surge of BLM did not significantly affect the dollar amount of each donation received by Black people. The effect is both statistically and economically close to zero.

5.3 Ruling Out Other Confounders

The crowdfunding platform is a typical two-sided market: we have the money demand side from the people who launch projects (beneficiaries), and the money supply side from the people who browse the profiles of the projects and make donations (donors). The BLM movement can drive the reduction in the racial gap through both sides of the platform.

5.3.1 Stable Temporal Pattern of Fund Demand

We provide further evidence that this racial gap reduction is not a result of strategic behaviors of Black beneficiaries on the money demand side. We examine whether Black beneficiaries set higher goals, embellished their profiles and pictures, or adjusted the crowdfunding in an unobserved way, in response to the nationwide Floyd protests.

First and most importantly, we show that Black people do not strategically set up higher fundraising goals. Table VI presents the estimation results to examine the effect of the Floyd movement on the fundraising goal set up by Black beneficiaries compared to non-Black beneficiaries. Across three specifications, we don't find any evidence supporting that Black beneficiaries set up a higher goal.

Secondly, we show that Black people do not strategically edit their project profiles and pictures to make them more "attractive" during the surge of the BLM movement. Table B.3 from Online Appendix tests this hypothesis using DID regressions with the observed profile characteristics as the outcomes. [12] The observed characteristics we consider are in three categories: (1) fundraising topics from the text description,

[12]To make these features numerical, we use the unsupervised Latent Dirichlet Allocation (LDA) model to categorize the topic of the projects' text description. In addition, the *LIWC* provides the index of of the tone of the description. The third-party facial reorganization API also provides us with the gender and expression index of the faces in a photo.

(2) language tones, and (3) and face expressions from updated photos. The regression results jointly show that for projects launched during the Floyd protests, Black fundraisers do not systematically change how they edit their profiles. Therefore, it is unlikely that donors made more donations to Black individuals because Black fundraisers upload more attractive profiles.

Additionally, we address the concern that some unobserved features of the Black people's profiles have changed systematically due to strategic profile adjustments by focusing on projects initiated between May 1 and May 26.. The unexpected nature of the murder of George Floyd ensures that fundraisers had no advanc information about the surge of BLM when editing and launching new projects during that period. Hence, the DID estimates based on this restricted sample reflect changes driven purely by the behavior of donors. One additional benefit of this sample is that like the specification in column (7) of Table V we can easily add project-fixed effects to the DID regression. The limitation is that we are analyzing a specific group of crowdfunding projects. Section A discusses the DID estimates when focusing on the restricted sample and reinforces our argument.

5.3.2 Using Window-varying DIDs to Rule Out Other Macro Events

What about other macro-level events that could affect both fundraising demand and supply? We develop a careful empirical strategy—DID with a varying window (or RDD with a varying window)—to rule out the influence of other concurrent events.

Our key identification assumption is that there were no other socioeconomic events that could contemporaneously affect fundraising processes disproportionately for Black and non-Black beneficiaries. The major concern arises from two most salient events:

the shock of the pandemic and the related policies in 2020.[13] Previous literature has shown that both COVID-19 and public health policies have heterogeneous effects across Black and non-Black people. These heterogeneous effects based on race could then be threats to our identification. The issue is particularly concerning since the timing of the COVID reopen policies across the states closely coincided with the onset of BLM.

We adopt a series of DID regressions that resemble Equation (1), but with varying windows around the onset of any event. For project j at date t, and for each bandwidth pick B, we have the following regression:

$$y_{j,t} = \gamma_0 Black_j \times 1(t > t^*) + \gamma_1 Black_j + X_{jt}\Gamma + \tau_t + \varepsilon_{jts} \tag{2}$$

where we focus on the sample satisfying $t \in [t^* - B, t^* + B]$. t^* denotes the event timing we want to examine, such as the surge of the BLM or the enactment/cancellation of SAH state policies. We then vary the window size B and trace the corresponding changes in our estimates.

The framework above follows the idea of detecting the discontinuity around the local cutoffs. As the window size B becomes smaller, we should expect a robust and large effect of the event if it is indeed impactful. If a small enough window size renders an insignificant estimate, we can exclude the role of such an event.

We briefly discuss our results and conclusions when applying this framework to

[13]Do the events we selected to test sufficiently support our identification? We use Google Search Trend API to report queries with the most significant increase in search frequency from April 1 to August 31, 2020. We find the top 10 search keywords are: "coronavirus," "stimulus check," "coronavirus symptoms," "popular google doodle games," "thank you coronavirus helpers," "coronavirus tips," "coronavirus news," "george floyd," "kobe bryant," "n95 mask." The popularity of these keywords increased by more than 1000%. In particular, the keyword "george floyd" increased by 3400%.

COVID cases and pandemic policies. The details of our methodology, data, and discussions are provided in Appendix A.3.

First, we use this method to demonstrate that the pandemic is not a confounding factor. We estimate how the incidence of BLM movement affects COVID-19 newly-infected cases for different races. Figure B.6 shows a smooth evolution in the number of COVID-19 cases among Black people relative to other races near the cutoff of May 26. This argues against COVID-19 as a contemporary confounding event following the outburst of BLM movement. Additionally, the Column (6) of Table V indicates that fundraising projects related to COVID do not contaminate the estimation of the effect of the BLM movement.

Second, we show that public health policy shocks do not contaminate our estimation of the BLM movement's effect. Figure B.7 shows that immediately before and after the COVID shutdown&reopening policies, there was no sudden change in the fundraising disparity. Notice that it is tempting to conclude that COVID policies had an impact if based on a large window. However, when the window size gradually shrinks to two week, the estimated effect becomes negligible. This occurs because the regression with a large window size captures some effects of the BLM movement and wrongly attributes them to COVID-19 policies.

5.4 Counterfactuals for Final Raised Outcomes

With the causal effect on the extensive margin of donations established, we then map it back to the effect on the disparities in final raised funds, which is our main interest. This subsection provides a simple back-of-the-envelope calculation to estimate the counterfactual pattern of final raised funds if the BLM had not occurred.

First, we calculate the effective duration each project was potentially affected by the onset of the Floyd protests. Second, we multiply the effective duration by the causal effect of BLM protests on daily donations received by Black people. Finally, we subtract the estimated amount of funds driven by the BLM protests from the actual raised funds. Although this back-of-the-envelope calculation does not recover the individual counterfactual for each project, it effectively imputes the counterfactual in an aggregate sense.

Figure VII presents the counterfactual funds pattern of Figure III when the BLM protests are absent. We verify that the BLM protests clearly reduced the gap in raised funds from 20% to 10%, thereby justifying the findings in Section 4 as a causal effect.

6 Mechanisms

We now turn to assess the mechanisms behind the impact of the BLM movement. The nature of these mechanisms addresses the second critical question raised in the introduction: whether and to what degree the movement succeeds in going beyond protesting themselves or pre-existing echo chambers. The best possibility would be influencing the awareness of systemic racial inequality for the whole general public, particularly places with long-rooted racial prejudice.

6.1 Cross-Race Atruism v.s. Ethnic Nepotism?

We first demonstrate that the impact of the BLM movement is a notion of cross-race altruism instead of *ethnic nepotism*.

Given the racial context and the polarization of political opinions in the U.S., a natural question is: Which racial group of donors is primarily responsive to the surge of the BLM movement? This question is vital for comprehending the impact of the BLM movement and gaining insight into the vulnerability of the informal social security net for the Black community. The overall effect of the rise of the BLM may be primarily driven by either Black or non-Black donors. On the one hand, donors might be more inclined to support beneficiaries of their own race. Consequently, the 2020 surge in BLM activity may primarily encourage Black donors to offer greater support to their Black peers. We refer to this as *ethnic nepotism* (Vanhanen (1999),Salter and Harpending (2013)). On the other hand, the influence of the BLM movement may also reach a substantial number of non-Black individuals, suggesting that donations to Black beneficiaries could primarily originate from non-Black donors. We refer to this as *cross-race altruism*.

The relevance of these two channels has different implications for social welfare and inequality. If the first mechanism prevails, the rise of the BLM movement may not necessarily reduce racial discrimination within society. Conversely, if the second mechanism dominates, it could indicate a partial move towards a more integrated society.

To test these channels, we first extract the racial information about donors. To estimate race, we employ the Python package *ethnicolr*.[14] The package uses U.S. census data, Florida voting registration data, and Wikipedia data to predict race and ethnicity based on first and last names or just the last name. This prediction has been proven to be highly accurate and is widely used in existing literature for racial classification (Chilton, Masur, and Rozema (2020)). In practice, when provided with the first and last names of a donor, the *ethnicolr* package returns the probability of that individual being classified as Asian, Hispanic, non-Hispanic White, or non-Hispanic Black. We define the first three categories as non-Black donors and the last category as Black donors. For each donation i to project j, we denote the probability

[14]Find the source here: https://github.com/appeler/ethnicolr

of donation i coming from a Black donor as $p_j^{i \in B}$, and from a non-Black donor as $p_j^{i \in nB}$. We calculate the expected number of donations from the race group $R \in \{B, nB\}$ (either Black or non-Black) received on date t as:

$$y_{j,t}^R \equiv \sum_i p_j^{i \in R} \times \mathbf{1}(i \text{ happens at } t)$$

To break down the effect of the surge of the BLM on Black and non-Black donors separately, we estimate regression Equations (3) for $R = B$ or $R = nB$ respectively:

$$y_{j,t}^R = \gamma_0^R Black_j \times \mathbf{1}(t > t_{May26}) + \gamma_1^R Black_j + X_{j,t}\Gamma + \tau_t + \mu_{State} + \varepsilon_{jt} \qquad (3)$$

γ_0^B and γ_0^{nB} represent the effects of the BLM movement on the expected number of donations from Black and non-Black donors, respectively. γ_1^B and γ_1^{nB} denote the initial disparities in the racial composition of donors who give to projects associated with Black and non-Black individuals.

Table VII presents the estimates of Equation (1) in Column (1), as well as the estimates of Equations (3) for Black donors and non-Black donors, respectively, in Columns (2) and (3). We first affirm the initial difference in the racial composition of donors across projects of Black and non-Black beneficiaries. In comparison to projects associated with non-Black individuals, those associated with the Black community receive an additional 0.187 donations per day from Black donors, while they experience 0.142 fewer donations per day from non-Black donors. This is consistent with the *ethnic nepotism* that a person prefers donating to their own peer races.

However, different impacts the BLM movement has made on different racial groups of donors. The overall effect of the BLM movement on the daily increase in donations to projects associated with the Black community primarily originates from non-Black donors. As reported in Column (1), the BLM surge results in an additional 0.421 donations per day to projects related to the Black community. This effect is composed of an additional 0.062 donations from Black donors and 0.360 donations from non-Black donors. In other words, over 85% of the BLM effect is attributable to non-Black donors. Consequently, the observed overall effect is not primarily driven by an influx of Black donors supporting projects related to Black beneficiaries during the treatment period.

6.2 Protesting Expressions?

Is donating a complementary behavior for attending on-street protests? In other words, as an alternative to physically being on the street, some people may choose to donate to Black individuals online. In an extreme case, charitable giving might only be confined to protest activists instead of the more general public. If this were the case, the increase in donors to Black beneficiaries could hardly be interpreted as an effort to reduce inequality by donors influenced by the surge of the Floyd protests.

To answer this question, we exploit rich geographical variations in protest gathering distributions and examine whether counties with more on-street rallies witness a greater or lesser effect of the BLM movement on fundraising disparity.[15]

We categorize our sample into four quantiles based on the aggregate number of on-street gathering occurrences in the residential county during the period. In categorizing, we account for the uneven distribution of Black projects across different counties, ensuring an equal number of projects associated with Black beneficiaries in

[15] One implicit assumption is that donors' locations are very close to beneficiaries location. This is verified by Smith, Windmeijer, and Wright (June 2015) that 60% donation comes from friends, families, colleagues and neighbors.

each quantile.[16] Consequently, we have the following quantiles from the smallest to the largest: *Quantile* 1 (0 to 3 gatherings), *Quantile* 2 (4 to 18 gatherings), *Quantile* 3 (19 to 41 gatherings), *Quantile* 4 (more than 41 gatherings).

We delve into the heterogeneous impacts the BLM made by protest quantiles. Panel A of Table VIII presents the estimation results under various specifications. Column (1) is the baseline specification, which reveals that for *Quantile* 4 where the most protest gatherings occurred, the BLM contributes to an increase of insignificant 0.1 donations per day to projects associated with the Black community. Notably, projects in *Quantile* 2, initiated in counties that witnessed a moderate number (4 - 18) of BLM gatherings, benefit from an additional 0.59 donations per day significantly during the treatment period. Counties in the *Quantile* 2 group witnessed the largest BLM effect on charitable giving behavior. Moreover, columns (2)-(4) feature specifications with different controls for the county-related fixed effects. Our conclusion remains robust across all alternative specifications from Column (1) to (4).

In Panel B of Table VIII, we present the heterogeneous effects by continuous protest intensity. Across four different specifications, we don't find any strong evidence showing that counties with higher on-street gathering experienced a larger or a lower BLM effect.

The heterogeneous effects of on-street gatherings suggest that, contrary to the theory of protest expression, we don't see any monotonic pattern where counties with more protest gatherings experience a larger or lower effect on crowdfunding. This finding suggests that the reduced racial gap through donations is neither a complement nor a substitute for physical protesting. If anything, we find that residents living in

[16] Appendix A.4 discusses more details on how the protests are distributed across counties, and how it relates to the number of crowdfunding projects.

the "marginal counties" of the Floyd protests, where a moderate number of BLM gatherings took place, were most influenced by the movement. Therefore, during BLM 2020, there was no significant overlap between those who attended on-street gatherings and those who donated to Black beneficiaries.

6.3 Social Media and Information Enhancement

We examine whether the effect of the BLM on-street protests is instead delivered through social media networks. That is, the concept of anti-racism permeates beyond the local activists to influence the general public, indicating an *information enhancement* channel.

We start with a simple regression to show the presence of the spillover effect of protest gatherings, and which places are the major receiver.

$$\begin{aligned} y_{jct} =& \beta_0 Black_j \times protest_{ct} + \beta_1 Black_j \times Protest_{-ct} + \beta_2 Black_j \\ & \times \mathbf{1}(t > t_{May26}) + \beta_3 Black_j + X_{jt}\Gamma_0 + \tau_t + \varepsilon_{jct} \end{aligned} \tag{4}$$

$protest_{ct}$ represents the number of gatherings that occurred in county c on day t. $Protest_{-ct}$ is the total number of gatherings with that occurred in the U.S. other than county c at the same time at day t. β_0 and β_1 are the coefficients of primary interest, representing the effect of local rallies and global gatherings. In this paper, we don't focus on the causality of the regression but rather use these estimated parameters as a handy way to test the presence of the spillover.

Table IX reports the estimates for regression equation (4), for our full sample and by four quantiles of protest intensity. Column (1) covers the estimates using projects from across the nation, while columns (2) through (5) report the estimates for projects from counties that witnessed a number of protest rallies ranging from the smallest quantile (*Quantile* 1) to the largest quantile (*Quantile* 4). Our primary conclusion is that the BLM movement mainly exerts its influence through its broad global impact originating from places with the highest on-street gatherings. This is seen in projects in *Quantile* 2, where we notice insignificant effects from local gatherings but significant effects from the outside national BLM protests. This explains why that *Quantile* 2 witnessed the largest BLM effect on donation behavior. Additionally, projects in *Quantile* 3 and 4 show effects related to local gatherings and negligible effects from the national shock. This does not change our conclusion, as these projects in *Quantile* 3 and 4 were initiated in areas with a high frequency of gatherings, where the protest effects of their own region dominate any information spillover from other regions.

We turn to explore the role of social media in conveying the effects of the BLM protests beyond one's original location. We focus on fundraising projects in *Quantile* 2, since they are the major receivers of global movements.

We construct an exposure measure of each county to all protests across the U.S., using the social connectivity index $SCI_{c,c'}$ from Bailey et al. 2018. The social connectivity index measures the probability of a Facebook friendship link between a given Facebook user in county c and a given user in county $c^{'}$. The local exposure to global protests Fcp_c is then constructed by using this connectivity index as a weight to calculate a county's exposure to protests from all other counties.

$$Fcp_c = \sum_{c'} SCI_{c,c'} \cdot protest_{c'}$$

This measure is de facto a Bartik instrument and reflects whether socially connecting to places where more protests happened will increase the protest effect. With the global protest distribution being fixed, we only use the cross-region variations in the social connectivity structure to all the outside protesting events.

Table X presents the estimates of the heterogeneous effects of the BLM movement by the level of social connectivity exposure. Panel (a) shows that a one standard deviation increase of the social connectivity to protests will increase the charitable donation to Black beneficiaries each day by 0.4. This result is robust to four different specifications. Moreover, in panel (b), we supplement our continuous heterogeneous analysis with a quantile group analysis of social connectivity. We continue to visualize that the greater the social connectivity to the outside protests is, the greater the BLM effect on charitable-giving behavior.

6.4 Temporary or Permanent Anti-Discrimination?

Does the donation effect indicate the removal of racial discrimination and stereotypes? Much evidence has been found that Americans sort themselves into politically similar counties and congress districts (Lang and Pearson-Merkowitz (2015), Kaplan, Spenkuch, and Sullivan (2022)). Therefore, it is sufficient to answer the question by examining the heterogeneous effects across units of different political chambers – i.e. either county or congress district, along the dimension related to measures of racial discrimination.

Existing studies in political science suggest that the BLM protests heightened the awareness of racial inequality and favoritism for Black communities(Reny and Newman (2021),Dunivin et al. (2022)). Panel (a) of Figure VIII presents this evidence replicating the concurrent surge in awareness of discrimination using Nationalscape data, following Reny and Newman (2021). However, there are still problems with interpreting this evidence as a change in the long-term systemic racism and racial prejudice rooted in U.S. On the one hand, the effect is short-lived for only 3 months.

On the other hand, we don't know whether this awareness can be transformed into real action, or if this lift of awareness is due to the social-desirability bias around that period.

More particularly, it is still unclear who is the main driver of this attitude switch. Would people who previously had more racial discrimination and prejudice against Black people tend to express more of awareness of racial inequality? As shown in Panel (b) of Figure VIII, people living in congress districts with higher explicit discrimination are more aware of "discrimination towards Black people is a problem in U.S". While conflicting with Panel (b), Panel (c) uses implicit discrimination and documents a slightly opposite pattern. Thus, this question remains unclear and could be subject to debate.

Along this line of logic, we examine the heterogeneous treatment effects of BLM on actual donation actions across locations with different degrees of racism and inequality. We consider three measures of local racial inequality: (1) county-level racial disparity in crowdfunding, (2) county-level explicit discrimination against Black people, measured through the Implicit Attitude Tests from 2008-2019, and (3) county-level implicit prejudice against Black people.

Columns (1)- (3) from Table XI presents the heterogeneous effects along these three dimensions. They jointly reveal that counties with higher crowdfunding racial disparity or higher prejudice towards Black people witnessed significantly lower levels of the influx of donation activities promoted by the BLM movement. More interestingly, the estimates from using implicit attitude and explicit attitude agree on the same qualitative answer.

The evidence implies that the structural racism and inequality embedded in one's local niche is stubborn such that residents can not easily respond to BLM movements by donating more to Black people. This is consistent with the theory that the county as a form of chamber that encompasses racial stereotypes echoing inside.

We continue to examine the cross-sectional relation between changes in the awareness of discrimination during the surge of BLM movements and the changes in charitable giving acts to Black people. The measure of local piqued awareness of discrimination is extracted from Nationalscape data at the congressional district level. We calculate the average change in the awareness of discrimination 3 months before and after May 26^{th} 2020, for each congressional district. Column (4) from Table XI presents the heterogeneous effects along this concurrent dimension. We find that places where more people realize the wide presence of racism in the U.S. in response to the BLM movement are witnessing more charitable acts towards Black beneficiaries of bad health. This implies that our charitable giving act is a result of the temporarily aroused sentiment of empathy and awareness of systemic discrimination.

To sum up, our evidence acknowledges that the charitable giving effects of BLM is likely through a temporary racial preference&empathy during this period, though long-term racial attitude or taste discrimination of the public remains stubborn. Thus, if anything, the function of the George Floyd protests in reshaping the U.S democracy is active but limited.

7 Conclusion

This study shows that racial justice movements can economically help disadvantaged races by motivating charitable donations from other races and increasing the inclusiveness of the social safety net. This indicates a strong discrimination-debiasing role of social movements in the U.S., where extremely polarized views on race and inequality persist.

Local protest actions per se do not matter during this movement. But massive movements and protests together matter for moving public empathy and charitable giving. Social media plays an essential role in amplifying and conveying the meaning of decentralized assembly. This indicates that, as central pillars of democracy, freedom of speech and assembly are complementary to one another.

The effectiveness of social movements fades over time as the protests cease. This is unsurprisingly consistent with the fact that numerous affirmative and equal opportunity legislations introduced since 1964 have had mixed and limited effects. People's racial stereotypes toward Black people, rooted in the legacy of prejudice, segregation, and discrimination, cannot be drastically altered. While this sounds discouraging, a potential hope to address racial disparity might be to consistently keep the public informed and aware of the issue of racial discrimination.

Our findings benchmark several new research questions for future studies: (1) How do we quantify and model the simultaneity, interplay, or spillover between social media coverage and protests? We highlight the potential strategic complementarity here. (2) How do we quantify the relevance of the *information enhancement channel*? That is, without explicit or implicit social media, what should the counterfactual effect on donation behaviors be reduced to? (3) Given that protest gatherings might be detrimental to the economy and safety of society while anti-racism discussions and articles are beneficial, how can government and social planners exploit the power of social media and minimize the side effects of protest rallies? Answering these questions will deepen our understanding of the functions and institutions that both sustain democracy and lay the constructive foundation for a climate of equal opportunity.

References

Agarwal, Saharsh,Ananya Sen. 2022. "Antiracist curriculum and digital platforms: Evidence from Black Lives Matter." *Management Science* 68 (4): 2932–2948.

Andrews, Kenneth T, Kraig BeyerleinTuneka Tucker Farnum. 2016. "The legitimacy of protest: explaining White Southerners' attitudes toward the civil rights movement." *Social Forces* 94 (3): 1021–1044.

Bailey, Michael, Rachel Cao, Theresa Kuchler, Johannes StroebelArlene Wong. 2018. "Social connectedness: Measurement, determinants, and effects." *Journal of Economic Perspectives* 32 (3): 259–280.

Bailey, Michael, Drew M Johnston, Martin Koenen, Theresa Kuchler, Dominic RusselJohannes Stroebel. 2020. *Social networks shape beliefs and behavior: Evidence from social distancing during the covid-19 pandemic.* Technical report. National Bureau of Economic Research.

Bosi, Lorenzo, Marco GiugniKatrin Uba. 2016. *The consequences of social movements.* Cambridge University Press.

Boxell, Levi, Matthew GentzkowJesse M Shapiro. 2017. *Is the internet causing political polarization? Evidence from demographics.* Technical report. National Bureau of Economic Research.

Buchanan, Larry, Quoctrung BuiJugal K Patel. 2020. "Black Lives Matter may be the largest movement in US history." *The New York Times* 3 (07): 2020.

Buchmueller, Thomas C, Zachary M Levinson, Helen G LevyBarbara L Wolfe. 2016. "Effect of the Affordable Care Act on racial and ethnic disparities in health insurance coverage." *American journal of public health* 106 (8): 1416–1421.

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

Carratala, Sofia,Connor Maxwell. 2020. "Health disparities by race and ethnicity." *Center for American Progress* 7.

Casanueva, Annalí, Vladimir Avetian, Sulin SardoschauKritika Saxena. 2022. "Social media and the broadening of social movements: Evidence from Black Lives Matter." *Available at SSRN 3831819.*

Castells, Manuel. 2015. *Networks of outrage and hope: Social movements in the Internet age.* John Wiley & Sons.

Chilton, Adam, Jonathan MasurKyle Rozema. 2020. "Political ideology and the law review selection process." *American Law and Economics Review* 22 (1): 211–240.

Chowkwanyun, Merlin,Adolph L. Reed. 2020. "Racial Health Disparities and Covid-19 — Caution and Context." *New England Journal of Medicine* 383 (3): 201–203. ISSN: 0028-4793, 1533-4406.

Cinelli, Matteo, Gianmarco De Francisci Morales, Alessandro Galeazzi, Walter QuattrociocchiMichele Starnini. 2021. "The echo chamber effect on social media." *Proceedings of the National Academy of Sciences* 118 (9): e2023301118.

Di Tella, Rafael, Ramiro H GálvezErnesto Schargrodsky. 2021. *Does social media cause polarization? Evidence from access to Twitter echo chambers during the 2019 Argentine presidential debate.* Technical report. National Bureau of Economic Research.

Dunivin, Zackary Okun, Harry Yaojun Yan, Jelani InceFabio Rojas. 2022. "Black Lives Matter protests shift public discourse." *Proceedings of the National Academy of Sciences* 119 (10): e2117320119.

Engist, Oliver,Felix Schafmeister. 2022. "Do political protests mobilize voters? Evidence from the Black Lives Matter protests." *Public Choice* 193 (3-4): 293–313.

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

Gentzkow, Matthew,Jesse M Shapiro. 2011. "Ideological segregation online and offline." *The Quarterly Journal of Economics* 126 (4): 1799–1839.

Giugni, Marco, Doug McAdamCharles Tilly. 1999. *How social movements matter.* Volume 10. U of Minnesota Press.

González-Bailón, Sandra,Yphtach Lelkes. 2023. "Do social media undermine social cohesion? A critical review." *Social Issues and Policy Review* 17 (1): 155–180.

Gorbatai, Andreea,Laura Nelson. 2015. "The narrative advantage: Gender and the language of crowdfunding." *Haas School of Business UC Berkeley. Research Papers,* 1–32.

Kaplan, Ethan, Jörg L SpenkuchRebecca Sullivan. 2022. "Partisan spatial sorting in the United States: A theoretical and empirical overview." *Journal of Public Economics* 211:104668.

Lang, Corey,Shanna Pearson-Merkowitz. 2015. "Partisan sorting in the United States, 1972–2012: new evidence from a dynamic analysis." *Political Geography* 48:119–129.

Lelkes, Yphtach, Gaurav SoodShanto Iyengar. 2017. "The hostile audience: The effect of access to broadband internet on partisan affect." *American Journal of Political Science* 61 (1): 5–20.

Levy, Gilat,Ronny Razin. 2019. "Echo chambers and their effects on economic and political outcomes." *Annual Review of Economics* 11 (1): 303–328.

Levy, Ro'ee,Martin Mattsson. 2023. "The effects of social movements: Evidence from# MeToo." *Available at SSRN 3496903.*

Levy, Ro'ee. 2021. "Social media, news consumption, and polarization: Evidence from a field experiment." *American economic review* 111 (3): 831–870.

Lillie-Blanton, Marsha,Catherine Hoffman. 2005. "The role of health insurance coverage in reducing racial/ethnic disparities in health care." *Health affairs* 24 (2): 398–408.

Luo, Hong,Laurina Zhang. 2022. "Scandal, social movement, and change: Evidence from# MeToo in Hollywood." *Management Science* 68 (2): 1278–1296.

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

Meyer, David S. 2021. *How social movements (sometimes) matter.* John Wiley & Sons.

Miller, Douglas L. 2023. "An introductory guide to event study models." *Journal of Economic Perspectives* 37 (2): 203–230.

Montenovo, Laura, Xuan Jiang, Felipe Lozano-Rojas, Ian Schmutte, Kosali Simon, Bruce A WeinbergCoady Wing. 2022. "Determinants of disparities in early COVID-19 job losses." *Demography* 59 (3): 827–855.

Moreland, Amanda, Christine Herlihy, Michael A Tynan, Gregory Sunshine, Russell F McCord, Charity Hilton, Jason Poovey, Angela K Werner, Christopher D Jones, Erika B Fulmer, et al. 2020. "Timing of state and territorial COVID-19 stay-at-home orders and changes in population movement—United States, March 1–May 31, 2020." *Morbidity and Mortality Weekly Report* 69 (35): 1198.

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

Orsi, Jennifer M, Helen Margellos-AnastSteven Whitman. 2010. "Black–white health disparities in the United States and Chicago: a 15-year progress analysis." *American journal of public health* 100 (2): 349–356.

Pennebaker, James W, Ryan L Boyd, Kayla JordanKate Blackburn. 2015. *The development and psychometric properties of LIWC2015.* Technical report.

Perry, Brea L, Brian AronsonBernice A Pescosolido. 2021. "Pandemic precarity: COVID-19 is exposing and exacerbating inequalities in the American heartland." *Proceedings of the National Academy of Sciences* 118 (8): e2020685118.

Qin, Bei, David StrömbergYanhui Wu. 2021. "Social media and collective action in China."

Reny, Tyler T,Benjamin 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.

Salter, Frank,Henry Harpending. 2013. "JP Rushton's theory of ethnic nepotism." *Personality and Individual Differences* 55 (3): 256–260.

Serengil, Sefik Ilkin,Alper Ozpinar. 2020. “Lightface: A hybrid deep face recognition framework.” In *2020 innovations in intelligent systems and applications conference (ASYU),* 1–5. IEEE.

Smith, Sarah, Frank WindmeijerEdmund Wright. June 2015. “Peer Effects in Charitable Giving: Evidence from the (Running) Field” [**inlang**en]. *The Economic Journal* 125, number 585 (): 1053–1071. ISSN: 00130133, visited on July 21, 2022. https://doi.org/10.1111/ecoj.12114. https://academic.oup.com/ej/article/125/585/1053-1071/5077361.

Tausanovitch, Chris, Lynn Vavreck, Tyler Reny, Alex Rossell HayesAaron Rudkin. 2019. “Democracy fund+ UCLA nationscape methodology and representativeness assessment.” *Democracy Fund Voter Study Group.*

Törnberg, Petter. 2022. “How digital media drive affective polarization through partisan sorting.” *Proceedings of the National Academy of Sciences* 119 (42): e2207159119.

Van Dyke, Nella,Verta Taylor. 2018. “The cultural outcomes of social movements.” *The Wiley Blackwell companion to social movements,* 482–498.

Vanhanen, Tatu. 1999. “Domestic ethnic conflict and ethnic nepotism: A comparative analysis.” *Journal of peace research* 36 (1): 55–73.

Webb Hooper, Monica, Anna María NápolesEliseo J. Pérez-Stable. 2020. “COVID-19 and Racial/Ethnic Disparities.” *JAMA* 323 (24): 2466–2467.

Xu, Kaiyuan, Brian NosekAnthony G Greenwald. 2014. “Psychology data from the race implicit association test on the project implicit demo website.” *Journal of open psychology data* 2 (1): e3–e3.

Yang, Kangning, Chaofan Wang, Zhanna Sarsenbayeva, Benjamin Tag, Tilman Dingler, Greg WadleyJorge Goncalves. 2021. “Benchmarking commercial emotion detection systems using realistic distortions of facial image datasets.” *The visual computer* 37:1447–1466.

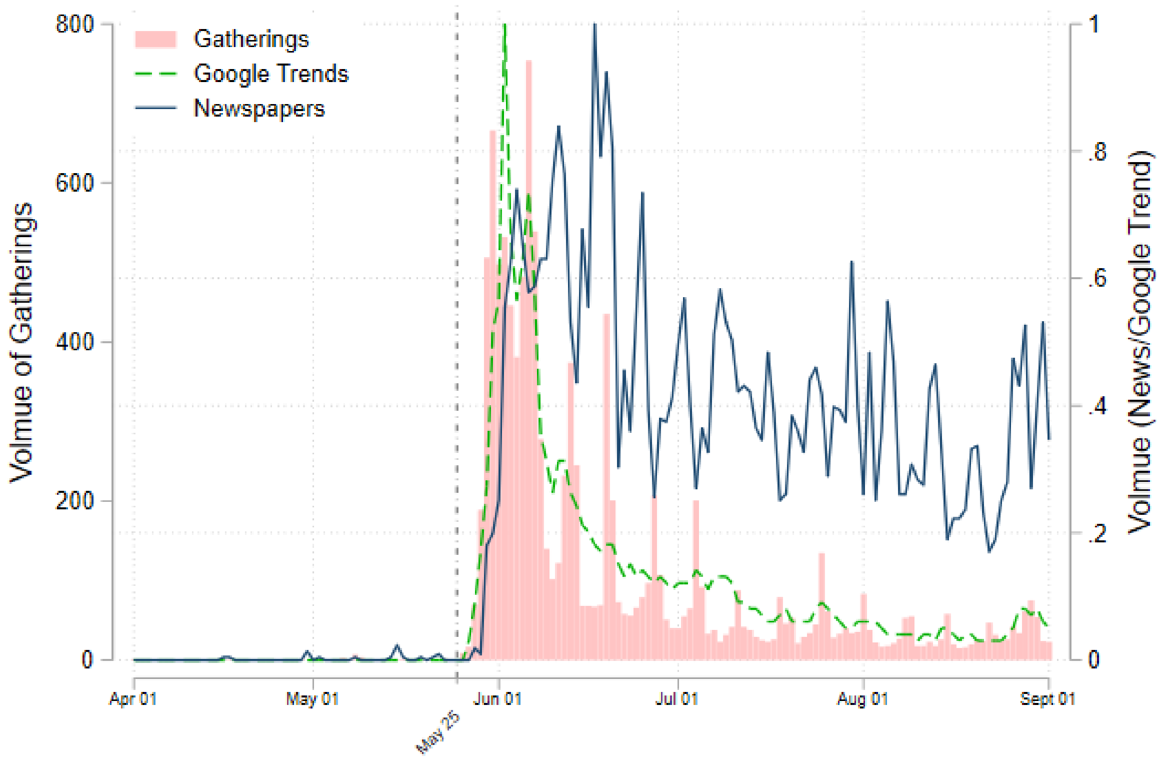
Yearby, Ruqaiijah. 2018. “Racial disparities in health status and access to healthcare: the continuation of inequality in the United States due to structural racism.” *American Journal of Economics and Sociology* 77 (3-4): 1113–1152.

Younkin, Peter,Venkat Kuppuswamy. 2018. “The colorblind crowd? Founder race and performance in crowdfunding.” *Management Science* 64 (7): 3269–3287.

Zhuravskaya, Ekaterina, Maria PetrovaRuben Enikolopov. 2020. “Political effects of the internet and social media.” *Annual review of economics* 12 (1): 415–438.

I. Figures

FIGURE I: George Floyd/BLM: Protest, Search Behavior and Media Coverage



Note: Figure I presents the time pattern of the national wide Floyd/BLM related protest gatherings, google search behavior and news coverage. y-axis on the left side is the number of protests at each date. y-axis on the right side is the normalized scale of: (i) Google search trends for related keywords of George Floyd or BLM; (ii) newspaper trends for these two topics.

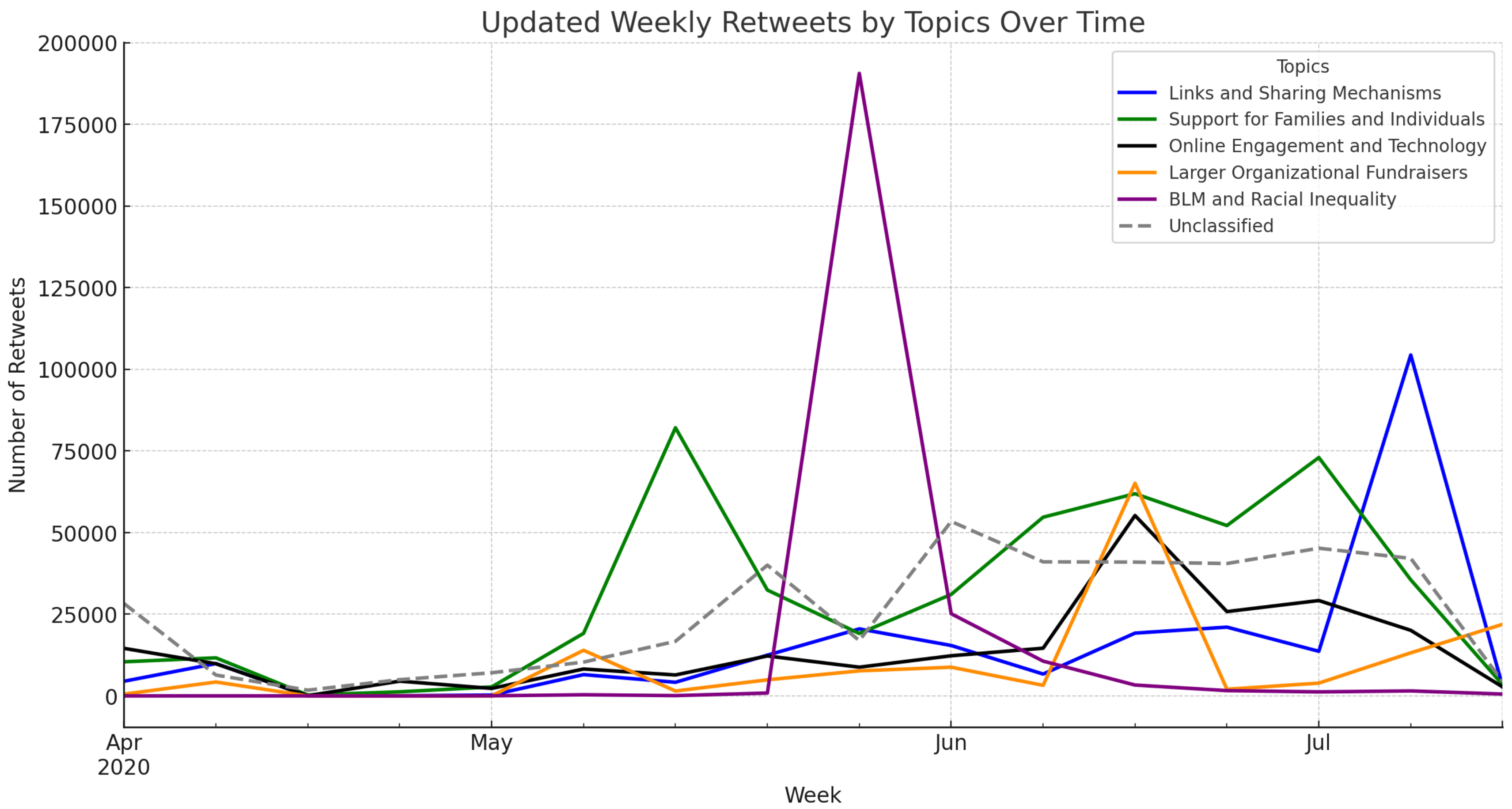
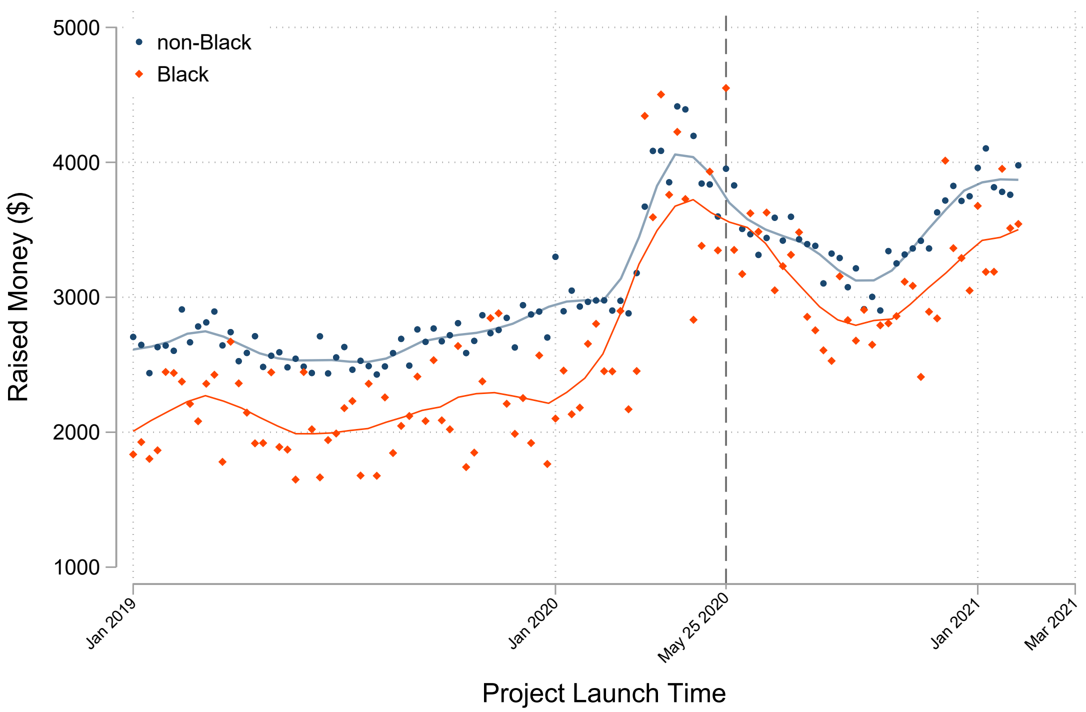


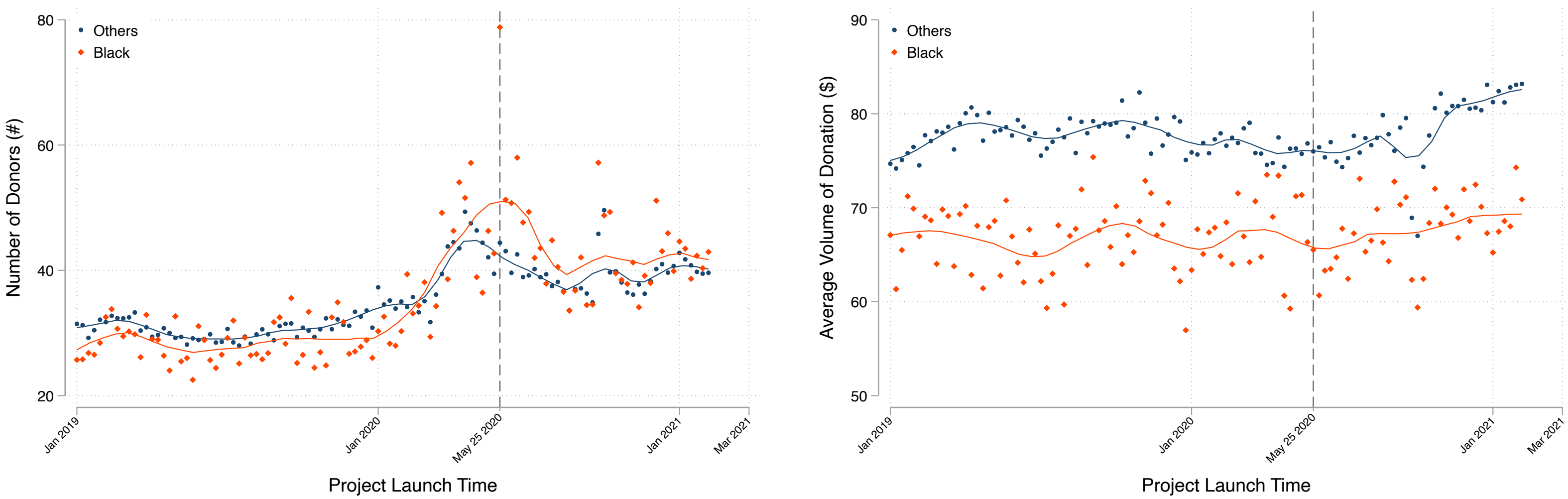
FIGURE II: Caption

FIGURE III: Amount of money eventually raised by launch time



Note: Figure III depicts the fundraising outcomes for projects launched at various times. Panel (a) (b) (c) focuses on total funds raised, number of eventual donors, and average donation amount($) respectively. The x-axis denotes the project launch date, and the y-axis signifies the respective outcome. We use orange dots to represent projects involving Black beneficiaries and navy dots for all other projects. Non-parametric fitted lines indicate trends for each group.

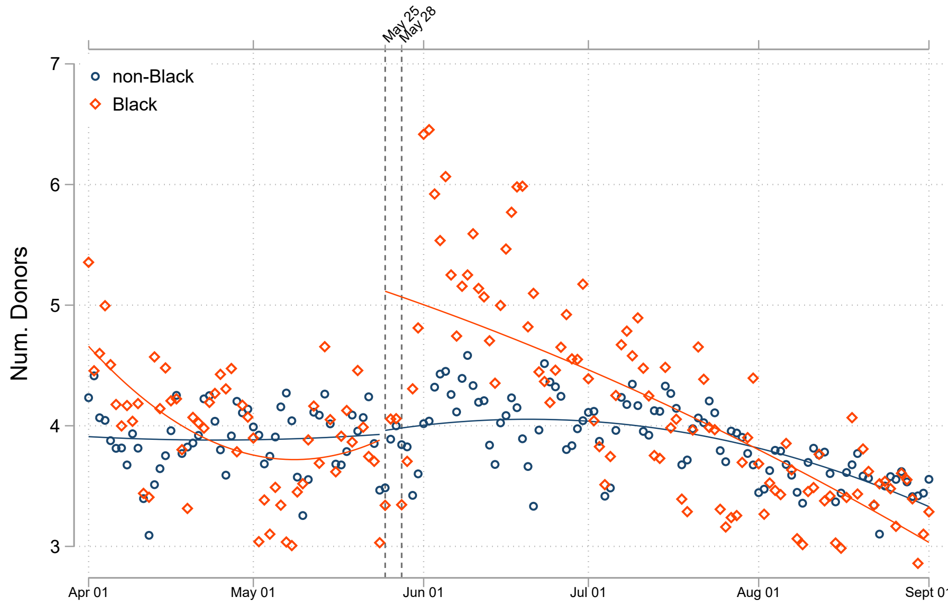
FIGURE IV: Evolution of Two Margins Over Launch Time



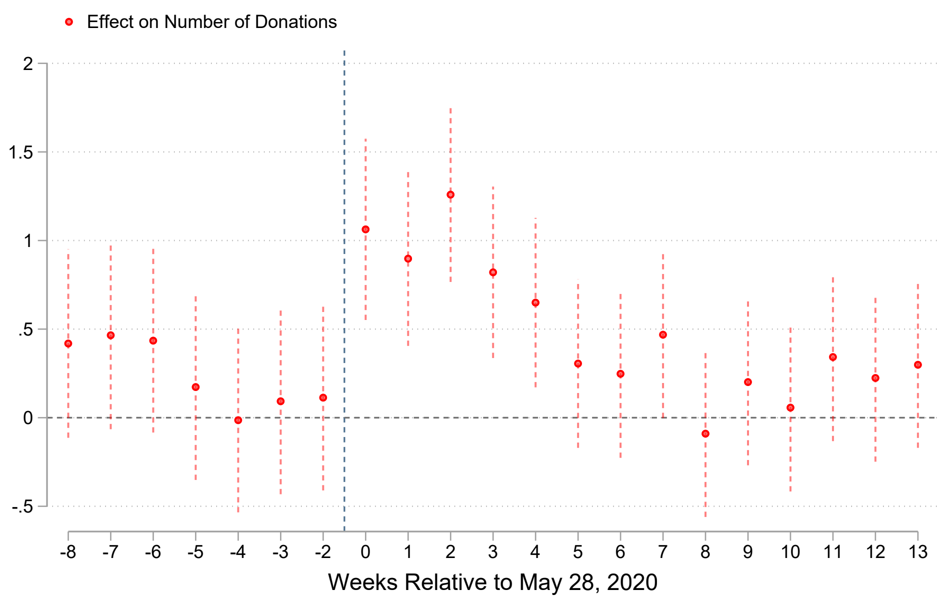
(a) (b)

Note: Figure III depicts the fundraising outcomes for projects launched at various times. Panel (a) (b) (c) focuses on total funds raised, number of eventual donors, and average donation amount($) respectively. The x-axis denotes the project launch date, and the y-axis signifies the respective outcome. We use orange dots to represent projects involving Black beneficiaries and navy dots for all other projects. Non-parametric fitted lines indicate trends for each group.

FIGURE V: The Daily Average Number of Donors Per Project



(a)



(b)

Note: Figure V (a) depicts the average number of donations received per active project per day. Each data point signifies the average number of donors per project on a given date t, calculated as the total number of donations made that day divided by the total number of active projects on that day. Panel (b) presents the event study estimates at weekly level.

FIGURE VI: The Effect of Floyd Movement in History

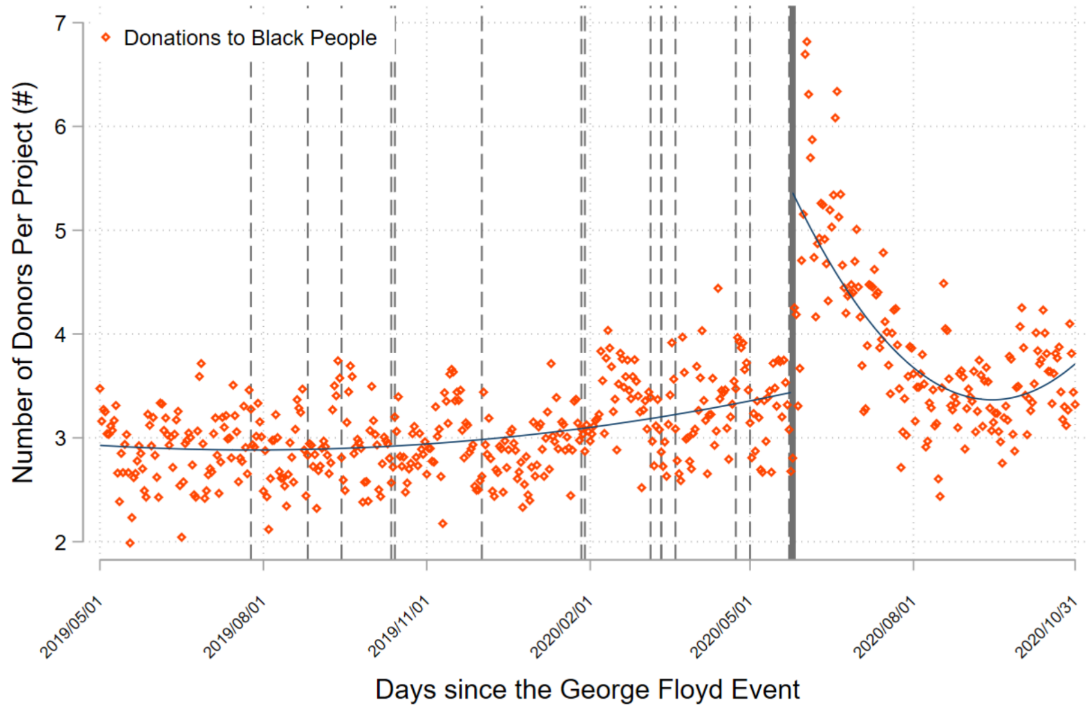
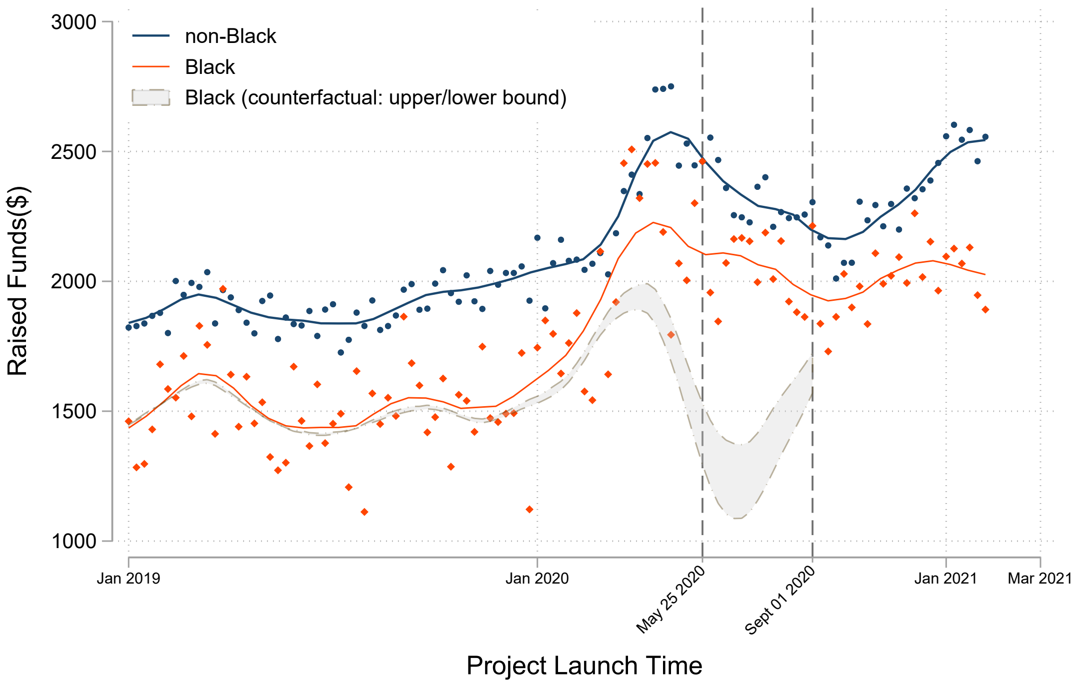


Table: Previous killings

Name	Date
Josef Delon Richardson	7/25/2019
Channara Tom Pheap	8/26/2019
Melvin Watkins	9/14/2019
Atatiana Jefferson	10/12/2019
Christopher Whitfield	10/14/2019
Michael Dean	12/2/2019
William Howard Green	1/27/2020
Jaquyn Oneill Light	1/29/2020
Barry Gedeus	3/6/2020
Breonna Taylor	3/12/2020
Donnie Sanders	3/12/2020
Mycael Johnson	3/20/2020
Fred Brown	4/23/2020
Shaun Lee Fuhr	5/1/2020
Maurice S. Gordon	5/23/2020

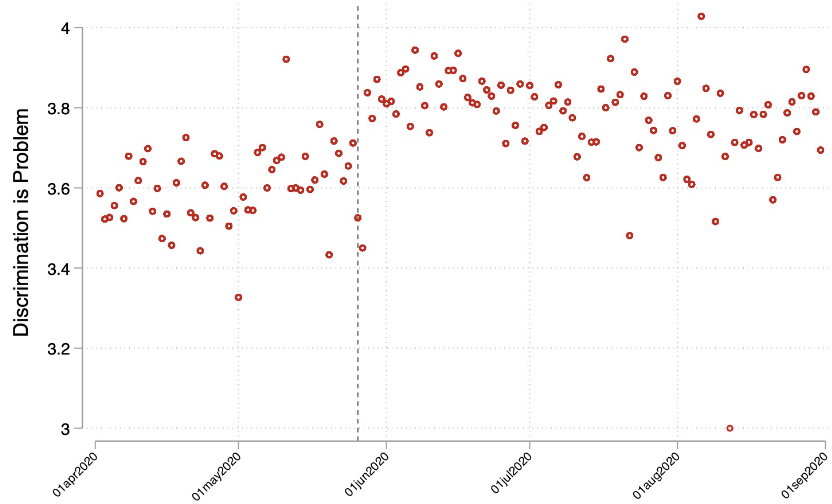
Note: Figure VI presents number of daily donations to Black project, tracing back to our earliest data, from May, 2019 to October, 2020. During this period, there are 15 police injustice killings and the corresponding BLM protests. We mark the timing of these events using dashed vertical lines.

FIGURE VII: Counterfactual Imputation For Rasied Fund If BLM were not Impactful

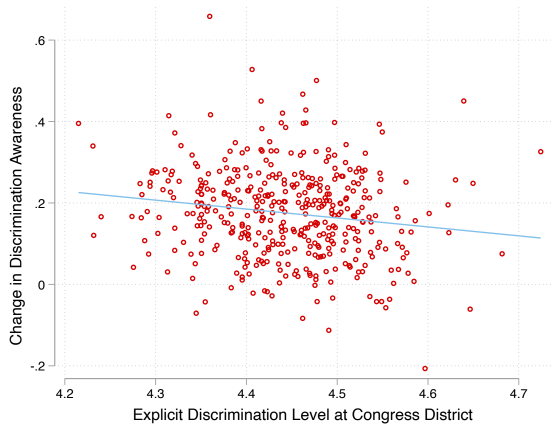


Note: Figure VII illustrates the raised fund evolution over launch time. In addition, we plot in red line, the counterfactual pattern of the raised funds if the BLM were not impactful.

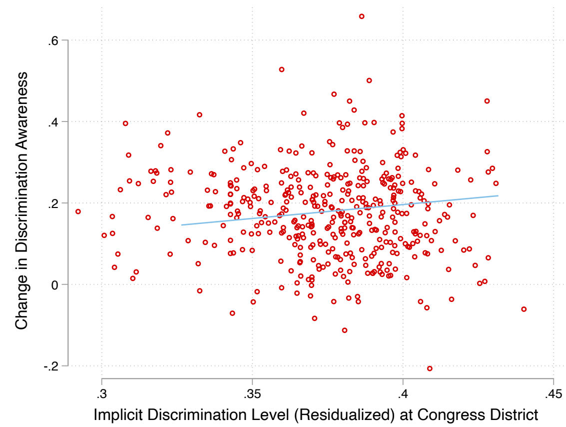
FIGURE VIII: Awareness of Racial Discrimination and Long-rooted Regional Discrimination



(a)



(b)



(c)

Note: Figure VIII (a) replicate the evolution of racial attitude and awareness of discrimination in U.S, following Reny and Newman (2021). Panel (b) presents the relationship between the change in racial attitude ("Discrimination is Problem") with the explicit discrimination (2008-2019) at the congress-district level. Panel (b) presents the relationship between the change in racial attitude and the residualized implicit discrimination (2008-2019). The change in racial attitude is calculated by taking the difference of measure "Discrimination is Problem" for each congress district before and after May 26^{th}. The residualized implicit discrimination is conditional on the explicit level and taking residuals.

II. Tables

TABLE I: Summary Statistics of Medical Crowdfunding Records (Projects Launched Between Jan 1, 2019 and Mar 31, 2021)

N=316,767 (# Black = 31,481 # non-Black = 285,286)	*Mean*	*Median*	*Std. dev*	*Min*	*Max*
Panel A: Fundraising Outcomes					
Fund Goal ($)	14939.79	6000	26479.72	1.00	500000
non-Black	14776.03	6000	26216.88	1.00	500000
Black	16423.82	6500	28710.14	1.00	300000
Raised Money ($)	3777.66	1265	6805.19	0	62190
non-Black	3834.54	1295	6861.95	0	62190
Black	3262.19	1065	6243.96	0	62190
Raised Money/Goal	0.43	0.23	0.57	0.01	12.31
non-Black	0.43	0.24	0.58	0.01	12.31
Black	0.37	0.18	0.52	0.01	12.31
Raised Money/Goal (within 2 weeks after launch)	0.02	0.01	0.03	0.00	0.24
non-Black	0.10	0.06	0.13	0.00	1.00
Black	0.08	0.04	0.12	0.00	1.84
Fully or Over Funded (0 or 1)	0.12	0	0.32	0	1
non-Black	0.12	0	0.32	0	1
Black	0.10	0	0.30	0	1
Number of Donors	43.50	18.00	72.05	2	1395
non-Black	43.51	18.00	71.67	2	1395
Black	43.41	18.00	75.46	2	1395
Number of Donors > 100 (0 or 1)	0.11	0	0.31	0	1
non-Black	0.11	0	0.31	0	1
Black	0.11	0	0.31	0	1
Average Donation ($)	80.99	67.14	72.85	0	5033
non-Black	82.10	68.26	73.63	0	5033.33
Black	70.92	58.33	64.52	0	3229.17
Panel B: Characteristics of Projects' Profiles					
Number of Faces in the Photo	1.97	1	1.95	1	20
non-Black	1.91	1	1.78	1	20
Black	2.53	1	3.06	1	20
Ratio of Male Faces in the Photo	0.52	0.50	0.43	0	1
non-Black	0.51	0.50	0.43	0	1
Black	0.61	0.67	0.41	0	1
Text Description: Number of Words	1566.93	1134	1530.63	0	32434
non-Black	1578.31	1140	1543.46	0	32078
Black	1463.73	1085	1404.81	0	32434
Text Description: Authenticity Index	20.19	7.66	26.56	0	99
non-Black	20.10	7.71	26.40	0	99
Black	21.07	7.18	27.90	0	99
Text Description: Positive Emotion Index	3.74	3.41	2.37	0	100
non-Black	3.72	3.39	2.35	0	100
Black	3.93	3.57	2.60	0	100
Text Description: Negative Emotion Index	1.55	1.36	1.31	0	100
non-Black	1.55	1.36	1.31	0	100
Black	1.52	1.33	1.31	0	25

Note: Table I summarizes the crowdfunding data during Jan 1, 2019 and Mar 31, 2021. We observe that 316767 medical crowdfunding projects actively received donations between April 1 and September 1, 2020. Panel A describes the eventual outcomes of these projects. Panel B describes the information extracted from the beneficiaries' photos and text descriptions on each project's profile.

TABLE II: Summary Statistics of Medical Crowdfunding Records (Projects Receiving Donations between Apr 1 and Sept 1, 2020)

N=70,364 (# Black = 7,381 # non-Black = 62,983)	Mean	Median	Std. dev	Min	Max
Panel A: Fundraising Outcomes					
Fund Goal ($)	17007.44	8000	28560.00	1	200000
non-Black	16446.84	8000	27448.23	1	200000
Black	18224.99	8000	31388.69	1	200000
Raised Money ($)	5316.94	2035	8807.30	0	54131
non-Black	5166.14	2030	8440.48	0	54131
Black	4607.77	1755	7923.08	0	54131
Raised Money/Goal	0.49	0.32	0.58	0.01	4.03
non-Black	0.49	0.32	0.58	0.01	4.03
Black	0.46	0.27	0.57	0.01	4.03
Raised Money/Goal (within 2 weeks after launch)	0.13	0.06	6.19	0.00	0.24
non-Black	0.02	0.01	0.20	0.00	0.24
Black	0.02	0.01	0.03	0.00	0.24
Fully or Over Funded (0 or 1)	0.13	0	0.34	0	1
non-Black	0.13	0	0.34	0	1
Black	0.13	0	0.34	0	1
Number of Donors	60.04	29	89.45	0	564
non-Black	57.33	28	83.91	1	564
Black	60.86	28	91.96	0	564
Number of Donors > 100 (0 or 1)	0.16	0	0.37	0	1
non-Black	0.15	0	0.36	0	1
Black	0.16	0	0.37	0	1
Average Donation ($)	81.96	70.45	65.70	0	5139.00
non-Black	82.95	71.54	65.35	0	5139.00
Black	72.79	60.37	69.31	0	3395.67
Panel B: Characteristics of Projects' Profiles					
Number of Faces in the Photo	2.03	1	2.02	1	20
non-Black	1.95	1	1.82	1	20
Black	2.65	1	3.17	1	20
Ratio of Male Faces in the Photo	0.52	0.50	0.42	0	1
non-Black	0.51	0.50	0.42	0	1
Black	0.60	0.67	0.40	0	1
Text Description: Number of Words	1642.97	1198	1573.18	1	32078
non-Black	1647.66	1198	1581.32	1	32078
Black	1539.63	1138	1450.27	6	30118
Text Description: Authenticity Index	19.63	7.58	26.10	0	99
non-Black	19.50	7.62	25.92	0	99
Black	20.91	7.38	27.74	0	99
Text Description: Positive Emotion Index	3.78	3.45	2.31	0	100.0
non-Black	3.75	3.43	2.30	0	100.0
Black	3.95	3.60	2.38	0	23.33
Text Description: Negative Emotion Index	1.54	1.36	1.26	0	37.50
non-Black	1.54	1.36	1.25	0	37.50
Black	1.55	1.35	1.30	0	20.00

Note: Table II summarizes the crowdfunding data. We observe that 70,364 medical crowdfunding projects actively received donations between April 1 and September 1, 2020. Panel A describes the eventual outcomes of these projects. Panel B describes the information extracted from the beneficiaries' photos and text descriptions on each project's profile.

TABLE III: The Average Reduction of Racial Gap in Raised Funds before/after February 2020

	(1)	(2)	(3)	
	Panel A: Total Raised Funds ($)			
$\mathbf{1}(t > Feb.2020)$	1100.280***	725.813***	762.486***	-
	[24.405]	[21.624]	[21.281]	-
$Black_j$	-581.989***	-699.577***	-689.202***	-658.147***
	[44.404]	[42.174]	[42.062]	[42.368]
$Black_j \times \mathbf{1}(t > Feb.2020)$	292.637***	193.362***	216.204***	185.860***
	[72.396]	[67.325]	[66.310]	[66.023]
	Panel B: log of Total Raised Funds			
$\mathbf{1}(t > Feb.2020)$	0.292***	0.196***	0.213***	-
	[0.006]	[0.006]	[0.005]	-
$Black_j$	-0.248***	-0.278***	-0.281***	-0.264***
	[0.014]	[0.013]	[0.013]	[0.013]
$Black_j \times \mathbf{1}(t > Feb.2020)$	0.149***	0.123***	0.130***	0.121***
	[0.020]	[0.018]	[0.018]	[0.018]
Fund Goal		Yes	Yes	Yes
Description & Face Features			Yes	Yes
State FE & Launching Date FE				Yes
Observations	289463	289463	289463	289462

standard error in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table III reports the estimation results of the following diff-in-diff regression Equation

$$y_{j,t} = \beta_0 + \beta_1 Black_j \times \mathbf{1}(t > Feb.2020) + \beta_2 Black_j + X_j\Gamma + \tau_t + \mu_s + \varepsilon_{j,t}$$

$y_{j,t}$ is the outcome of project j launching at date t. $\mathbf{1}(t > Feb.2020) = 1$ if the launching date t is later than February, 2020. $Black_j = 1$ if project j contains any Black beneficiaries. X_j is the optional control variables, including project j's goal setting and features of its text description or profile photo. τ_t is the fixed effect of the launching date. μ_s is the optional state fixed effect. Panel A reports the results of the absolute value of the raised money. Panel B reports the estimates using the log value as the outcomes.

TABLE IV: The Average Reduction of Racial Gap in Total Number of Donors and Average Amount of Donations before/after January 2020

	(1)	(2)	(3)	(4)
	Panel A: Total Number of Donors			
$\mathbf{1}(t > Feb.2020)$	12.490***	9.075***	9.430***	-
	[0.241]	[0.217]	[0.214]	-
$Black_j$	-1.989***	-3.061***	-2.102***	-2.039***
	[0.469]	[0.446]	[0.446]	[0.449]
$Black_j \times \mathbf{1}(t > Feb.2020)$	6.398***	5.492***	5.636***	5.261***
	[0.813]	[0.765]	[0.756]	[0.751]
	Panel B: Average Amount of Donation			
$\mathbf{1}(t > Feb.2020)$	2.086***	0.157	0.351*	-
	[0.204]	[0.197]	[0.195]	-
$Black_j$	-11.639***	-12.245***	-13.760***	-13.051***
	[0.440]	[0.428]	[0.426]	[0.427]
$Black_j \times \mathbf{1}(t > Feb.2020)$	1.061*	0.549	0.747	0.706
	[0.593]	[0.578]	[0.572]	[0.570]
Fund Goal		Yes	Yes	Yes
Description & Face Features			Yes	Yes
State FE & Launch Date FE				Yes
Observations	289463	289463	289463	289462

standard error in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table IV reports the estimation results of the following diff-in-diff regression Equation

$$y_{j,t} = \beta_0 + \beta_1 \mathbf{1}(t > Feb.2020) \times Black_j + \beta_2 Black_j + X_j \Gamma + \delta_t + \sigma_s + \varepsilon_{j,t}$$

$y_{j,t}$ is either the total number of donors or the average amount of donation received by project j launching at date t. $\mathbf{1}(t > Feb.2020) = 1$ if the launching date t is later than February, 2020. $Black_j = 1$ if project j contains any Black beneficiaries. X_j is the optional control variables, including project j's goal setting and features of its text description or profile photo. τ_t is the fixed effect of the launching date. μ_s is the optional state fixed effect.Panel A reports the results of the total number of donors and Panel B reports estimates for the average amount of donation.

TABLE V: DID estimation of the effect of the surge of BLM On Extensive Margin of Donation

	Number of Daily Donation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Black_j$	-0.036	-0.033	0.003	0.055	0.045	0.018	-
	[0.065]	[0.066]	[0.065]	[0.065]	[0.065]	[0.069]	-
$Black_j \times \mathbf{1}(t > t_{May26})$	0.344***	0.332***	0.375***	0.405***	0.422***	0.424***	0.456**
	[0.078]	[0.078]	[0.077]	[0.076]	[0.076]	[0.095]	[0.119]
Fund Goal		Yes	Yes	Yes	Yes	Yes	Yes
Description & Face Features			Yes	Yes	Yes	Yes	Yes
State & Date FE & Launch Date FE				Yes	Yes	Yes	Yes
$Black_j \times$ Post COVID Polices					Yes		
Whether COVID Project						Yes	
Project ID FE							Yes
Control group mean value	4.08	4.08	4.08	4.08	4.08	4.08	4.08
Num. projects	69,779	69,779	69,779	69,779	69,779	69,779	14748
Observations	578,696	578,696	578,696	578,696	578,696	578,696	184,625

standard error in brackets

$^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$

Note: Table V presents the results of the estimation of Equation (1). Column 1 is the baseline regression. Column 2 controls for fundraising goal. Column 3 adds text description and face features of photos. Column 4 adds state and time-fixed effects. Column 5 includes controls for the interaction between the indicator for Black individuals and the state-level Stay-at-Home (SAH) shock time dummy. Column (6) controls for whether the fundraising is for covid symptoms. Column 7 controls for project fixed effects.

TABLE VI: DID estimation of the effect of the surge of BLM On Goal

	Log of Project Goal ($)			Project Goal		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{1}(t > t_{May26})$	-0.311***	-	-	-5980.957***	-	-
	[0.010]	-	-	[310.494]	-	-
$Black_j$	0.016	0.020	0.029	1299.422*	1086.337	1028.968
	[0.024]	[0.023]	[0.023]	[743.165]	[769.032]	[844.378]
$Black_j \times \mathbf{1}(t > t_{May26})$	0.050	0.042	0.038	753.584	855.425	859.913
	[0.032]	[0.031]	[0.030]	[870.294]	[911.913]	[924.367]
State & Launch Date FE		Yes	Yes		Yes	Yes
Description & Face Features			Yes			Yes
Observations	69,779	69,779	69,779	69,779	69,779	69,779

standard error in brackets $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$

Note: Table VI reports the DID estimation results that examine whether the BLM movement affects the fundraising goal of Black beneficiaries relative to non-Black beneficiaries.

TABLE VII: Donor Decomposition by Race

	Num. Daily Donation	Num. of Black Donors	Num. of non-Black Donors
	(1)	(2)	(3)
$Black_j$	0.045	0.187***	-0.142**
	[0.65]	[0.009]	[0.057]
$Black_j \times \mathbf{1}(t > t_{May26})$	0.421***	0.062***	0.360***
	[0.076]	[0.011]	[0.068]
Fund Goal	Yes	Yes	Yes
State & Date & Launch Data FE	Yes	Yes	Yes
Description & Face Features	Yes	Yes	Yes
$Black_j \times SAH_{st}$	Yes	Yes	Yes
Mean: Black projects ($t \leq$ May 26)	4.046	0.582	3.464
Mean: non-Black projects ($t \leq$ May 26)	4.089	0.403	3.686
Num. projects	69,779	69,779	69,779
Observations	578687	578687	578687

standard error in brackets
$^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$

Note: Table VII provides estimations of Equation (3) for donations given by Black donors v.s. by non-Black donors. For comparison, baseline results for equation (1) is presented in column (1). We have the result for number of black donors in column (2) and the result for number of non-Black donors in column (3).

TABLE VIII: HETEROGENEITY ANALYSIS BY LOCAL ON-STREET PROTEST GATHERINGS

Panel A: CATOGORICAL HETEROGENEITY				
	NUM. DAILY DONATION			
	(1)	(2)	(3)	(4)
$\mathbf{1}(t > t_{May26}) \times Black_j \times Q_1$	0.342	0.289	0.323	-0.399*
	[0.230]	[0.224]	[0.223]	[0.242]
$\mathbf{1}(t > t_{May26}) \times Black_j \times Q_2$	0.585***	0.570***	0.596***	0.234
	[0.212]	[0.207]	[0.208]	[0.217]
$\mathbf{1}(t > t_{May26}) \times Black_j \times Q_3$	0.048	0.173	0.175	-0.110
	[0.217]	[0.212]	[0.212]	[0.218]
$\mathbf{1}(t > t_{May26}) \times Black_j$	0.097	0.113	0.117	0.288*
	[0.154]	[0.150]	[0.151]	[0.157]
Panel B: CONTINUOUS HETEROGENEITY				
	NUM. DAILY DONATION			
$\mathbf{1}(t > t_{May26}) \times Black_j \times protest_c$	-0.001	-0.001	-0.002*	0.001
	[0.001]	[0.001]	[0.001]	[0.001]
$\mathbf{1}(t > t_{May26}) \times Black_j$	0.421***	0.461***	0.483***	0.242**
	[0.089]	[0.087]	[0.088]	[0.095]
Fund Goal	Yes	Yes	Yes	Yes
Description & Face Features	Yes	Yes	Yes	Yes
State & Date & Launch Date FE		Yes	Yes	Yes
County FE			Yes	Yes
County $\times \mathbf{1}(t > t_{May26})$				Yes
County $\times Black_j$				Yes
Observations	57,8631	57,8631	57,8631	57,8631

standard error in brackets
*p<0.10 ** p<0.05 *** p<0.01

Note: Table VIII shows the estimates of the heterogeneous effects by on-street protests at the county level. Panel A presents the results by four quantiles of protest intensity, where the projects in the counties with the highest number of gatherings (*Quantile* 4) serve as the base level. The coefficients of $\mathbf{1}(t > t_{May26}) \times Black_j \times Q_k$, where $k = 1, 2, 3$, are the additional impact experienced by Black beneficiaries' projects beyond the base group. Panel B presents the estimates of the continuous heterogeneous effects. Notice that across all specifications of the above, we have full control of the interaction terms $Q_k \times Black_j$ and $Q_k \times \mathbf{1}(t > t_{May26})$ included but not shown.

TABLE IX: EFFECTS OF LOCAL GATHERINGS AND NATIONAL PROTESTS

	NUM. DAILY DONATION				
	(1)	(2)	(3)	(4)	(5)
$Black_j \times protest_{ct}$	0.114*	-1.134	-0.496	0.145	0.165**
	[1.86]	[-1.28]	[-1.61]	[1.05]	[2.53]
$Black_j \times Protest_{-ct}$	0.003***	0.003**	0.004***	0.002	0.002
	[3.72]	[2.14]	[3.04]	[1.22]	[1.35]
Fund Goal	Yes	Yes	Yes	Yes	Yes
Description & Face Features	Yes	Yes	Yes	Yes	Yes
State & Date FE	Yes	Yes	Yes	Yes	Yes
County	Yes	Yes	Yes	Yes	Yes
County $\times$ Black	Yes	Yes	Yes	Yes	Yes
County $\times \mathbf{1}(t > t_{May26})$	Yes	Yes	Yes	Yes	Yes
Sample	Full	Quantile 1	Quantile 2	Quantile 3	Quantile 4
Observations	578,437	150,534	169,552	119,626	138,652

standard error in brackets
* p<0.10 ** p<0.05 *** p<0.01

Note: Table IX presents the OLS estimates of Equation (4) for measuring the effect of local protest rallies and the effect of the global national protests. Column (1) presents the results with a full sample. Column (2) - (5) presents the estimates for quantiles 1-4 respectively.

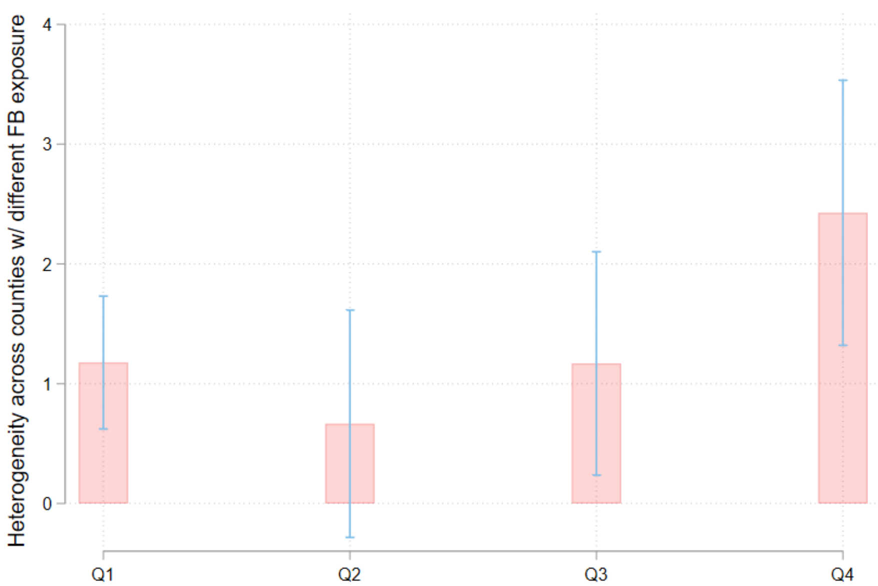
TABLE X: Heterogeneous Analysis By Social Connectivity to Protests for the Major Receiver Counties *Quantile* 2

(a)

	Num. Daily Donation			
	(1)	(2)	(3)	(4)
$\mathbf{1}(t > t_{May26}) \times Black_j \times Fcp_c$	0.444**	0.449**	0.419**	0.428*
	[0.197]	[0.196]	[0.195]	[0.219]
$\mathbf{1}(t > t_{May26}) \times Black_j$	0.683***	0.645***	0.690***	0.465***
	[0.145]	[0.145]	[0.145]	[0.161]
Fund Goal	Yes	Yes	Yes	Yes
Description & Face Features	Yes	Yes	Yes	Yes
State & Date & Launch Date FE		Yes	Yes	Yes
County FE			Yes	Yes
County $\times \mathbf{1}(t > t_{May26})$				Yes
County $\times Black_j$				Yes
Observations	16,9552	16,9552	16,9552	16,9552

standard error in brackets
*p<0.10 ** p<0.05 *** p<0.01

(b)



Note: Table X presents the heterogeneous effect of BLM movement by social connectivity to the national protests. We focus on the sample of crowdfunding that belongs to the *Quantile* 2 group, who are shown in Table IX to be the major receiver of the national protests. Panel (a) shows the heterogeneous regression results for the continuous measure of standardized social connectivity measure. Panel (b) graphically shows the effect of BLM for four quantile groups of social connectivity. $Q1$ represents the lowest quantile; $Q4$ represents the highest quantile.

TABLE XI: Heterogeneity Analysis By Discrimination and the Piqued Awareness of Discrimination

	Num. Daily Donation			
	(1)	(2)	(3)	(4)
$Black_j \times \mathbf{1}(t > t_{May26})$	0.492***	0.569***	0.733***	0.085
	[0.109]	[0.111]	[0.098]	[0.157]
$Black_j \times \mathbf{1}(t > t_{May26}) \times$ High Implicit Discrimination	-0.169			
	[0.153]			
$Black_j \times \mathbf{1}(t > t_{May26}) \times$ High Explicit Discrimination		-0.298*		
		[0.153]		
$Black_j \times \mathbf{1}(t > t_{May26}) \times$ High Crowdfunding Inequality			-0.610***	
			[0.158]	
$Black_j \times \mathbf{1}(t > t_{May26}) \times$ High Piqued Awareness of Slavory and Racism				0.435**
				[0.179]
Fund Goal	Yes	Yes	Yes	Yes
Description & Face Features	Yes	Yes	Yes	Yes
State & Date & Launch Date FE	Yes	Yes	Yes	Yes
Observation	578624	578624	578624	578624

Note: Table XI presents the heterogeneous effects by location of different discrimination levels. Column (1) considers the county-level implicit discrimination from 2008-2019. Column (2) considers the county-level explicit discrimination from 2008-2019. Both implicit and explicit discrimination come from the Implicit Attitude Test datasets. Column (3) considers the zip code level crowdfunding inequality prior to BLM, which is calculated internally using our crowdfunding data. Column (4) considers the changed in the awareness of slavery and racism in U.S during the BLM. This simultaneous change is measured at the congressional district level.

For Online Publication

A Online Appendix

A.1 Robustness check

A.1.1 Restricting to Projects Started Before BLM

First, to address the concern that Black fundraisers might strategically react to the surge of the BLM movement, we restrict our sample to projects that were started from May 1 to May 26. As we have discussed, the DID estimated effect based on these projects is purely owing to the changes in donors' behaviors during the treatment period.

Table B.4 reports the DID estimates of the surge of BLM's effect based on the restricted sample. Comparing column (1) and column (2) with Table V, one can tell the estimated effect from the restricted sample is still positive and economically significant. We lose the statistical significance owing to the reduction of data points. B.4 report the results, and in our main analysis, we still get a significantly positive effect from the BLM's surge. These robust checks reinforce the argument that the effect that BLM brings to the Black people's projects is due to the BLM's effect on the donors' behaviors.

A.1.2 DID Estimation With A Varying Window

The second robustness check is to use the DID estimation with a varying window to estimate the surge of BLM's local causal effect within each racial group. For project j at date t, and for each bandwidth pick B, we have the following regression:

$$y_{j,t} = \gamma_0 Black_j \times 1(t > t^*) + \gamma_1 Black_j + X_j \Gamma + \tau_t + X_{jt}\beta + \varepsilon_{jts} \tag{5}$$

Here we have $t \in [t^* - B, t^* + B]$. $t^* = t_{May26}$ since we examine the sugrge of BLM protests. In this method, time is used as the "running variable," measured as the number of days before (represented by negative values) and after (represented by positive values) the widespread protests that followed Floyd's killing.

Figure B.5 presents our estimation results with different bandwidths. As one can observe, with a relatively short bandwidth in time, we have enough power to identify the effect of the surge of BLM. Our DID estimates show that the surge of BLM has a significant positive effect on the number of donations to Black people's projects. This estimated effect stays robust with the reduction of the bandwidth (down to 7 days during which BLM has not exerted its influences). The estimated effect suggests that the surge of BLM caused Black people's projects to receive more donations right after the start of the spread of the movement. Besides, we also report the estimates for non-Black people. As is clear, while Black people experience more donation volume, the donations to non-Black people do not shrink.

A.2 Imputation Methods of Donation Records

Our main analysis takes a proportional imputation method to allocate the time position of the donations beyond the most recent 100 of them. We first illustrate the method used in our main analysis here.

Think about the following example: Suppose there is a project happens at May 23^{th} 2022, and the it has 110 donations. We only observe its most recent 100 donations. Further suppose that the earliest donation we observe is at May 25^{th}. Therefore, our goal is to allocate 10 donations to 2 dates (May 25^{th} and May 26^{th}).

There are two weighting strategies. First, in the main body of the paper, we use the proportional weight. The proportional weight is calculated from the donation flow of all the crowdfunding projects that have collected less than 100 donations in total.

From this sample, we know that N_1 donations are collected in the first date since the launch, and N_2 in the second data. We calculate the relative proportion of the first date donation v.s. second data donation by $(\hat{p}_1, \hat{p}_2) = (\frac{N_1}{N_1+N_2}, \frac{N_2}{N_1+N_2})$. Using this weight, we assign $10 \times \hat{p}_1$ to the first date and $10 \times \hat{p}_2$ to the second date.

On the other hand, we can also try alternative weighting rules. We consider an equal weighting rule to test the robustness of our main DID estimates. That is we consider a $(1/2, 1/2)$ weight in this case, without considering the dynamic attribute of donation flows.

We use the equal weighting rules to assign all donations and apply DID estimation specified in Equation 1 of Section 5. We show our main results of the BLM effects in Table B.5.

A.3 Testifying Other Confounding Events: Empirical Details

A.3.1 Confounder 1: Pandemic

The first example of the threat is the pandemic per se. We observe the leap of the new COVID-19 cases in mid-March and mid-June, 2020 in the US. Previous research showed that Black people were more susceptible to COVID-19 and their health status is more adversely affected, leading to a greater demand for medical services (Chowkwanyun and Reed 2020; Webb Hooper, Nápoles, and Pérez-Stable 2020).

The pandemic may contaminate our estimation of the surge of the BLM movement's effect if it disproportionately affects Black people as a "sudden" shock around the start point of the explosion of the Floyd protests. In particular, a simultaneous issue may happen in which large gatherings due to BLM protests might cause an outburst of COVID-19 cases among Black people.

To address these concerns, we begin by investigating whether the pandemic had a sudden impact on Black individuals, similar to section A.1.2. We use a regression-discontinuity design structure with varying windows to testify the role of other confounding factors. The method takes the following regression, for project j at date t, and for each bandwidth pick B:

$$R_{B-nB,s,t} = \gamma_0 \times 1(t > t_{May26}) + \gamma_1 1(t > t_{May26}) \cdot (t - t_{May26}) + \mu_S + \varepsilon_{ts} \qquad (6)$$

where we focus on $t \in [t_{May26} - B, t_{May26} + B]$, with B being our chosen bandwidth. $R_{B-nB,s,t}$ denotes the covid infection ratio between Black and non-Black at time t for state s. The outcome of interest is γ_0. We use this specification to examine whether there were any significant changes in the infection rates across different races around the beginning of BLM movement.

Shown in Panel (a) of Figure B.6, newly the infection ratio of Covid experienced a very smooth change around the start point of our treatment period. Panel (b) of Figure B.6 plots the RDD estimates against the corresponding bandwidth. Overall, there is no discontinuity of the COVID pattern around the neighborhood of the surge of the Floyd protests. Hence, it is hard to believe that COVID cases would cause swift surges in any mediator that will finally contribute to the upticks in donations to Black people.

A.3.2 Confounder 2: Stay-at-home orders

Another crucial threat to our identification comes from the mandatory stay-at-home orders (SAH) across states. U.S. states began implementing these policies in March 2020 and rescinded these orders in late April. Different states implemented and canceled their staying-home order at different times. On average, the state governments implemented SHA around late March 2020, and they canceled SAH around mid-May 2020 (Moreland et al. 2020).

Both the start and the end of the SAH can be threats to our identification assumptions. Black people are overrepresented in positions that require physical presence or direct interaction with customers and have limited access to remote work. Thus, SAH shocks can affect Black people disproportionately (Perry, Aronson, and Pescosolido 2021; Montenovo et al. 2022). For example, the rescinding of the SAH, which happened very close to the Floyd protests, might increase the Black donors' budgets particularly. These Black donors might then give more money to Black beneficiaries. Thus, part of our estimated effect of the BLM movement is from the cancellation of the SAH.

To address this possible simultaneous problem, we rely on our daily level data and show there is no abrupt change in the fundraising outcomes right after the announcement/cancellation of SAH. We employ the DID strategy with varying windows to explore whether there exists an effect of the SAH's enactment or cancellation. For project j at date t, and for each bandwidth pick B, we have the following regression:

$$y_{j,t} = \gamma_0 Black_j \times 1(t > t_s^*) + \gamma_1 Black_j + X_j\Gamma + \tau_t + X_{jt}\beta + \varepsilon_{jts} \tag{7}$$

where we focus on $t \in [t_s^* - B, t_s^* + B]$. t_s^* denotes either the enactment of the SAH policies or the cancellation of them for state s. γ_0 represents the effect of SAH on the donation gap between Black people and non-Black people.

The challenge to excluding the effect of the SAH is the fact that they happen at a time tightly close to the start time of our treatment. Many states just rescinded the SAH a few days before the surge of the Floyd protests (average timing is May

15^{th}). However, by leveraging the daily-level data, we can solve this issue based on the bandwidth-indexed regressions above. If the SAH did not take effect on the donations, then we expect the estimated $\hat{\gamma}_0$ to show a pattern that (I) When the bandwidth B does not overlap with the treatment period, we shall observe negligible effect from the SAH shock; (II) When B covers the dates after May 28, 2020, we shall get a significant estimated $\hat{\gamma}_0$. However, the significance here is not from the SAH's effect but from the BLM's effect.

Figure B.7 plots the relationship between our estimates $\hat{\gamma}_0$ and our choice of bandwidth B from Equation (7). Panel (a) shows the effect of SAH's enactment and panel (b) shows the effect of SAH's cancellation. The figures show a pattern that indicates that the SAH did not take effect on the donations. First, when the bandwidth B is small and does not overlap with the treatment period, the "effect" of SAH enactment/cancellation policies is statistically indistinguishable from zero. It suggests that the SAH has a trivial effect on the donations. Second, when B is large enough to overlap with the treatment period, $\hat{\gamma}_0$ is significantly positive. With the larger B we include the sample affected by the BLM movements in our analysis and mistakenly attribute the effect of the BLM to the "effect" of SAH enactment/cancellation policies. For the SAH enactment, when B is larger than 62 days (the average duration between SAH enactment and the treatment start), $\hat{\gamma}_0$ starts to increase and become increasingly significant. For the SAH cancellation, the $\hat{\gamma}_0$ becomes significant when B is larger than 10 days (the cancellations of SAH happened around May 15th of 2022). Taken together, both the pandemic and the SAH are unlikely to be the confounders that break out identification assumptions.

We also controlled for these covid policies in our main analysis. Column (3) in Table V controls for the interaction between the indicator of Black people and the time dummy of the SAH shocks. By controlling for the SAH shock, our estimates does not show significant change.

A.4 Geographical Distribution of Black Projects and Protests

The crowdfunding projects in our analysis encompass 2,612 counties across the entire country. Figure B.8 from the Online Appendix presents the geographical distribution of the total occurrence of protest gatherings in each county and state in the U.S. The Figure shows quite a large geographical variation in protest gatherings for us to explore.

What is the relationship between the geographical distribution of fundraising behaviors and that of protest occurrence? It is noteworthy that both Black and non-Black fundraisers are disproportionately located in areas with higher occurrences of BLM-related rallies that were sparked by the murder of George Floyd. This observation is particularly pronounced for Black beneficiaries. Figure B.9 from Online Appendix illustrates the distribution of projects across counties with varying levels of BLM-related gatherings between May 26 and September 1, 2020. Although most counties, in terms of sheer numbers, only experience a few gatherings during the treatment period, they only account for a small proportion of the initiated projects. Conversely, a small number of counties experience a high number of gatherings and see the launch of a significant proportion of projects. Of the 2,612 counties, approximately 2,200 experience no more than four gatherings, with only a quarter of the projects relating to the Black community being launched in these counties. On the other hand, only 38 counties experience more than 42 gatherings, yet these counties see the launch of a quarter of the projects related to the Black community. This reveals a notable contrast in the distribution of gatherings and projects, in that the majority of projects were concentrated in a small number of counties where a massive number of gatherings occurred.

Therefore, in reference to contrast in the distribution of gatherings and projects, we categorize our sample into four quantiles, based on the number of gatherings in each project's associated county. In categorizing, we account for the uneven distribution of Black projects across different counties, thus ensuring an equal number of projects associated with Black beneficiaries in each quantile. Consequently, we have the following quantiles: *Quantile* 1 (0 to 3 gatherings), *Quantile* 2 (4 to 18 gatherings), *Quantile* 3 (19 to 41 gatherings), *Quantile* 4 (more than 41 gatherings). Such division of protests intensity ensures that the Black beneficiaries are nearly equal distributed across these four quantiles.

A.5 Construction of Social Media Coverage

Google Search Trends

On a given keyword, Google Search Trends reports cross-DMA (Nielsen's Digital Metropolitan Area) indexes. To translate into a county/zip level number, we get access to the cross-walk data linking each zip code in the U.S. with the DMA code from a third-party researcher.[17] The method to construct the cross-walk data is to calculate the center point of every zip code geo boundary, plot those points on a DMA boundary map, and find the containing DMA of each zip centroid. Currently, this is the only free source that provides zipcode-to-DMA crosswalks. Nielsen's original cross-walk data is restricted to public users since a 2011 court decision found that Nielsen's DMA maps are copyright-protected.[18]

We query Google Search API on the keyword "Black Lives Matter" during the pe-

[17]https://gist.github.com/clarkenheim/023882f8d77741f4d5347f80d95bc259
[18]See https://pub.bna.com/ptcj/0806446Aug29.pdf

riod from April to October, 2020. Then using the cross-walk linking DMAs with zip/counties, we construct the county-level Google search trend index on "Black Lives Matter" through taking an average of DMA-level index while weighting by the population size of the county.

News Coverage

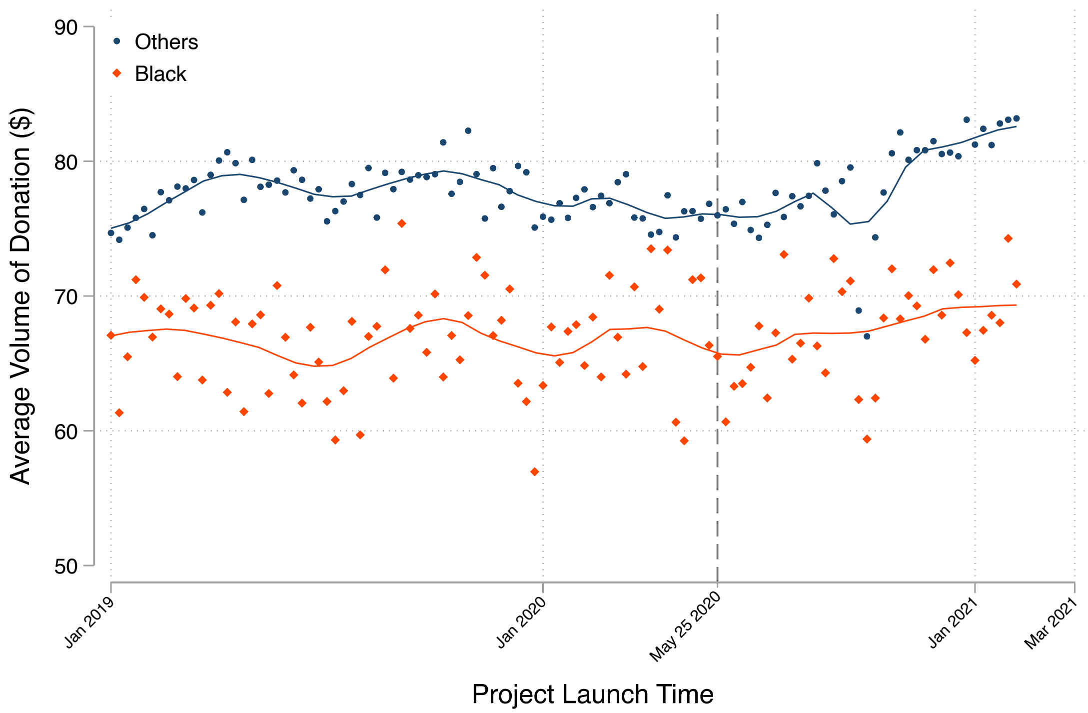
Our data to construct newspaper coverage measure is the NewsLibrary data base (newslibrary.com). We use an automated script to search for all the newspaper coverages that contain at least one of the keywords "Black Lives Matter" "Floyd" "protest" and "racial justice". We have located 10,937 articles containing one of our specified keywords since May 26, 2020. We have information regarding the name of the newspaper the article is posted on, the title of the article, the major content, and the location where it was posted. Our measure of newspaper coverages on "BLM" calculates the total number of articles published in each state.

B Online Appendix: Figures and Tables

FIGURE B.1: A Example of Medical Fundraising Project in GoFundMe

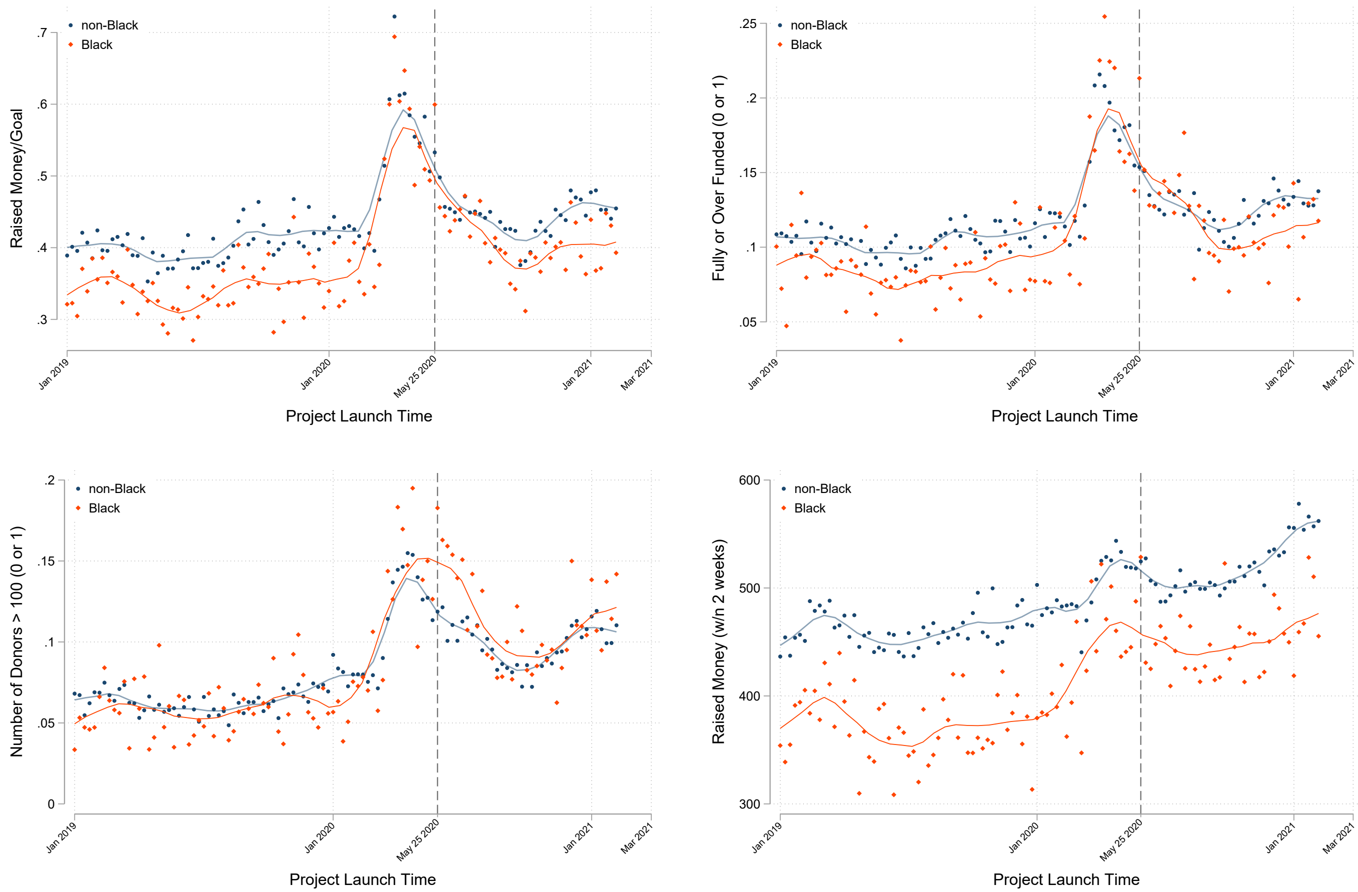
Note: Figure B.1 presents a representative profile of a medical crowdfunding project. It displays the stock variables: the fundraising goal, the amount of money raised, and the number of donors. It also shows the flow of donations to this project. Additionally, the static characteristics of the project, including the launch date, text description, and a photo of the beneficiary, are also observable.

FIGURE B.2: Average amount of donation by launch time



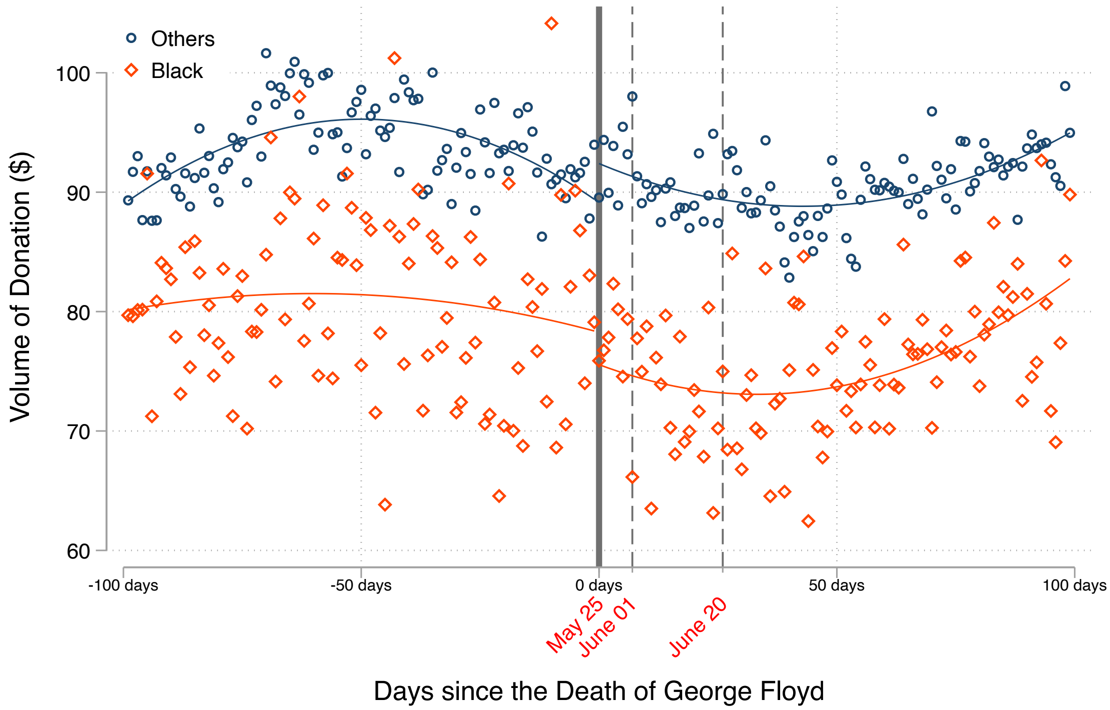
Note: Figure B.2 presents the average donation amount for projects launched at various times. The x-axis represents the launch date of the projects, while the y-axis represents the average donation amount. Each data point signifies the mean value of the average donation for projects initiated in a given week. Projects involving Black beneficiaries are denoted by orange dots, and other projects are indicated by navy dots. The curves illustrate the non-parametric fitted lines for each group. The figure shows that both the relative gap between Black and non-Black beneficiaries' projects and the absolute level of the average donation amount remain steady regardless of the projects' launch dates.

FIGURE B.3: Evolution of Other Crowdfunding Quality Measures Over Launch time



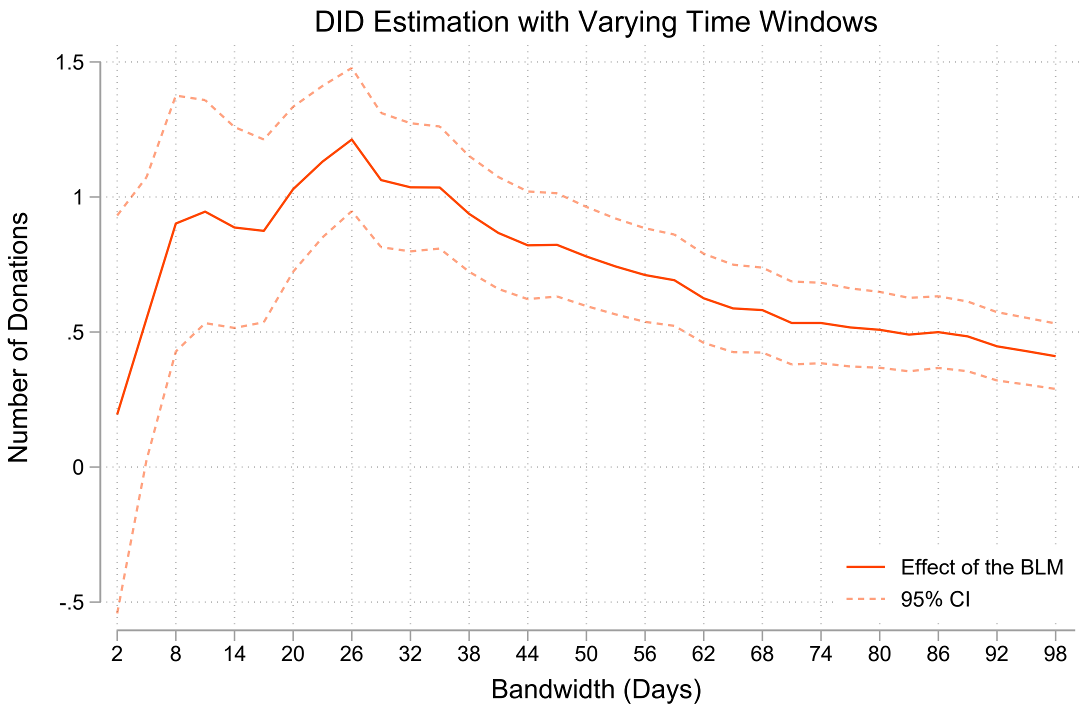
Note: Figure B.3 presents evolution of other fundraising outcomes over launch time. These outcomes include: (1) the fraction of the goal achieved, (2) whether the goal is achieved, (3)whether the number of donations exceeds 100, (4) funds raised in the first two weeks since its initialization.

FIGURE B.4: The Daily Average Amount ($) of Donation



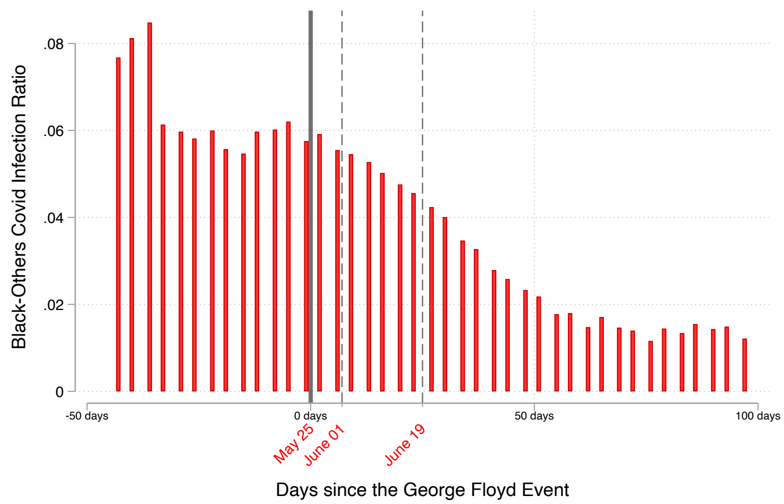
Note: Figure B.4 illustrates the average donation amount per day, relative to the date of George Floyd's death. The x-axis represents the date relative to this event. Each data point represents the total donation amount received by Black/non-Black individuals on date t, divided by the total number of donations given to accounts associated with Black/non-Black individuals on that day.

FIGURE B.5: THE EFFECT OF BLM PROTEST: DID ESTIMATION WITH VARYING BANDWIDTHS

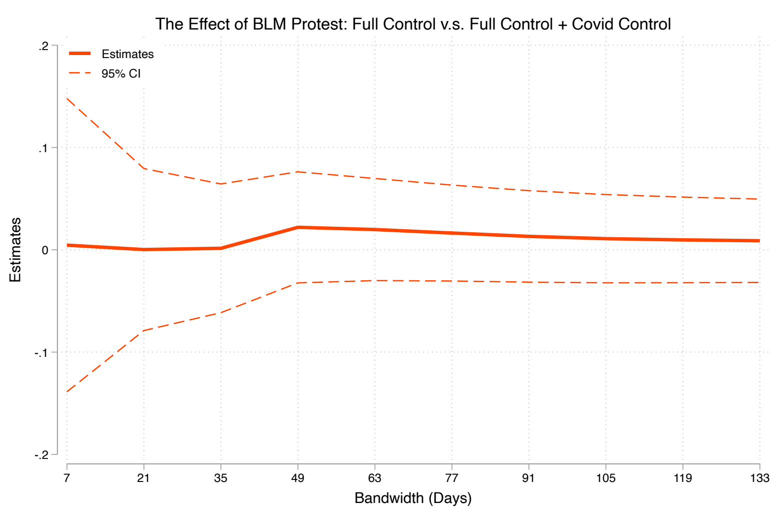


Note: This figure represents DID estimates against bandwidth choices, using the empirical setup in Equation 5. Our main specification contains control of state fixed effects, date fixed effects, project goal, characterization variables featuring the text description and picture of the project.

FIGURE B.6: The Effect of Post George Floyd Event on the Portion of the Black People Infected COVID-19



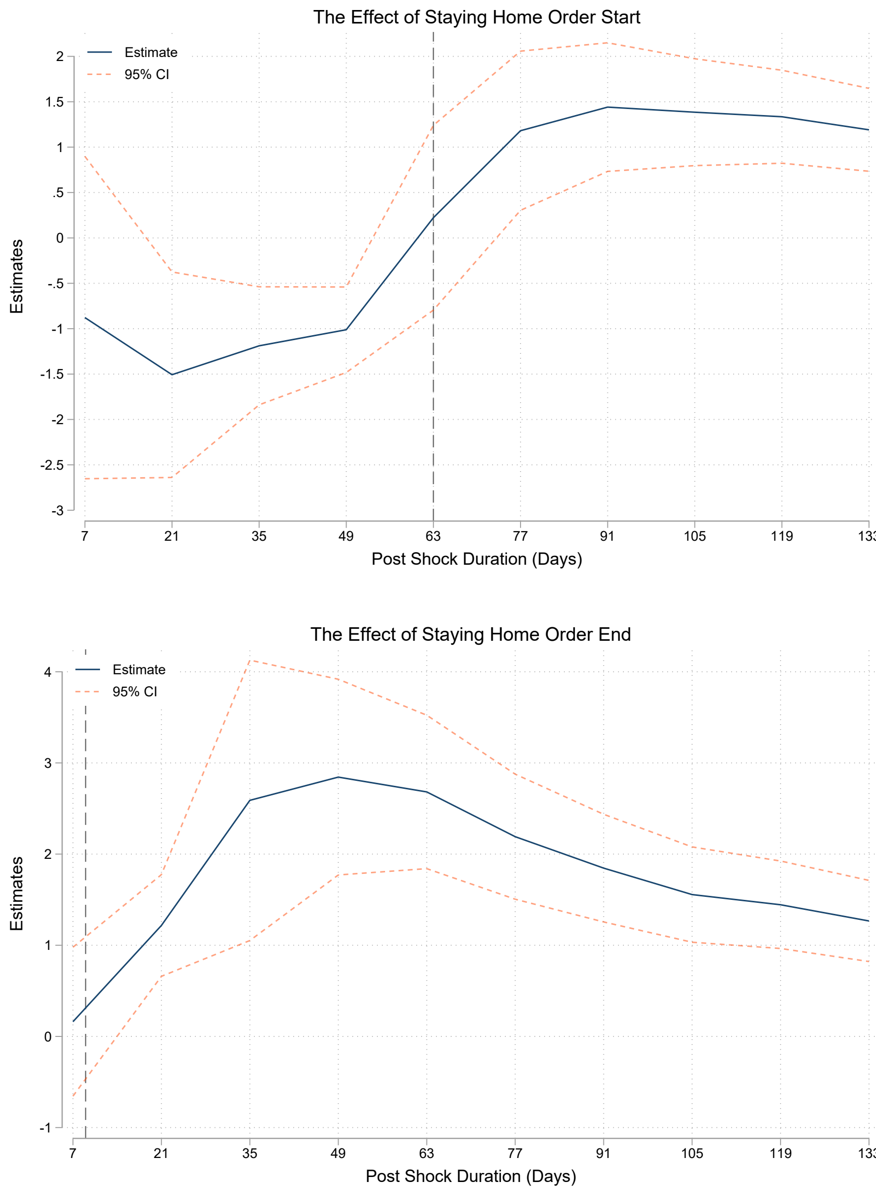
(a) Covid Ratio: Black v.s. non-Black



(b) RDD estimate

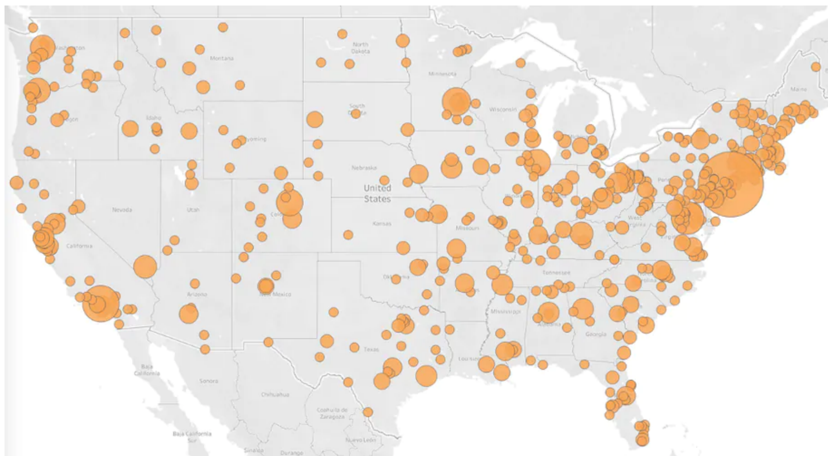
Note: Figure B.6 presents examination of the discontinuity in Covid inflection rate. Panel (a) presents the proportion of Black people inflected by Covid among all infected population. Panel (b) presents the RDD estimates against a running bandwidth.

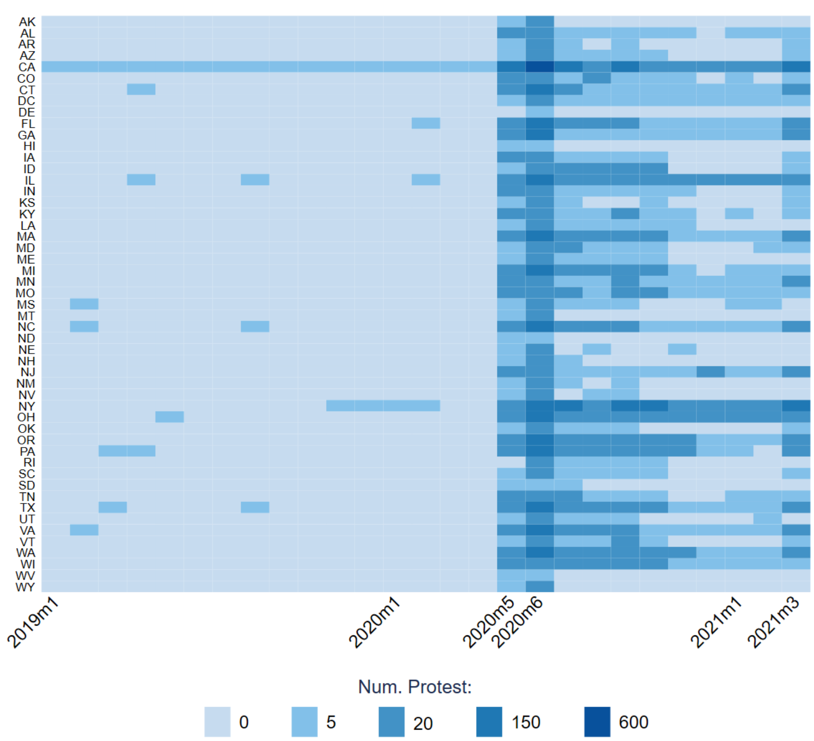
FIGURE B.7: The "Effect" of Stay-at-Home Orders



Note: Figure B.7 depicts the estimated effects ($\hat{\gamma}_0$) of the initiation and cancellation of Stay-at-home Orders over various bandwidths (B) as per Equation (7). The bandwidth begins at 7 days (non-overlapping with the BLM period) and progressively extends to coincide with the BLM period. The vertical dashed lines mark the cutoff points when the bandwidths overlap with the BLM period. The pattern in the estimated $\hat{\gamma}_0$ suggests that the Stay-at-home Orders did not significantly influence donation patterns.

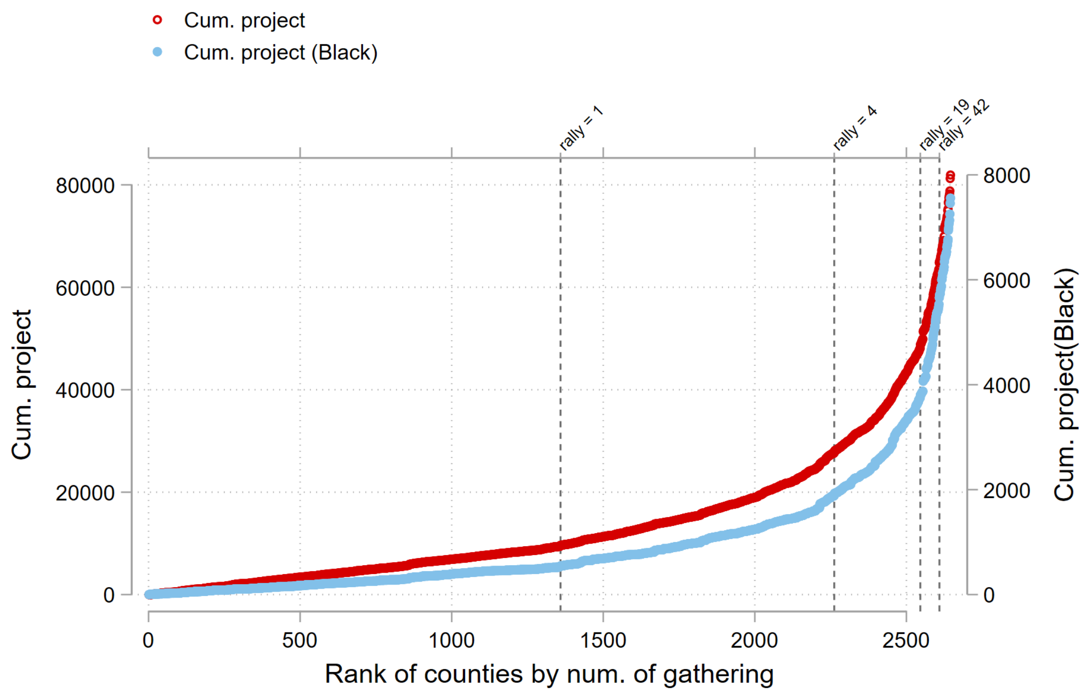
FIGURE B.8: GEOGRAPHICAL DISTRIBUTION OF THE PROTEST RALLIES





Note: Figure B.8 presents protests in solidarity with George Floyd/in support of Black Lives Matter, May 26-June 4, 2020. Circle size reflects the number of separate events. Data are from Crowdcounting.org; map by Gabriel Perez-Putnam. Figure below presents the panel view of protest intensity by states over time, Jan 2019 - March 2021.

FIGURE B.9: PROJECTS' DISTRIBUTION ACROSS COUNTIES WITH DIFFERENT NUM. OF GATHERINGS



Note: Figure B.9 presents the distribution of projects across counties with varying levels of BLM-related gatherings from May 26 to September 1, 2020. The x-axis represents the ranking of the counties based on the total number of BLM-related gatherings. The y-axis indicates the cumulative number of projects. The vertical dashed lines depict the number of gatherings at each rank. The red curve corresponds to all projects, while the blue curve represents projects associated with the Black community.

TABLE B.1: THE AVERAGE REDUCTION OF RACIAL GAP BEFORE/AFTER JANUARY 2020: OTHER IMPORTANT OUTCOMES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Panel A: RAISED FUNDS/PROJECT'S GOAL				*Panel B*: PROJECT ACHIEVED THE GOAL				*Panel C*: MORE THAN 100 DONATIONS				*Panel D*: RAISED FUNDS IN 2 WEEKS			
$\mathbf{1}(t > Feb.2020)$	0.044***	0.067***	0.071***	-	0.023***	0.033***	0.034***	-	0.039***	0.026***	0.028***	-	-0.004***	0.003***	0.004***	-
	[0.002]	[0.002]	[0.002]	-	[0.001]	[0.001]	[0.001]	-	[0.001]	[0.001]	[0.001]	-	[0.000]	[0.000]	[0.000]	-
$Black_j$	-0.066***	-0.059***	-0.061***	-0.057***	-0.022***	-0.019***	-0.019***	-0.017***	-0.008***	-0.012***	-0.008***	-0.008***	-0.014***	-0.012***	-0.014***	-0.013***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
$Black_j \times \mathbf{1}(t > Feb.2020)$	0.027***	0.033***	0.035***	0.032***	0.014***	0.016***	0.017***	0.016***	0.023***	0.020***	0.020***	0.019***	0.002	0.004***	0.004***	0.004***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.003]	[0.003]	[0.001]	[0.001]	[0.001]	[0.001]
Goal		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Description&Picture Features			Yes	Yes			Yes	Yes			Yes	Yes			Yes	Yes
State FE & Date FE				Yes				Yes				Yes				Yes
Observations	289463	289463	289463	289462	289463	289463	289463	289462	289463	289463	289463	289462	289463	289463	289463	289462

standard error in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table B.1 reports the estimation results that resemble Table III, while the outcome variables are other four important aspects of fundraising: (1) the ratio between the raised funds and the goal of the project, (2) whether the goal has been achieved, (3) whether the number of donations exceeds 100, and (4) funds raised as the fraction of the goal in the first two weeks since its initialization.

TABLE B.2: DID estimation of the effect of the surge of BLM On Extensive Margin of Donation

	Number of Daily Donation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Black_j$	-13.422***	-13.388***	-12.428***	-14.675***	-14.675***	-14.848***	-
	[0.814]	[0.801]	[0.804]	[0.814]	[0.814]	[0.854]	-
$Black_j \times \mathbf{1}(t > t_{May26})$	1.019	0.390	0.237	1.681*	1.680*	1.098	-1.532
	[0.958]	[0.941]	[0.940]	[0.946]	[0.946]	[1.227]	[1.808]
Fund Goal		Yes	Yes	Yes	Yes	Yes	Yes
State & Date FE & Launch Date FE			Yes	Yes	Yes	Yes	Yes
Description & Face Features				Yes	Yes	Yes	Yes
$Black_j\times$ Post COVID Polices					Yes		
Whether COVID Project						Yes	
Project ID FE							Yes
Control group mean value	4.08	4.08	4.08	4.08	4.08	4.08	4.08
Num. projects	70,364	70,364	70,364	70,364	70,364	70,364	70,364
Observations	578,696	578,696	578,696	578,696	578,696	578,696	578,696

standard error in brackets
$^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$

Note: Table B.2 presents the counterpart results of Table V, while the outcome variable is the dollar amount of each donation.

TABLE B.3: Observed Characteristics of Text Descriptions

Panel A : Description Topics				
	Text Length	Topic: COVID	Topic: Cancer	Topic: Surgery
	(1)	(2)	(3)	(4)
$Black_j$	-0.072***	0.019***	-0.052***	-0.017**
	[0.015]	[0.007]	[0.006]	[0.007]
$Black_j \times \mathbf{1}(t > t_{May26})$	0.017	-0.010	0.012	0.006
	[0.020]	[0.010]	[0.008]	[0.009]
Panel B: Language Tone				
	Positive	Authentic	Muscular	Female
	(1)	(2)	(3)	(4)
$Black_j$	0.196***	1.643***	0.046	-0.191***
	[0.045]	[0.490]	[0.052]	[0.054]
$Black_j \times \mathbf{1}(t > t_{May26})$	0.003	-0.433	0.094	0.058
	[0.059]	[0.678]	[0.072]	[0.075]
Panel C: Face Expressions				
	Male	Happy	Calm	Grimace
	(1)	(2)	(3)	(4)
$Black_j$	0.094***	-0.013	0.041***	-0.007***
	[0.007]	[0.008]	[0.006]	[0.001]
$Black_j \times \mathbf{1}(t > t_{May26})$	-0.008	0.007	0.013	0.002
	[0.010]	[0.011]	[0.008]	[0.002]
Observations	69,779	69,779	69,779	69,779

t statistics in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table B.3 reports the estimation results to examine whether the project topic, language tone, and face expressions changed following the impact of BLM movement. The regression specification follows that of Table VI, but without state-fixed effects and date-fixed effects.

TABLE B.4: DID estimation of the effect of the surge of BLM (for projects launched from May 1 to May 26, 2020)

	Num. Daily Donation			
	(1)	(2)	(3)	(4)
$Black_j$	0.060	0.053	-0.155	
	(0.30)	(0.27)	(-0.64)	
$Black_j \times \mathbf{1}(t > t_{May26})$	0.329	0.344	0.201	0.303
	(1.54)	(1.61)	(0.95)	(0.93)
$ln(Goal)_j$	0.915***	0.917***	0.918***	
	(24.86)	(24.88)	(24.89)	
$1(Covid)_j$		0.431***	0.431***	
		(5.57)	(5.58)	
Description	Yes	Yes	Yes	
Date FE	Yes	Yes	Yes	
State FE	Yes	Yes	Yes	
Project launch-date FE	Yes	Yes	Yes	
$Black_j \times SAH_{st}$			Yes	Yes
Project FE				Yes
Control group mean value	6.597	6.597	6.597	6.597
Num. projects	5644	5644	5644	5644
Observations	68167	68167	68167	68167

t statistics in brackets

$^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$

Note: Table B.4 shows the estimation results of Equation (1), restricting to the projects initiated between May 1 and May 26, 2020. Columns 1 and 2 report the main specifications, with column 2 controlling for the fixed effects of COVID-19 related projects. Column 3 includes controls for the interaction between the indicator for Black individuals and the state-level Stay-at-Home (SAH) shock time dummy (marking the start and end of SAH orders). Column 4 accounts for project fixed effects. 5,644 projects, which launched from May 1 to May 26, 2020, were actively receiving donations. Prior to the treatment period, projects related to non-Black individuals received on average 6.597 donations per day.

TABLE B.5: DID estimation of the effect of the surge of BLM (Using Equal Weighting Strategy)

	Number of Daily Donation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Black_j$	-0.026	-0.025	-0.045	0.038	0.027	-0.005	-
	[0.058]	[0.058]	[0.058]	[0.058]	[0.058]	[0.061]	-
$Black_j \times \mathbf{1}(t > t_{May26})$	0.303***	0.289***	0.298***	0.357***	0.374***	0.334***	0.389***
	[0.069]	[0.069]	[0.069]	[0.067]	[0.067]	[0.083]	[0.098]
Fund Goal		Yes	Yes	Yes	Yes	Yes	Yes
Description & Face Features			Yes	Yes	Yes	Yes	Yes
State & Date FE & Launch Date FE				Yes	Yes	Yes	Yes
$Black_j \times$ Post COVID Polices					Yes		
Whether COVID Project						Yes	
Project ID FE							Yes
Control group mean value	4.08	4.08	4.08	4.08	4.08	4.08	4.08
Num. projects	69,779	69,779	69,779	69,779	69,779	69,779	14748
Observations	578,696	578,696	578,696	578,696	578,696	578,696	184,625

standard error in brackets
$^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$

Note: Table B.5 shows the estimation results of Equation (1), when we use a equal weighting strategy to impute the donation records beyond the latest one hundreds. The results presentation of columns (1)-(7) resemble Table V.