Market Response to Racial Uprisings*

Bocar A. Ba Roman G. Rivera Alexander Whitefield

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Abstract

Do investors anticipate that demands for racial equity will impact companies? We explore this question in the context of the Black Lives Matter (BLM) movement—the largest racially motivated protest movement in U.S. history—and its effect on the U.S. policing industry using a novel dataset on publicly traded firms contracting with the police. It is unclear whether the BLM uprisings were likely to increase or decrease market valuations of firms contracting heavily with police because of the increased interest in reforming the police, fears over rising crime, and pushes to "defund the police". We find, in contrast to the predictions of economics experts we surveyed, that in the three weeks following incidents triggering BLM uprisings, policing firms experienced a stock price increase of seven percentage points relative to the stock prices of non-policing firms in similar industries. In particular, firms producing surveillance technology and police accountability tools experienced higher returns following BLM activism–related events. Furthermore, policing firms' fundamentals, such as sales, improved after the murder of George Floyd, suggesting that policing firms' future performances bore out investors' positive expectations following incidents triggering BLM uprisings. Our research shows how—despite BLM's calls to reduce investment in policing and explore alternative public safety approaches—the financial market has translated high-profile violence against Black civilians and calls for systemic change into shareholder gains and additional revenues for police suppliers.

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> "I had a really interesting call with a major city police chief, where we were talking about the defunding phenomenon and whatnot, and what he related to me was that actually they did reassign portions of its budget to other portions of the city. So, basically, they just shifted some resources out of police to other city agencies, and then his net budget was actually increased fairly significantly for body cameras and transparency tools. So, in that respect, he was pleasantly surprised that the whole defunding discussion actually lead for their agency to a better place, [...]"

Earnings call, August 2020, **Axon Enterprise**

1 Introduction

As social movements grow in size and power, institutions and corporations cannot dismiss their demands. However, the impact of such movements on governments and firms remains uncertain due to their potential conflicting political, social, and fiscal implications (Hart et al., 1997; Hart and Zingales, 2017).[1] One possible consequence of social movements is a decline in firm valuations as investors anticipate pressure on products and services that are no longer seen as prosocial (Hong and Kacperczyk, 2009). Additionally, shareholders with nonpecuniary motives may choose to divest from companies involved in controversial industries (Bénabou and Tirole, 2010; Fisman et al., 2014). As an information aggregator, the stock market provides insight into how events (e.g., elections, war, coups, and, in our case, uprisings), are expected to influence firms' performance and future policy (Wolfers and Zitzewitz, 2004). Thus, the question arises: do investors view social movements as crises or opportunities for companies?

To explore this question, we focus on the Black Lives Matter (BLM) movement, which gained significant traction in the United States in 2020, culminating in the largest sustained protest in the country's history New York Times (2020). The BLM movement has popularized the slogan "Defund the Police" and has brought to the forefront issues of systemic racism and police brutality. In this paper, we analyze the impact of the BLM movement on the law enforcement industry, investigating how investors perceive the movement and its potential implications for the industry.[2]

This paper provides a quantitative assessment of the market's expectations regarding the impact of the BLM uprisings on the police industry. We begin by highlighting the theoretical ambiguity of the effect of BLM activism on the industry, and we demonstrate that economists did not expect the killing of George Floyd to increase the stock prices of companies that contract with police departments. To empirically investigate this issue, we construct a novel data set on firms in the police industry ("policing firms"). Our analysis reveals that policing firms experienced a seven

[1] For example, companies with ties to law enforcement have expressed concerns that the fiscal health of cities might impact the companies' ability to contract with them: "Some of our customers use funds seized through civil forfeiture proceedings to fund the purchase of our products. [...] Changes in civil forfeiture statutes or regulations are outside of our control and could limit the amount of funds available to our customers, which could adversely affect the sale of our products" (Axon, 2019).

[2] Throughout the paper, we use "BLM" to refer to the broader social movement, i.e., individuals or organizations who have advocated the message of Black Lives Matter, rather than the national and local BLM organizations.

percentage point (pp) increase in stock prices relative to the stock prices of nonpolicing firms in similar industries during the three weeks following Black Lives Matter–related events. Notably, the killing of George Floyd led to excess returns of 16.5 pp for policing firms relative to the returns of their nonpolicing peers. Our results are driven primarily by investments in firms that provide surveillance technologies and body-worn cameras. Furthermore, we observe higher returns for policing firms after viral incidents involving Black victims than after viral incidents involving white supremacists or mass shootings. Finally, we confirm that police suppliers experienced higher sales after summer 2020. Our findings indicate that investors expected the Black Lives Matter movement to increase public spending on policing for both reform- and crime control–focused products and services rather than leading to funding reductions or "defunding" of police. Overall, our study contributes to the understanding of the economic implications of social movements and sheds light on the market's perception of the police industry in the wake of the Black Lives Matter movement.

Evaluating the impact of racial uprisings on firms tied to police requires us to overcome several challenges. First, we need to understand the implications of the discourse on the role of police in US society. This includes understanding the demands of BLM advocates, such as reducing the scale of policing in society (Davis, 2011) and reallocating the associated resources to nonpolice alternatives. Second, there is no readily available dataset that tracks the performance of firms contracting with the police, and endogenous factors associated with firms' decision to supply police departments can make it difficult to isolate the causal effect of the social movement from the effects of other unobserved confounding factors.

We address these challenges in several steps. First, we provide background on the policy discourse on policing and discuss two traditional views on policing in economics, focusing on crime control (Becker, 1968) and (reforming) police behavior (Becker and Stigler, 1974). We also present a third view that has received increased attention since the events of summer 2020: abolitionism, a framework that aims to reduce the scale of policing in society.[3] Using the different views on policing, we provide a simple model for analyzing social movements' impact on publicly traded firms' stock returns. In our framework, a firm's return is a function of its exposure to BLM activism and the demand for three types of goods and services: those unrelated to policing, those related to police reform, and those related to crime control. For example, in response to viral incidents triggering BLM uprisings, there could be a reduction in the scale of policing or an increase through investments in crime control and/or police reform technologies. Overall, our framework reveals that theory yields ambigious predictions regarding the effect we should expect of these viral incidents on policing firms' performance.

We incorporate a survey of economic experts (DellaVigna et al., 2019) to gain insight into their

[3]While positive coverage of police has a positive effect on crime control and a focus on police reform maintains the status quo (Bursztyn et al., 2022), little is known about the efficacy of policing alternatives and abolitionist policies (Davis, 2011; Davies et al., 2021). Because BLM's demands (e.g., "Defund the police") often derive from prison and police abolitionist concepts, we incorporate this framework into our analysis to provide a holistic evaluation of the causes and consequences of this social movement's activism.

beliefs about the market's response to the murder of George Floyd. As experts (Sapienza and Zingales, 2013) shape policies and affect public support, this approach offers a valuable opportunity to understand economists' beliefs about the economic consequences of the BLM movement. We build on the idea that stock market movements can be informative of future economic outcomes and can inform policy decisions (Wolfers and Zitzewitz, 2004; Snowberg et al., 2007; Wolfers and Zitzewitz, 2009; DellaVigna and La Ferrara, 2010). Our survey results indicate that the majority of experts expected the 2020 BLM protests to yield little to no change or a slight decrease in the stock values of policing firms. Moreover, the experts often accounted for their expectations by citing the pushes for police reform or budget cuts associated with "defunding the police." In other words, the surveyed economists tended to associate the events of summer 2020 with police reform and the abolitionist framework while expecting a negligible impact on the financial performance of policing firms.

To examine the actual impact of racial uprisings on the police industry and evaluate the predictions made by the surveyed economic experts, we build a new dataset of publicly traded firms connected with US law enforcement and policing. First, using directories of vendors from police conferences, police magazines, and policing websites from 2010 to 2022, we construct a roster of firms contracting with police. Second, we conduct text analysis of the publicly traded firms' 10-Ks, following Hassan et al. (2021), to identify the firms' exposure to policing, categorizing them as strongly or weakly connected to policing. Third, for firms linked to policing, we manually code each firm's types of products and services using the vendor directories, which enables us to differentiate firms' exposure to police reform from their exposure to crime control. Finally, using other publicly traded firms, we create a comparison group of firms that are in industries and locations similar to those of the policing firms but that do not contract with police, enabling us to identify the causal effect of BLM activism on policing firms' performance. We use our newly constructed dataset to estimate the impact of viral incidents linked to BLM uprisings on firm performance, where our primary empirical strategy uses a synthetic difference-in-difference (SDID) estimator (Arkhangelsky et al., 2021) comparing firms exposed to policing to synthetic counterfactuals constructed from firms in the control group.[4]

Our first set of results focuses on the short-run effect of viral incidents triggering BLM uprisings, such as the killings of Trayvon Martin, Michael Brown, and George Floyd. We show that the cumulative abnormal returns (CARs) of strongly connected policing firms are seven percentage points (pp) ($p < 0.01$) higher than those of their nonpolicing peers in the three weeks after such viral incidents, but we find no effect for weakly connected policing firms. Furthermore, the two viral incidents sparking the greatest outrage over police violence, the killings of Michael Brown and

[4]In one of the robustness checks, we also use the synthetic control (SC) estimator from Abadie and Gardeazabal (2003) and Abadie et al. (2010) and show that the results are similar to those from our main specification. For identification, the SDID (SC) estimator assumes that connected firms and their counterfactual firms would have experienced parallel (similar) trends in the absence of viral incidents linked to BLM uprisings.

George Floyd, led to the largest increases in CARs for strongly connected policing firms: in the 21 trading days following Floyd's murder, these firms' CARs increased by more than 16.5 pp relative to the CARs of nonpolicing firms. This indicates that the market anticipated increased demand for products and services tailored for law enforcement agencies.

Next, we explore the effects of these viral incidents by firms' exposure to the government to identify potential implications for government spending (Hart et al., 1997) such as a trading-off of private and public security investment (Heaton et al., 2016). We use data on policing firms' prominent clients to identify the firms' shares of public-sector customers. For the viral incidents before the killing of Michael Brown in 2014, only policing firms with low government exposure experienced CARs higher than their nonpolicing peers' in the wake of the incidents triggering BLM activism. However, after the killing of Michael Brown and subsequent BLM activism–related events, we observe the opposite pattern: only policing firms with a high share of government clients experienced higher CARs. For example, following the killings of Michael Brown and George Floyd, the CARs of strongly connected policing firms with high exposure to government increased by at least 22 pp ($p < 0.01$). Notably, the Ferguson protests were the first uprising tied to police violence, while prior incidents triggering BLM activism involved violence inflicted by civilians against Black fellow civilians. Thus, these results are consistent with the financial market anticipating higher returns for firms contracting with private security, i.e., those with a low share of government clients, after incidents involving violence by civilians against Black civilians. In contrast, events involving the police led to higher returns for firms with a higher share of public-sector customers.

We can identify the market's expectations regarding the policy response to the racial uprisings by examining the products and services provided by firms with strong connections to the police. We find that companies providing body-worn cameras, video cameras, and other surveillance equipment experienced a significant increase in CARs after the viral incidents (11 pp to 33 pp ($p < 0.01$)). We also find that vendors of police accountability tools related to training equipment and courses experienced higher returns. These findings suggest that the racial uprisings led the financial market to anticipate increased demand for devices to surveil police and civilians, improve police accountability, and manage crime suspects. However, we find no evidence of better performance among firms providing tools related to the civilian demands, such as 911-dispatched products or data analysis.

We next analyze whether societal and racial preferences lead the market to price mass shootings and killings perpetrated by white supremacists differently from how it prices viral acts of violence against Black civilians. In other words, does the market anticipate more investment in security after other violent deaths that attract viral attention? We find that the increased CARs of firms connected to policing generated by white supremacist attacks are one-third the size of those generated by the incidents triggering BLM uprisings. Moreover, we do not find evidence that mass shootings impact the performance of firms connected to the police. For investors, these results indicate excess gains in market valuation for firms contracting with police after incidents involving Black victims relative to the gains after killings perpetrated by white supremacists or mass shootings. Our results show how discrimination can translate into gains in the financial markets (Wolfers, 2006; Ferguson and Voth, 2008; Fisman et al., 2014; Hjort et al., 2021; Do et al., 2021). Our findings are also consistent with the racial capitalism framework[5] in that corporations connected with policing benefit from high-profile incidents of violence against marginalized groups in the US (Robinson, 2005).

We also document the long-run impact of the killing of Trayvon Martin in 2012—the event that later sparked the BLM movement—on the performance of firms contracting with law enforcement.[6] We find that from the killing of Trayvon Martin in 2012 to December 2020, a passive investor's portfolio of shares of strongly connected policing firms would have increased by 76.4 pp more ($p < 0.05$) than a portfolio of their nonpolicing peers. These findings are consistent with the idea that markets anticipate that local governments will increase investment in police in response to racial uprisings, which has also been documented in other contexts such as the Great Migration and residential segregation (Derenoncourt (2022); Cox et al. (2022)).[7]

In the last section, we discuss the implications of our findings for the "Defund" movement using the events of summer 2020 as a case study. We find that the valuation of the twenty firms strongly connected to policing increased by almost half a billion dollars in the weeks following the killing of George Floyd. This potential gain for shareholders is equivalent to half the federal Community-Oriented Policing Services (COPS) program's annual budget (Evans and Owens, 2007; Mello, 2019), which is allocated for hiring additional police officers. Furthermore, our analysis reveals that these firms experienced higher profits in the two years following summer 2020 attributable to an increase of almost one billion dollars in sales and a reduction in the costs of goods sold. While there is active research aiming to advance our understanding of alternatives to policing (Dee and Pyne, 2022), our paper confirms that the events of summer 2020 resulted in significant financial gains for shareholders of companies in the police industry and that police suppliers enjoyed increased profits.

Literature Review Our paper relates to several strands of literature. Motivated by the literature exploring the social, political, and economic impacts of protest movements (King and Soule, 2007; Acemoglu et al., 2018; Wasow, 2020; Beraja et al., 2021; Archibong et al., 2022), we focus on Black Lives Matter. Specifically, our work is motivated by the research documenting the disparate historical treatment of Black Americans in various sectors of society (Darity and Mason, 1998; Bayer and Charles, 2018; Mason et al., 2022). Moreover, we contribute to the literature exploring the

[5]Racial capitalism is "the process of deriving social and economic value from the racial identity of another person" (Leong, 2013). See also Jenkins and Leroy (2021) for an overview.

[6]Our analysis considers passive investors with market value–weighted portfolios of firms connected to policing at the beginning of our sample period. Similarly to the short-run analysis, in this case, we compare these portfolios' performance to their synthetic counterfactuals'. We compare buy-and-hold portfolios of stocks connected to policing to portfolios composed of nonconnected firms in similar industries.

[7]For example, Derenoncourt (2022) finds that police spending increased in urban areas that were exposed to arrivals of Black Americans during the Great Migration and where civil unrest occurred in the 1960s.

impact of firm-level exposure to risks such as those arising from political connections (Fisman, 2001; Knight, 2006; Jayachandran, 2006; Ferguson and Voth, 2008; Fisman et al., 2012; Acemoglu et al., 2016), climate conditions (Hong et al., 2019; Giglio et al., 2021), economic or political uncertainties (Abadie and Gardeazabal, 2003; Snowberg et al., 2007; Baker et al., 2016; Hassan et al., 2019), labor practices (Lee and Mas, 2012; Fisman and Wang, 2015)), taxes (Cutler, 1988), and conflicts (Abadie and Gardeazabal, 2003; Guidolin and La Ferrara, 2007; DellaVigna and La Ferrara, 2010; Dube et al., 2011).

Budgetary and political constraints imposed by federal and local governments impact law enforcement agencies' ability to purchase goods and services from corporations connected to policing. Hence, our work contributes to the literature on the impact of government contracts on firm performance (Hart et al., 1997; Garicano and Heaton, 2010; Ferraz et al., 2015; Beraja et al., 2020; Kang and Miller, 2021; Beraja et al., 2021; Spenkuch et al., 2021). In particular, the debate on investing in vs. "defunding" policing could motivate either an increase or a decrease in the performance of firms connected to policing depending on the allocation of public funds (to either the police or alternatives).

Our work adds to the research documenting the externalities that policing may have on cities and individuals (DiPasquale and Glaeser, 1998; Cunningham and Gillezeau, 2019; Ang, 2020). For instance, studies have investigated whether Black and brown neighborhoods have higher rates of police misconduct and aggressive policing (Ba, 2018; Fryer, 2019; Hoekstra and Sloan, 2020; Ba et al., 2021), police presence (Chen et al., 2021; Zhuo et al., 2023), surveillance and predictive policing (Benjamin, 2019; Acemoglu, 2021), and traffic stops (Feigenberg and Miller, 2021; Grosjean et al., 2022) and whether they are subject to a greater financial burden related to fines and forfeitures (Sances and You, 2017; Makowsky et al., 2019; Goncalves and Mello, 2021).

Alongside the BLM movement, a growing literature has documented the impact of police violence on nonpolice sectors of the economy. Recent studies document the effect of George Floyd's murder on firms' corporate response to uprisings (Denes and Seppi, 2023), diversity on corporate boards (Bogan et al., 2021)), investment in Black-founded startups (Cook et al., 2022), and workplace productivity (Alston and Jacobson, 2023). Our findings suggest that, with the recent uprisings and protests against racial injustice, markets have anticipated that local governments will increase investment in police due to BLM activism. Our work sheds light on which firms benefit from these investments.

Plan The rest of this paper is organized as follows. The next section provides a brief background on the Black Lives Matter movement, major incidents triggering BLM uprisings, and the relevant policy discourses on policing. To motivate our analysis, Section 3 presents a conceptual framework linking the potential impact of the BLM movement on the policing industry. We link the model to economic experts' forecasts, which will help guide our analysis. Section 4 describes the data used for the analysis. Section 5 presents the empirical strategy and the main short-run results. We explore the impact of mass shootings and white supremacist–related events on the performance of firms contracting with police in Section 6. In the long-run analysis in Section 7, we present the impact of Trayvon Martin's death on the performance of firms connected to policing. Section 8 discusses the implication of our results for the "Defund" movement. Section 9 provides the robustness check. Finally, we conclude in the last section.

2 Background

Policy Discourse on Policing As expressed by Dunivin et al. (2022), public discourse immensely impacts sociopolitical behavior in the United States. Individuals frame their understanding of social problems by suggesting appropriate response strategies, assessing the consequences of collective action, and selecting the tactics that they believe correspond to the most effective solution. To frame our analysis, we categorize social views on and priorities for the role of policing in the US into three groups: (1) views emphasizing crime control ("crime"), (2) views emphasizing police reform ("reform"), and (3) views proposing abolition of policing ("abolition").

Adherents of the first view, focusing on crime control, prioritize providing the police with more resources to fight crime, identify suspects, and conduct investigations, without emphasizing the negative externalities associated with policing. Proponents of crime control often advocate for investment in predictive policing or other surveillance technologies (e.g., data analytics tools, gunshot detection, dispatch, drones) in the deployment of resources. While the focus on crime reduction has been the dominant view in the US in recent history, high-profile police violence against marginalized communities in recent years has fostered a debate among activists and policymakers on how to reduce police violence. This debate has brought to a newly broadened audience views other than the crime control perspective, namely, the police reform and abolition views.[8]

Adherents of the second view, prioritizing reform, call for policy changes to reform the police by implementing more accountability tools (e.g., training, body-worn cameras, oversight agencies, community policing, and diversity within police forces). One of the main criticisms of this perspective is that "reformist reforms" continue or expand the reach of policing without reducing harm and violence against marginalized groups (Gilmore (2007); Vitale (2017); Critical Resistance (2020)).

Adherents of the final view, abolition, promote eliminating government spending on policing and surveillance while increasing funding for police alternatives such as community-based accountability, mutual aid, housing, or healthcare for all (Davis, 2011). Citing incidents of police violence against Black and Brown Americans, health disparities in Black communities, and the disproportionately high incarceration rates of Black people in the US, proponents of abolition endorse the dismantling of oppressive state institutions. In particular, advocates of abolition urge a systemic reconsideration of modern policing and criminal justice. This demand to reduce the scale of polic-

[8] See, for example, 8cantwait.com for reformist policy positions and 8toabolition.com for abolitionist policy positions.

ing in the US or to "defund the police" arose from the abolitionist movement (Davis, 2011; Akbar, 2020; Davies et al., 2021).[9] Advocates of "defunding the police" argue that police reforms are costly in terms of taxpayer-funded settlements, reform efforts, and evaluation costs. They support shifting funds from police departments to nonpolicing alternatives (e.g., investments in housing and mental health resources).

Timeline Using data from Dunivin et al. (2022), Figure 3 reports the logged daily count of tweets with the hashtags #BlackLivesMatter, #AllLivesMatter, #BlueLivesMatter, and #WhiteLivesMatter on Twitter. The dashed vertical lines indicate the dates of seven high-profile incidents of interest for our analysis. Except for the first two, these events correspond to the largest daily change in #BlackLivesMatter tweets per quarter. We utilize the timeline and classification of Giorgi et al. (2020) to identify the circumstances around each event. These events involved violence against Black Americans by police or non-Black civilians. The events selected for our analysis can be summarized as follows:

1. **Death of Trayvon Martin on February 26, 2012**: Trayvon Martin, 17 years old, was fatally shot by George Zimmerman, a 28-year-old neighborhood watch coordinator.

2. **Acquittal of George Zimmerman on July 13, 2013**: Zimmerman was acquitted of murder and manslaughter, sparking the creation of the #BlackLivesMatter hashtag and the beginning of the BLM movement.

3. **Mistrial in the Jordan Davis shooting case on February 15, 2014**: Jordan Davis, 17 years old, was killed in November 2012 by Michael Dunn, a 45-year-old software developer. In February 2014, Dunn was convicted of attempted murder, but jurors could not agree on the first-degree murder charge for killing Davis, leading to a mistrial.[10]

4. **Death of Michael Brown on August 9, 2014**: The first high-profile BLM protests in connection to incidents of police violence occurred in the summer of 2014, following the death of Eric Garner in July. Shortly after that, in August 2014, Michael Brown was killed by police officer Darren Wilson in Ferguson, Missouri, prompting further BLM protests. The killing of Michael Brown triggered an investigation by the Department of Justice into the city of Ferguson in 2014.[11]

[9] While the events of summer 2020 popularized some of the demands of the abolitionist movement, such as those to "defund the police" and abolish the prison industrial complex, activism, and academic work by (Gilmore, 2007; Davis, 2011) and Critical Resistance were foundational in developing a long-term vision of lasting alternatives to punishment and imprisonment.

[10] See NBC News.

[11] The DOJ investigation found that the municipality incentivized the police to generate more revenue through municipal fines and fees by enforcement. Following the report's release, Moody's downgraded Ferguson's general obligation by seven grades, from Aa3 to Ba1 (Moody's, 2015).

5. **Death of Tamir Rice on November 22, 2014**: Tamir Rice, a 12 year old, was killed by Cleveland police officer Timothy Loehmann. [12]

6. **Death of Alton Sterling on July 5, 2016**: Police in Baton Rouge killed Alton Sterling. Shortly thereafter, an officer in the Minneapolis–Saint Paul metropolitan area killed Philando Castile. This month also saw the killings of police officers in Dallas and Baton Rouge.

7. **Death of George Floyd on May 25, 2020**: A Minneapolis police officer, Derek Chauvin, killed George Floyd. This event led to massive protests across the US and around the world.

As the BLM movement grew, countermovement hashtags such as #AllLivesMatter, #WhiteLivesMatter, and #BlueLivesMatter became more prevalent. However, the BLM hashtag remains significantly more popular than the counter hashtags. #BlueLivesMatter is particularly relevant to our study; it indicates support for law enforcement. The #BlueLivesMatter hashtag appeared after the death of Tamir Rice, and its usage showed significant spikes following the death of Alton Sterling and the police officer killings in Dallas and Baton Rouge.

3 Conceptual Framework and Expert Predictions

3.1 Simple Model

There are several ways in which the BLM movement could affect the performance of firms contracting with law enforcement. This section discusses the expected magnitudes and signs on the firms' returns corresponding to the different views about policing. This framework provides testable implications on the market's expectations for firms associated with the (i) crime control, (ii) police reform, and (iii) police abolition positions.

Assume that the return π_i of stock i is a function of the future demand for products provided by firm i such that N_i are goods not related to policing, C_i are goods related to crime control, and R_i are goods related to police reform. The products are a function of the firm's exposure to BLM activism, b. The relationship between the three goods and the return of firm i can be expressed as

$$\pi_i = \pi(N_i(b), C_i(b), R_i(b)) \tag{1}$$

Moreover, to match our empirical analysis, nonpolicing firms produce only N_i such that $C_i = R_i = 0$; i.e., they do not produce any goods or services linked to crime control or police reform. However, firms tied to policing have $C_i > 0$, $R_i > 0$, or both.

[12] Financial news outlets lagged in their coverage of BLM. For instance, the *Wall Street Journal* only started discussing the BLM movement in the month of Tamir Rice's death, i.e., sixteen months after the emergence of the social movement and three months after the events in Ferguson (see Figure A.1 for more details).

In theory, the effects that BLM uprisings triggered by violence against Black civilians were likely to have on the returns of firms connected to policing is ambiguous. The change in the returns of firm i, dp_i, as a change in exposure to BLM activism, db, is expressed as

$$\frac{d\pi_i}{db} = \underbrace{\frac{\partial \pi_i}{\partial C_i}\frac{dC_i(b)}{db}}_{Crime} + \underbrace{\frac{\partial \pi_i}{\partial R_i}\frac{dR_i(b)}{db}}_{Reform} + \underbrace{\frac{\partial \pi_i}{\partial N_i}\frac{dN_i(b)}{db}}_{Nonpolicing} \tag{2}$$

By equation 2, the BLM uprisings have three potential modes of influence: benefitting $Crime$, $Reform$, or $Nonpolicing$. We assume that $\frac{\partial \pi_i}{\partial q} > 0$ for all $q \in \{N_i, C_i, R_i\}$, i.e., that there is a positive relationship between the return of a stock and the demand of product q. While the net effect depends on the sign and magnitude of each part of equation 2, this expression helps clarify the implications of the different views on policing explained previously, corresponding to (i) investment in crime control tools as a response to BLM, i.e., $\frac{dC_i}{db} > 0$; (ii) investment in police accountability tools as a response to BLM, i.e., $\frac{dR_i}{db} > 0$; and (iii) reducing the scale of police, i.e., $\frac{dC_i}{db} < 0$ and $\frac{dR_i}{db} < 0$. Finally, the $Nonpolicing$ effect could be null if the product N_i is unrelated to policing. It could also be positive (or negative) if there is an increase (decrease) in demand for product N_i as a response to BLM, i.e., $\frac{dN_i}{db} > 0$ ($\frac{dN_i}{db} < 0$).

Before turning to the empirical analysis, we provide concrete examples of the types of firms in our sample that we map to the model above. Smith & Wesson Brands Inc produces firearms and contracts heavily with police departments by selling firearms (and other equipment), making it mainly a crime-control firm. In contrast, Axon Enterprise, Inc, provides body-worn cameras for police departments, a product promoted by reformists, as well as crime-control products and services, such as less-than-lethal weapons in the form of Tasers. If investors believed the incidents triggering BLM activism would increase demand for crime-control products and services, we would expect the related firms to increase in value. In contrast, if investors believed that increased public funds would flow toward policing reform in the form of purchases of more body-worn cameras instead of firearms, we would expect the shares of Axon to rise. Publicly traded companies such as Apple, Boeing, and Johnson & Johnson represent nonpolicing firms but are in the same industries and are used in the control group for our analysis.

3.2 Expert Predictions

We supplement the simple model above by collecting data on economic experts' beliefs about the market response to George Floyd's murder. We focus on this event as it was likely the most salient to survey participants. This approach offers an opportunity to understand the role of economists' expertise in accounting for the consequences of the summer 2020 events for government spending on policing.

Survey Design The survey started with an attention check verifying that participants understood the prediction exercise. If respondents failed the attention test, the survey was terminated. As a "warm-up" exercise, the participants made a prediction related to a travel company at the beginning of the COVID-19 pandemic. Next, the respondents received information about George Floyd's murder and products related to policing (discussed below). Then, we asked participants to forecast the stock price movements after the killing of George Floyd for a portfolio of firms that contract intensely with police. Following Manski (2004) and Hanspal et al. (2021), we also collected the respondents' probabilistic expectations of the accuracy of their own forecasts.

All respondents received the same information about George Floyd's murder. Figure 1 presents the information provided to survey participants. We provided various narratives associated with viral incidents of police violence: their impact on crime, police reform, protests, and police resources. We also included narratives related to the "Defund the Police" movement, which gained wider attention following the murder of George Floyd.

Our survey focused on economics researchers working on crime-related topics. We followed DellaVigna et al. (2019) and used the Social Science Prediction Platform (SSPP) to survey the economics experts. We posted the survey on the SSPP from November 7, 2022, to December 31, 2022. We also collected emails from researchers with crime-related papers published in economics journals between 2010 and 2023, using the database of crime-related papers published in economics journals from Jennifer Doleac. We randomly selected 100 authors and contacted them using the SSPP platform in November 2022. We excluded individuals who failed the attention checks, did not complete the comprehension question, or did not provide their demographic information. Our analysis is based on a final sample of 19 responses, consisting of 36.8% researchers outside academia, and the remainder are students and faculty. The majority of the sample (89.5%) comes from the field of economics.[13]

Results Figure 2 presents the experts' forecasts of the stock price of firms contracting with the police 21 days after the murder of George Floyd. Panel A of Figure 2 represents the experts' average subjective probabilities for each forecasted range. The experts were more likely to predict a slight change (in either direction) in stock price than to predict no movement, with the median forecaster expecting no change and the average forecast indicating a decrease. However, on average, the experts believed it to be unlikely that the stock price would increase significantly.[14]

[13] In ongoing work, we emailed tenure-track faculty at the top 100 finance departments based on the 2021 ASU ranking (Stroebel and Wurgler (2021)) and financial professionals in the US to participate in a similar survey. We discuss the results in footnotes below.

[14] Finance experts (N=143) predicted that the portfolio would be worth \$102.8, with 57% predicting an increase. In a complementary survey experiment, we recruited finance professional experts (N=119) and nonexperts from Prolific (N=585), and one treatment arm was asked the following question: "How much would a portfolio worth \$100 of stocks from companies that contract intensively with police be worth 21 days after the killing of George Floyd?" We find that nonexperts and finance professionals, respectively, predicted that the portfolio would be worth \$82.2 and \$93.7, i.e., that the George Floyd murder would lead to a significant decline in the stock price of the firms tied to police.

Panel B of Figure 2 represents the shares of the experts' stated reasons for their predictions about the stock price changes. The most commonly stated reason was police reform, including the purchase of surveillance equipment and increased training, followed by budget cuts, which included mentions of police defunding and a subsequent loss of ability to purchase equipment. The least commonly stated reasons were related to crime, pro-police sentiment, and investors' reputational concerns.

4 Data and Summary Statistics

4.1 Data Sources

Roster of Firms Connected to Policing We use multiple data sources to construct our roster of publicly traded firms connected to policing. First, we compile firms referenced in Police1.com from November 2021, *Police Chief Magazine*'s buyers guide from 2010 to 2021, and exhibitor lists from the International Association of Chiefs of Police (IACP) conferences from 2010 to 2021. These resources provide a directory of vendors contracting with law enforcement agencies to procure products and services.

Then, to categorize publicly traded firms based on their exposure to policing, we use annual 10-K form filings from EDGAR, which provides all the relevant reports available since 2001. The 10-Ks are particularly useful because they contain detailed and audited information about firms' performance and are uniformly available. For each firm, we construct a time-varying measure of exposure to policing using a method similar to that in Hassan et al. (2021). Specifically, we count the number of times that words associated with policing appear within a firm's 10-K and then divide this number by the total number of words in the report to account for differences in document length. The time-varying exposure to policing for a firm i during year t is given by

$$Exposure_{it}^{Police} = \frac{1}{K_{it}} \sum_{k=1}^{K_{it}} \mathbb{1}(k \in \Gamma_{Police}) \tag{3}$$

where $k = 0, ..., K_{it}$ indexes the words contained in firm i's 10-K in year t, K_{it} is the total number of words in the 10-K, and Γ_{Police} is the set of words or word combinations associated with policing: police, policing, sheriff, trooper, and law enforcement. We compute the average exposure for each firm and identify firms appearing in one of the references from Police1 or the IACP. Finally, we define firms as having strong connections if their police exposure is above the 75th percentile. We categorize the remaining firms appearing in one of the police resources as having weak ties. For example, Motorola Solutions Inc. and Cisco Systems are both technological equipment companies, and both contract with law enforcement providing surveillance, video equipment, and other products. However, Motorola more frequently discusses law enforcement in its 10-Ks and provides a much larger range of products and services to law enforcement. Thus, Motorola is classified as a strongly connected policing firm, while Cisco is classified as a weakly connected policing firm.

Exposure to Government To disentangle the effect of investment into private versus public safety after the viral incidents, we construct an index of exposure to government funding. To quantify this exposure, we manually collect client lists for firms contracting with law enforcement in the fall of 2022 using Bloomberg. Then, we identify government entities' clients using words associated with the public sector (e.g., DOJ, DOD, law enforcement, city). Finally, we compute the share of government clients for each firm.

Finance Data We collect financial data from Wharton Research Data Services (WRDS) for each publicly traded firm in our sample. We use Beta Suite to compute firms' abnormal returns. In addition, we use the daily and monthly stock information from the Center for Research in Security Prices (CRSP). Firms' geographical information and Standard Industrial Classification (SIC) codes are collected from Compustat. To merge the data of firms connected to policing with the financial data, we fuzzy-name-match the roster with firm names from Compustat.

Sample Selection We restrict our analysis to publicly traded firms incorporated in the US and listed any time between July 2013 (when the BLM movement emerged) and December 2020. To construct the control group, we select publicly traded firms facing similar economic and labor market conditions to firms connected to the police industry. Hence, our sample consists of publicly traded firms in the same states and 4-digit SIC codes as policing firms. The final sample includes 859 publicly traded firms: 88 classified as policing firms, composed of 23 strongly and 65 weakly connected policing firms, and 771 firms in the control group.

4.2 Summary Statistics

Table 1 presents the descriptive statistics of the firms in our sample. Columns (1) and (2) report the mean and standard deviation for strongly and weakly connected policing firms, respectively, while column (3) presents the statistics for the control firms.

Differences in exposure to policing in the year before the incidents of interest confirm that strongly connected policing firms use more terms associated with policing in their financial reports than their counterparts (with firms with weak ties and control firms averaging nearly zero mentions of such terms). Moreover, half of the customers of strongly connected policing firms are public-sector customers—more than three times the number for weakly connected policing firms. For financial measures, we find that weakly connected policing firms are larger (as measured by logged total assets) and more profitable (as measured net income over market equity) and have higher leverage (debt over shareholders' equity) than both strongly connected policing firms and control firms. Moreover, compared to the control firms, strongly connected policing firms are smaller and more profitable but have lower leverage.

5 Short-Run Analysis

5.1 Empirical Strategy

Setup To study whether high-profile incidents related to BLM led to differences in returns for policing firms relative to those of nonpolicing firms in similar industries, our outcome of interest is the abnormal returns, AR_{it}, of firm i on the relevant date t. Abnormal returns account for general market movements and measure gains (or losses) in excess of the general market. We use the Carhart four-factor model (Fama and French (1993); Carhart (1997); Fisman and Wang (2015)) to compute the abnormal return for a firm i on day t as

$$AR_{it} = R_{it} - [\hat{\alpha}_i - \hat{\beta}_{MKT,i}RM_t - \hat{\beta}_{SMB,i}SMB_t - \hat{\beta}_{HML,i}HML_t - \hat{\beta}_{UMD,i}UMD_t] \tag{4}$$

where R_{it} is the return to the asset i in excess of the T-bill rate at date t and the intercept, $\hat{\alpha}_i$, is the estimated four-factor alpha; the Fama–French factors during period t are the excess return on the market (RM_t), size factor (small minus big) (SMB_t), and value factor (high minus low) (HML_t); the Carhart factor captures momentum (up minus down), denoted as UMD_t. We recover the estimated parameters $\hat{\alpha}_i$,$\hat{\beta}_{MKT,i}$, $\hat{\beta}_{SMB,i}$, $\hat{\beta}_{HML,i}$, and $\hat{\beta}_{UMD,i}$ by estimating the following equation with ordinary least squares (OLS): $R_{it} = \alpha_i + \beta_{MKT,i}RM_t + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{UMD,i}UMD_t + \epsilon_{it}$.

We follow Li and Lie (2006), Jayachandran (2006), and Acemoglu et al. (2016) to estimate these parameters on a pre-incident period of 252 trading days ending 30 days before the relevant event date. For each firm i, we calculate the cumulative abnormal returns between trading days n and m as $CAR_i[n,m] = \sum_{t=n}^{m} AR_{it}$.

Performance of Firms Connected to Policing To motivate our analysis, we report the monthly performance of policing firms and control firms.[15] Figure 4 shows that the monthly abnormal returns (ARs) of strongly connected policing firms were higher than those of control firms in the month after George Zimmerman's acquittal, the events in Ferguson, and the murder of George Floyd. We do not see higher monthly abnormal returns for weakly connected policing firms. These figures suggest that only firms with strong ties to policing experienced better financial performance during periods with high-profile incidents related to the BLM movement.

Synthetic Difference-in-Differences We estimate the impact of high-profile incidents related to BLM activism on the performance of policing firms. The central assumption for identifying the

[15] We select from publicly traded firms between 2010 to 2021.

effect of the high-profile incidents on these firms' stock performance is that there would have been no systematic differences between the returns of the policing and control firms in the absence of the high-profile incidents tied to BLM uprisings, conditional on the set of covariates included in the regression. However, both the treated and control firms might differ on other dimensions. For instance, the pre-incident behavior of firms may differ.

To construct the counterfactuals of policing firms around the time of the incidents triggering BLM activism, we use the synthetic difference-in-differences method (SDID) (Arkhangelsky et al., 2021). This approach compares firms that are similar in terms of pre-incident trends. To build the set of counterfactual firms, SDID reweights and matches pre-exposure trends between treated (policing) firms and control firms. Before presenting the estimator, we first define the equation of interest. For each firm i at date t, the outcome y_{it} is given by

$$y_{it} = \mu + \alpha_i + \gamma_t + Police_{it}\beta + \varepsilon_{it} \tag{5}$$

where α_i is a firm fixed effect, γ_t is a time fixed effect, μ is a constant, and ϵ_{it} is the error term. The dummy variable $Police_{it}$ denotes exposure to the binary treatment, i.e., whether a firm is a "policing firm" and whether t is after the incident. In our application, we separately consider the two levels of connection to policing, such that $Police_{it} = \{Strong_{it}, Weak_{it}\}$, describing firms with strong and weak connections, respectively. The SDID estimator captures the average effect of exposure to high-profile incidents, $\hat{\beta}^{sdid}$, written as

$$(\hat{\beta}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\gamma}) = argmin_{\mu,\gamma,\alpha,\beta} \sum_i \sum_t (y_{it} - \alpha_i - \mu - \gamma_t - Police_{it}\beta)^2 \hat{\omega}_i \hat{\lambda}_t \tag{6}$$

where $\hat{\omega}_i$ correspond to the weights for each firm that align pre-exposure trends in the outcome of control firms with those of the treated group. The SDID estimator includes firm fixed effects, α_i, and time weights, λ_t, that balance the pre-treatment period with the post-treatment periods. As a result, the SDID estimator assumes that unit and time weights exist such that the trends of the treated firms and the weighted average of the control units satisfy the parallel trends assumption. Finally, we use Arkhangelsky et al. (2021) to compute the standard errors using a placebo analysis by applying the SDID estimator to firms not exposed to treatment. As a robustness check, we also use the synthetic control method (Abadie and Gardeazabal, 2003; Abadie et al., 2010; Acemoglu et al., 2016) (see Appendix A.1).

5.2 Daily Impact of High-Profile Incidents

5.2.1 Pooled

Figure 5 presents the daily impact of the BLM events on firms' CARs. We report the trajectory of the CARs before and after the events for policing firms and their SDID counterfactuals. The figure shows that the SDID counterfactuals approximate the actual CAR trajectories, with similar pre-incident behavior for both strongly and weakly connected policing firms during the pre-incident period. After the events, strongly connected policing firms outperform their counterfactuals between the 3rd and 21st trading days, suggesting that the performance effect of high-profile incidents on strongly connected firms takes a few days to materialize. We find that the high-profile incidents triggering BLM uprisings led to higher CARs for firms with strong connections with policing ($\hat{\beta}_{strong} = 0.07(SE = 0.01)$). Firms with weak ties to policing exhibit trends similar to those of their counterfactuals after a high-profile incident ($\hat{\beta}_{weak} = -0.001(SE = 0.006)$).

5.2.2 Heterogeneity by Incident

We report the SDID estimates of the daily impact of high-profile incidents triggering BLM activism in the subsequent 21 trading days by incident in Figure 6 along with the 95% confidence interval for each estimate.

The results indicate that the effect of high-profile incidents sparking BLM uprisings varies by firms' level of connection to policing. For weakly connected policing firms, the SDID estimates are virtually zero for the incidents before Tamir Rice's death, while for the incidents after the deaths of Tamir Rice and Alton Sterling, we find small and not statistically significant increases in weakly connected policing firms' CARs (less than 1.5 pp). Finally, the murder of George Floyd had a negative but not statistically significant effect on weakly connected policing firms' CARs ($\hat{\beta}_{weak} = -0.036(SE = 0.024)$).

In contrast, the high-profile incidents triggering BLM uprisings consistently led to higher CARs for strongly connected policing firms. In particular, the killings of Michael Brown and George Floyd led to sharp increases in CARs of 8.5 pp ($SE = 0.018$) and 16.5 pp ($SE = 0.035$), respectively. Other incidents—the acquittal of George Zimmerman, the deaths of Trayvon Martin and Alton Sterling, and the mistrial in the Jordan Davis murder case—are also associated with a rise in CARs (of between 3.9 pp and 5 pp) for strongly connected policing firms. Figures A.4 and A.5 indicate that the SDID counterfactuals and actual CARs follow similar trends for the period before the incidents. This test suggests that the trends for treated units and a given weighted average of the control units satisfy the parallel trends assumption.

To summarize, viral violence against marginalized communities led to higher abnormal returns for firms with strong ties to the police industry. The effects were largest in the wake of the killings of Michael Brown and George Floyd, which were associated with considerable public outrage. These results are consistent with these incidents triggering a change in the market's expectations of future demand for products and services tied to policing. However, we do not find evidence that firms with weak connections to policing benefited from these incidents, meaning that the gains were concentrated in firms dealing heavily in policing-related products and services.

5.3 Exposure to Government Agencies

The "defund" debate motivates our analysis of the daily impact of the focal high-profile incidents on firms' CARs by the firms' level of exposure to government (i.e., public-sector clients). Figure 7 presents the SDID estimates and their 95% CIs for strongly and weakly connected policing firms with shares of public-sector clients below and above 50%, with imprecisely estimated or small effects across events. Overall, there is no significant effect on weakly connected policing firms, regardless of government exposure.

However, for strongly connected policing firms, there are, across incidents, significant increases in CARs of 3.87 pp ($SE = 0.015$) and 9.99 pp ($SE = 0.014$) for companies with low and high shares of public-sector customers, respectively. Interestingly, there is a notable shift in which strongly connected policing firms benefitted from incidents triggering BLM uprisings over time. Before Ferguson and the killing of Michael Brown, the increases in CARs were concentrated among strongly connected policing firms with low shares of public-sector clients: 9.16 pp ($SE = 0.031$), 6.57 pp ($SE = 0.026$), and 6.65 pp ($SE = 0.034$) after the deaths of Trayvon Martin, the acquittal of George Zimmerman, and the mistrial in the Jordan Davis shooting case, respectively. However, those firms with high shares of public-sector clients saw no gains on average.

The killing of Michael Brown in Ferguson seems to have been a turning point. From Ferguson onward, the pattern reverses, and the gains almost entirely correspond to strongly connected policing firms with high exposure to government, whose CARs increase by at least 5.45 pp ($SE = 0.029$) per incident. For example, the killings of Michael Brown and George Floyd led to significant increases in CARs of 23.09 pp ($SE = 0.026$) and 22.62 pp ($SE = 0.06$), respectively, for strongly connected policing firms with high exposure to government agencies. In contrast, the killing of Michael Brown led to a drop in CARs of 5.24 pp ($SE = 0.025$) for strongly connected policing firms with low shares of government customers.

As government expenditures can lead to a tradeoff between investments in private vs. public security (Heaton et al. (2016)), these findings are consistent with the financial market's expectation of higher returns for companies providing private security, i.e., firms with a low share of government clients, when the incidents involved violence by bystanders against Black civilians. In contrast, incidents involving the police resulted in greater profits for businesses with a higher proportion of consumers from the public sector.

5.4 Market Expectations on Product Performance

This section explores the impact of the viral incidents on firms' performance by type of product and service provided. Disaggregating the effects by product category allows us to distinguish between reform- and crime-focused firms benefitting from the incidents triggering BLM activism. One of the main challenges to our understanding the effects of racial uprisings on firms' products and services is that there are no comprehensive datasets about the product classification of the firms tied to policing. We overcome this challenge by manually coding firms' products and services using categories from issues of *Police Chief Magazine* from 2010 to 2021. For example, we can disentangle firms that provide accountability tools (e.g., training, body-worn cameras (BWCs)) from firms providing crime-focused and surveillance equipment (e.g., predictive policing equipment, firearms, CCTV cameras). Overall, we identify 35 unique products and services among the 23 firms with strong ties to law enforcement.[16].

For each event of interest, we recover the effect of the incidents (pooled) on the CARs for a portfolio of firms focusing on each set of products and services. We restrict our analysis to products and services associated with at least two publicly traded firms. We report on bundles of tools and services among the same firm's products.[17]

Figure 8 presents the daily impact of the high-profile incidents on firms' CARs by-products and services; the effects vary significantly by category. Panel A focuses on groups of products that performed relatively well. We find a significant increase in CARs of firms that provide body-worn cameras, video cameras, and other surveillance equipment. Overall, the returns of firms providing those tools increase by between 11 pp and 33 pp ($p < 0.01$) in the three weeks after incidents triggering BLM uprisings relative to the returns of their synthetic counterfactuals. These results are consistent with the idea that the financial market anticipated increased demand for monitoring and surveillance of civilians and police officers simultaneously. In addition, other products such as restraints, equipment, firearms, and less-than-lethal weapons experience a significant increase in the days after viral incidents. In other words, there is an anticipation that the demand for products to manage criminal suspects will increase in response to incidents triggering BLM uprisings. Finally, demand for police accountability tools is expected to increase, as the CARs for firms providing training equipment, courses, and seminars increase by at least 6.5 pp ($p < 0.05$).

Panel B focuses on products and services for which we find no evidence of better or worse performance after viral incidents tied to BLM activism. In short, we find that firms providing crime analysis tools, mobile or communication devices, tools performing network analysis, or computer-aided dispatch experience negative returns after the viral incidents. However, these estimates are too noisy to draw strong conclusions on the impact of the incidents triggering BLM uprisings on products and services related to data analysis, predictive policing, or civilian demand for police (e.g., 911).

[16]Four companies—Vista Outdoor, Calamp Corp., Aware Inc., and Intellicheck Inc.—did not appear under any categories in *Police Chief Magazine*. Therefore, they are not included in the heterogeneity analysis.

[17]Specifically, GDWR (GPS + detention equipment + evidence storage + report writing), PPNM (personnel management + predictive policing + networks + mobile devices) and Alarms (alarms, evacuation + public address equipment).

6 Market Responses to Other Viral Violent Incidents

This section evaluates the impact of other types of viral violent incidents on the performance of policing firms. One could argue that such events may lead market actors to anticipate increased demand for goods and services related to private and public security. To test this conjecture, we focus our analysis on the effects of viral incidents related to mass shootings and murders perpetrated by white supremacists.[18]

Impact of Mass Shootings Because policing and crime are closely related to the discussion on guns in the US (Duggan, 2001; Manski and Pepper, 2018; Donohue et al., 2019), stocks of firms connected to policing may also respond to high-profile incidents related to gun violence. If, for example, one believes that crime rates would increase due to racial uprisings and the demand for guns increases as a means of self-protection, we should expect that policing firms might perform better than their nonpolicing peers. Using the fact that demand for guns increases after mass shootings (Levine and McKnight, 2017; Koenig and Schindler, 2021), we test whether such surges impact the performance of policing firms.

We use the comprehensive "Violence Project Mass Shooter Database" (Version 4.0, July 2021), which covers all public mass shootings from 1966 to 2020 in the US. We restrict our sample to the deadliest shootings during our period of interest (2010–2020). In particular, we focus on eleven mass shootings between 2012 and 2019, in which 12 to 58 individuals were killed during each shooting (see Table A.8 for event details).

Panel A of Figure 9 presents the SDID results of the daily impact of mass shootings on policing firms. In panel C, we also report the treatment effects of the incidents triggering BLM uprisings, the same results as in panel A of Figure 5. Panel A indicates that policing firms follow trends similar to those of their SDID counterfactuals before and after mass shootings. In other words, there is no evidence that the mass shooting events affect the performance of firms contracting with law enforcement agencies, in contrast with the large effects that we find for the incidents triggering BLM uprisings in panel C.[19]

Impact of Murders by White Supremacists In parallel to the recent racial uprisings, the radical right has been growing worldwide (Dal Bó et al., 2021). As documented previously in Figure 3,

[18] In another context, there is a growing literature on the negative externalities of mass shootings on education outcomes (Rossin-Slater et al., 2020; Bharadwaj et al., 2021; Brodeur and Yousaf, 2022) and consumer confidence (Lagerborg et al., 2022).

[19] Anecdotal evidence suggests that mass shootings increase gun manufacturers' stock prices. Surprisingly, little empirical evidence confirms this hypothesis (Brodeur and Yousaf, 2022). To the best of our knowledge, only Gopal and Greenwood (2017) explore this question by evaluating the impact of mass shootings on stock prices of gun manufacturers between 2009 and 2013, finding a negative impact of these events. However, the results disappear when the authors focus on post-2010 incidents. Section A.2 documents patterns similar to those in Gopal and Greenwood (2017) for firearms manufacturers in our sample.

the US is also impacted by this movement, as the #WhiteLivesMatter hashtag rose in popularity in response to the #BlackLivesMatter hashtag. The Anti-Defamation League classifies "White Lives Matter" as a white supremacist slogan promoted by many extremists group around the country as a countermovement to Black Lives Matter and its protest against police brutality aimed at Black Americans (see the ADL website for more details). Moreover, there is growing concern about hate crimes and terrorist attacks by far-right extremists against marginalized groups and the general population. Using the fact that viral murders perpetrated by white supremacists are likely related to White Lives Matter supporters (Panizo-LLedot et al., 2019), we test whether firms connected to police exhibit better or worse performance after such events than their synthetic counterfactuals.

We use data from the Anti-Defamation League to investigate the impact of 8 violent incidents linked to white supremacist extremists in the US that targeted African Americans, LGBTQ+ people, or the Jewish community. Each of these events resulted in the murder of at least one person. To ensure that we consider only incidents that draw viral attention, we restrict our analysis to incidents with at least 100 news articles on Google News when we type " white supremacy + [full name of the attacker]". See Table A.9 for the incident details.

Panel B of Figure 9 presents the SDID results of the daily impact of viral murders by white supremacists on the performance of firms connected to policing. These incidents lead to a modest increase in the CARs of strongly connected policing firms of approximately 1.8 pp. However, these effects are significant only at the $p < 0.1$ level, with no effect on the performance of weakly connected policing firms. Overall, our results indicate that viral violent incidents triggering BLM uprisings or linked to white supremacists result in higher performance of firms with strong ties to law enforcement. However, the effect size is more than three times larger for the viral incidents related to the killings of Black civilians than for the viral murders perpetrated by white supremacists.

7 Long-Run Analysis

7.1 Estimation Strategy

To understand the long-run impact of incidents triggering BLM uprisings on policing firms' performance, we construct buy-and-hold portfolios of stocks of strongly and weakly connected policing firms. This approach is similar to that in Abadie and Gardeazabal (2003). Our analysis considers passive investors' portfolios with market value-weighted portfolios of strongly and weakly connected policing firms at the beginning of our sample period. This design allows us to investigate the effect of the emergence of the BLM movement on policing firms' aggregate stock performance. [20]

The portfolios of strongly and weakly connected policing firms comprise the 23 and 65 firms

[20] Moreover, with the portfolio approach, we do not have to restrict our analysis to a balanced panel of publicly traded stocks for an extended period.

studied in the short-run analysis. For each portfolio (strong or weak ties), we construct a donor pool of 100 portfolios that include nonpolicing firms in the same SIC industry. The donor portfolios of weakly and strongly connected policing firms contain 58 and 18 randomly drawn firms with market value–weighted monthly returns in our sampling period.[21] Similarly to what we do in the short-run analysis, we compute the abnormal returns for each portfolio using the Carhart four-factor model with an estimation window of 60 months ending 30 months before the month of interest.

After constructing the treated portfolios and their donor pools, we estimate the impact of Trayvon Martin's death on the CARs from January 2010 to December 2020 using the SC and SDID methods from Abadie et al. (2010); Arkhangelsky et al. (2021). For the SDID (SC) approach, identification of the effect of Trayvon Martin's death relies on the assumption that the portfolios of connected firms and those of the donor pool would have experienced parallel (similar) trends in the absence of his death. Similarly to our approach the short-run analysis, we follow Arkhangelsky et al. (2021) to compute the standard errors using a placebo analysis.

7.2 Results

Panel A of Figure 10 presents the long-run impact of the killing of Trayvon Martin on the cumulative abnormal portfolio returns of firms with weak or strong connections to the police industry. Overall, the figure indicates that the portfolio composed of firms with strongly connected policing firms experiences a significant increase in abnormal returns relative to the returns of other portfolios after the killing of Trayvon Martin in the long run. Compared to the portfolio of synthetic counterfactuals, the portfolio of strongly connected policing firms increases by 76.4 pp ($SE = 0.355$). In contrast, the portfolio of weakly connected policing firms does not outperform their counterfactual group. Interestingly, the growth is not monotonic for the strongly connected policing firms: the CARs of firms with strong ties to policing increased from February 2012 to November 2014 (between the killings of Trayvon Martin and Tamir Rice) before declining and stagnating until summer 2020, when the gains increased following the murder of George Floyd.

Overall, the long-run analysis suggests that the killing of Trayvon Martin, which triggered the emergence of the BLM movement, led to significantly higher returns for firms with strong ties to policing while not impacting the returns of those firms with weak connections. This finding adds to the results from the short-run analysis by documenting that the short-term effects are not temporary or transient. In other words, there is a large cumulative impact of the viral incidents of violence against Black Americans and related to BLM uprisings on the performance of firms with strong ties to the police.

[21] These numbers correspond to the median number of firms in each incident.

8 Discussion on the "Defund" Movement

As the "Defund the Police" policy discourse entered the mainstream after the murder of George Floyd, it is critical to understand whether firms' stock returns were reflected in their future profits. This section explores the impact of the viral incidents of interest on firms' performance by type of product and service provided. We discuss the effects of the "Defund" movement on the market's expectation of (1) the performance of firms strongly connected to policing and (2) the sales and cost of goods sold of these firms.

Economic Expert Predictions vs. Market Expectations As documented in Section 3.2, the events of summer 2020 significantly increased the value of firms with strong ties to policing. Figure 11 indicates that the return of a portfolio of stocks tied to police is 16.5 pp ($SE = 0.035$) higher than that of a portfolio of their nonconnected peers three weeks after the viral event. This finding contrasts with the expert economist forecasts in panel A of Figure 2, which shows that our survey respondents tended to predict that the valuations of these firms would decrease or remain unchanged.

Recall that the economic experts were more likely to provide reasons associated with "police reform" and "Defund the Police and budget cuts" when asked about the impact of George Floyd's murder (see panel B of Figure 2). To complement the data on the experts' beliefs, we report the market expectation of the daily effect of George Floyd's murder by showing the impact on firms' CARs by product and service in Figure 12. This figure indicates that events of summer 2020 led to a significant increase in the values of firms supplying goods and services related to police reform (e.g., BWC, training) or crime control (e.g., cameras, firearms, restraint/defense devices), indicating that the financial market did not expect that police would be defunded in response to the outrage and protests during summer 2020.

Sales and Cost of Goods Sold We explore how the events of summer 2020 impacted the sales and cost of goods sold for firms contracting with the police. These outcomes allow us to understand better whether the "Defund" movement has impacted the profitability of companies supplying police departments and whether the markets' positive expectations of future profits were incorrect.

We consider strongly connected firms and their peers in the same SIC industry for which we have data on sales and cost of goods sold from 2018Q4 to 2022Q1. The final sample includes 19 firms with strong ties to policing and 81 in the donor pool. Our outcomes of interest are the cumulative changes relative to the first period in sales and the cost of goods sold. To recover the effect of George Floyd's murder on the supply of products and services from strongly connected policing firms, we use the synthetic difference-in-differences and synthetic control methods.

Figure 13 shows the impact of George Floyd's murder on the actual sales and costs of goods and services for strongly connected policing firms based on the SDID method. Panel A indicates that sales growth doubled in the quarters after George Floyd's death relative to that of the synthetic counterfactuals ($p < 0.01$). Although the figures show pretrends, one should be cautious about interpreting these results as causal; the SC estimates reported in Figure A.20 are similar in magnitude. In contrast, the cost of goods sold decreased by 49.2 pp ($SE = 0.337$) for the SDID estimates and 1.06 pp ($SE = 0.318$) for the SC estimates.

Discussion Our analysis documents that the valuation of the twenty firms contracting intensively with police increased by $474 million in the three weeks following the death of George Floyd. In other words, the protests and outrage associated with the "Defund" movement led to significant gains for the shareholders of companies contracting with police. Moreover, we find that the profitability of strongly connected policing firms increased significantly through two channels. First, we find that their sales increased by $974 million when we convert the SDID estimates to dollars for the two years after George Floyd's murder (from 2020Q2 to 2022Q1). Second, the cost of goods sold declined by $161 million. Overall, the "Defund" movement did not negatively impact the profits of police suppliers, and this incident triggering a major BLM uprising had no negative effect on the profitability of policing firms.

We compare the dollars gained for the shareholders and police contractors with the allocations made under the Community-Oriented Policing Services (COPS) program of, on average, one billion dollars annually for the hiring of more police officers. Evaluations from Evans and Owens (2007) and Mello (2019) show that relative to cities that applied but did not receive the funding, cities receiving the grant experienced a significant decline in crime. In other words, in the three weeks after the Floyd murder, the value of shareholders investing in firms contracting intensively with police increased by half the amount of the annual budget of the COPS program. In the years after Floyd's murder, the nineteen publicly traded firms supplying police departments in our sample experienced an additional one billion dollars in sales—equivalent to the annual budget of the COPS program for the hiring of 64,000 officers from 1995 to 2005 (Evans and Owens, 2007).

In contrast, advocates of the reallocation of funds to nonpolice alternatives recommend increasing the budget for mental health and substance use services. For example, Dee and Pyne (2022) find that a pilot of the Support Team Assistance Response (STAR) program in Denver, Colorado, where healthcare workers responded to emergency calls instead of the police, led to fewer arrests for minor offenses without a corresponding increase in serious crimes. Another program similar to STAR is Crisis Assistance Helping out on the Streets (CAHOOTS) in Eugene, Oregon, which reduced police involvement in cases related to mental health, homelessness, and substance use.[22] These or similar programs could be funded by the American Rescue Plan, which allocates $1.5 billion for states and localities to cover mobile crisis intervention services.

[22]For more details, see CBPP and PRA.

9 Robustness

Event Study As a complement to the SDID and SC analyses, we also employ a standard event study approach to evaluate the impact of the high-profile incidents on firms' $CAR_i[0, m]$ such that $m = \{1, 7, 14, 21\}$, i.e., the m days after the viral incident. Our estimating equation evaluates the change in CARs for strongly and weakly connected firms relative to the returns of nonconnected firms in similar industries. We include firm-level covariates such as size, profitability, leverage, and fixed effects for location, industry, and incident. The identification assumption requires that there would have been no systematic differences between the returns of the different types of firms in the absence of these high-profile incidents after we control for the aforementioned factors. We provide more details about the estimation strategy in Section A.1.2 of the appendix.

Table A.2 in the appendix reports the results of the event study design. Similarly to what we find using the SDID and SC methods, we do not find that the CARs of firms with weak ties to policing are significantly affected after the high-profile incidents. Overall, the effects for weakly connected firms are close to zero and not statistically significant. We also confirm that the high-profile incidents significantly impact firms with strong ties to the police. For example, we find that, in the 14 and 21 trading days after the events, strongly connected firms' CARs are 5.75 pp ($SE = 0.027$) and 6.43 pp ($SE = 0.03$) larger than those of peers in similar industries. These patterns are consistent with those found under the SDID approach presented in Figure 5.

Moreover, the impact of the viral incidents on the trading day after the event is negligible. The effect is initially modest and statistically nonsignificant but grows over time and becomes significant within a week of the incidents. Overall, our results suggest that the impact of a viral incident triggering BLM activism on the stocks of strongly connected firms is not immediate. However, the increased effects over time are consistent with investors purchasing more stocks of strongly connected firms if the event is associated with more protests.

Alternative Thresholds for Defining Strong Connections We verify that our results are robust to our using alternative thresholds to define the firms in the strongly connected group. As a descriptive, Figure A.10 shows the cumulative distribution function of the measure of exposure to policing and its frequency for firms with strong and weak ties to policing. Overall, Figure A.11 provides the SDID estimates and 95% confidence intervals for each high-profile incident using the 25th and 50th percentile thresholds to define strong connections relative to the estimates from the main specification. We find that the effects are economically and statistically more significant for firms that tend to be more associated with policing. The results still hold when we use the 25th percentile as our threshold, but they become noisier.

Volatility We investigate the impact of the incidents triggering BLM uprisings on stock volatility by firms' priorities related to policing. Although some firms benefited from the incidents by enjoying increased share prices, it is also possible that connected firms' risk increased. We evaluate this possibility by estimating the effect of the incidents on idiosyncratic volatility from Ang et al. (2006) using SDID. This measure of risk is the volatility of the difference between realized returns and expected returns calculated from the Carhart four-factor model.

Figure A.8 shows the daily impact of the high-profile incidents on the volatility of connected firms by incident. This figure indicates that, for firms with a strong connection to policing, volatility also increases with viral incidents triggering BLM uprisings. The results for each event are too noisy to conclude that the risk associated with these firms is impacted; however, the pooled estimate for strongly connected firms is positive and significant at the 5% level. Finally, the volatility estimates for firms with weak connections are smaller than those for their peers strongly connected to policing but are nonsignificant. Combined with the results from the CAR analysis, this indicates that some of the viral incidents triggering BLM activism led to higher returns but more volatility for firms with strong ties to policing, indicating an increase in risk is associated with those firms for the pooled estimates.

SDID vs. SC Methods To test the robustness of our primary estimation strategy, we also use the synthetic control (SC) approach from Abadie and Gardeazabal (2003); Abadie et al. (2010). The main difference between this method and the SDID approach is that the SC method reweights the treated and control units to match their pre-exposure trends, and the SDID estimator assumes that unit and time weights exist such that the trends of the treated firms and the weighted average of the control units satisfy the parallel trends assumption. (Section A.1.1 of the appendix provides details.) Overall, the SC results (Figures A.6 and A.7) and the SDID results(Figures A.4 and A.5) are highly similar. Both sets of results suggest that high-profile violence against marginalized groups leads to a significant increase in CARs in the 21 trading days after the incidents for strongly connected firms only, with similar pretrends in actual and counterfactual CARs in the days before the events.

Cumulative Returns and CARs based on the CAPM As another robustness check, we estimate the daily impact of the viral incidents on cumulative and abnormal returns using the capital asset pricing model (CAPM) rather than the Carhart four-factor model as in our main specification. Panels A and B in Figure A.9 compare the results for the three specifications for firms with strong and weak connections to policing. Overall, we find very similar results, indicating that our results are robust to our using alternative market models to compute the abnormal or cumulative returns.

Product Performance over Incidents As the discourse around policing changed between the killing of Trayvon Martin in 2012 and the killing of George Floyd in 2022, different firms dealing in different products and services saw the largest gains after each incident triggering BLM activism. Figures A.12 to A.17 display the CARs after each incident prior to George Floyd's killing for each product category. After the first incidents, the top-performing products were mainly crime-focused products, such as restraints, firearms, imaging, less-than-lethal weapons, and surveillance. However, following Michael Brown's killing, reform-focused products, such as body-worn cameras, recorders, and training, saw the largest gains.

Long-Run Analysis Finally, our results for the long-run impact of BLM activism on the performance of firms are robust to using alternative specifications. Figure A.18 shows that using equally weighted firms rather than market value-weighted portfolios leads to results that are qualitatively similar to those from our main specification. We summarize the results from the alternative specifications in Figure A.19, which uses combinations of SC or SDID estimations and equally weighted portfolios or market value–weighted portfolios. Overall, the various specifications lead to similar conclusions.

10 Conclusion

Recent incidents of violence against Black Americans have generated unprecedented awareness of the intersections between race, inequality, power, and violence across sectors of society. The rise of racial uprisings and movements such as BLM sparked policy demands on policing to end police brutality and violence against Black communities. Demands from actors involved in organizing related to racial justice led to an active debate on the role of policing in US society, particularly whether law enforcement should receive more resources to fight crime or implement reforms and thereby improve the treatment of civilians. An alternative proposal is to reduce the scope of policing and invest in nonpolicing resources that impact public safety. As a result, these demands have significant implications for firms connected to the American police industrial complex.

We evaluate the impact of major incidents triggering BLM uprisings on the performance of publicly traded firms that contract with law enforcement. We first delineate the three main policy approaches to policing and the timeline of viral incidents sparking BLM uprisings. Next, using a simple conceptual framework, we outline how different policy views on policing (crime control vs. police reform vs. police abolition) map to potential investor behavior and impact the performance of firms contracting with law enforcement. We find that firms with strong ties to policing experienced better performance after viral incidents triggering a BLM response. These results indicate that investors had no expectations that abolitionist demands ("defunding the police") would succeed.

Our research also shows how high-profile violence against Black Americans and calls for systemic change translate into gains via the public market for shareholders of stocks of firms contracting with police. These findings align with the literature on racial capitalism (Robinson (2005)) in that corporations connected with policing profit from high-profile incidents of violence against Black civilians in the US. Our findings are also consistent with "reformist reforms" expanding the reach of policing while sidelining alternative approaches to reducing harm and violence against marginalized groups (Gilmore (2007); Vitale (2017); Critical Resistance (2020)).

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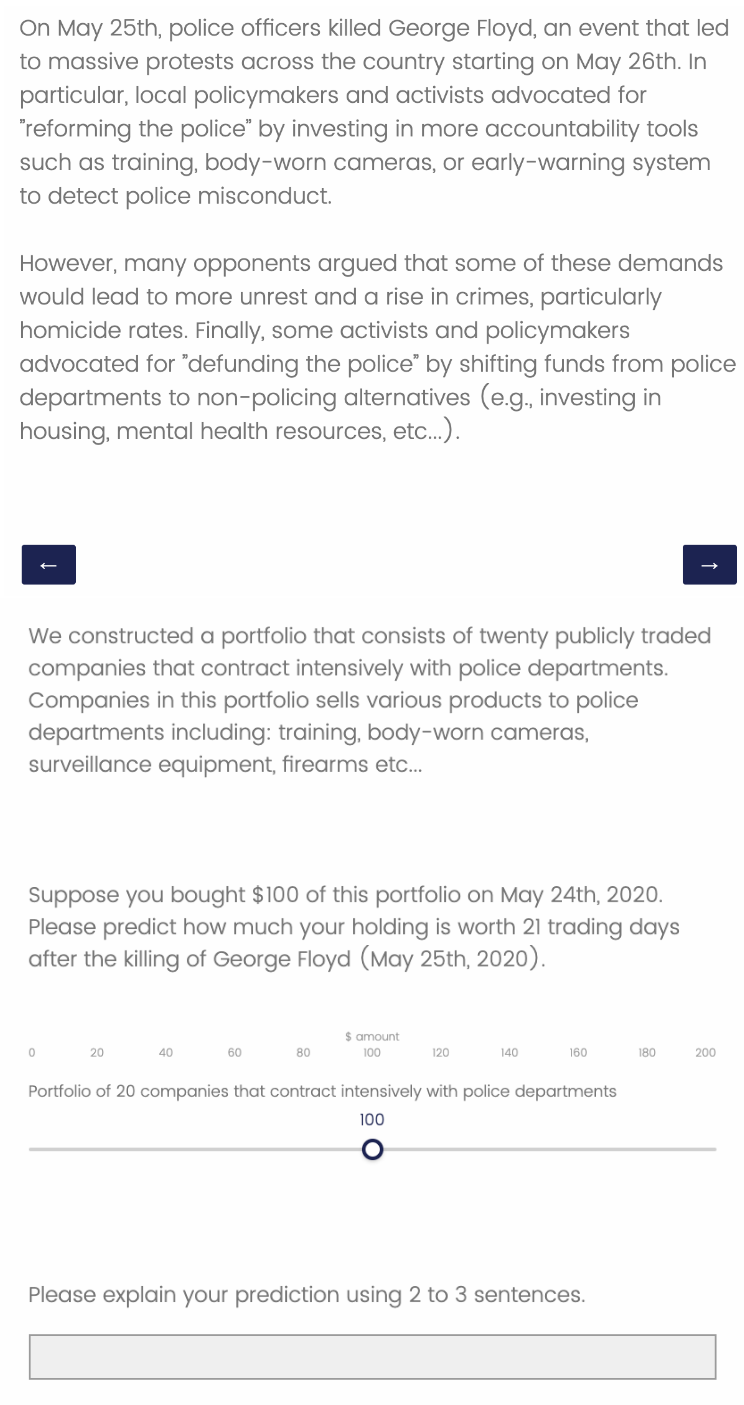
Figure 1: Survey about the Impact
of George Floyd's Murder on Stock Prices



On May 25th, police officers killed George Floyd, an event that led to massive protests across the country starting on May 26th. In particular, local policymakers and activists advocated for "reforming the police" by investing in more accountability tools such as training, body-worn cameras, or early-warning system to detect police misconduct.

However, many opponents argued that some of these demands would lead to more unrest and a rise in crimes, particularly homicide rates. Finally, some activists and policymakers advocated for "defunding the police" by shifting funds from police departments to non-policing alternatives (e.g., investing in housing, mental health resources, etc...).

← →

We constructed a portfolio that consists of twenty publicly traded companies that contract intensively with police departments. Companies in this portfolio sells various products to police departments including: training, body-worn cameras, surveillance equipment, firearms etc...

Suppose you bought $100 of this portfolio on May 24th, 2020. Please predict how much your holding is worth 21 trading days after the killing of George Floyd (May 25th, 2020).

$ amount

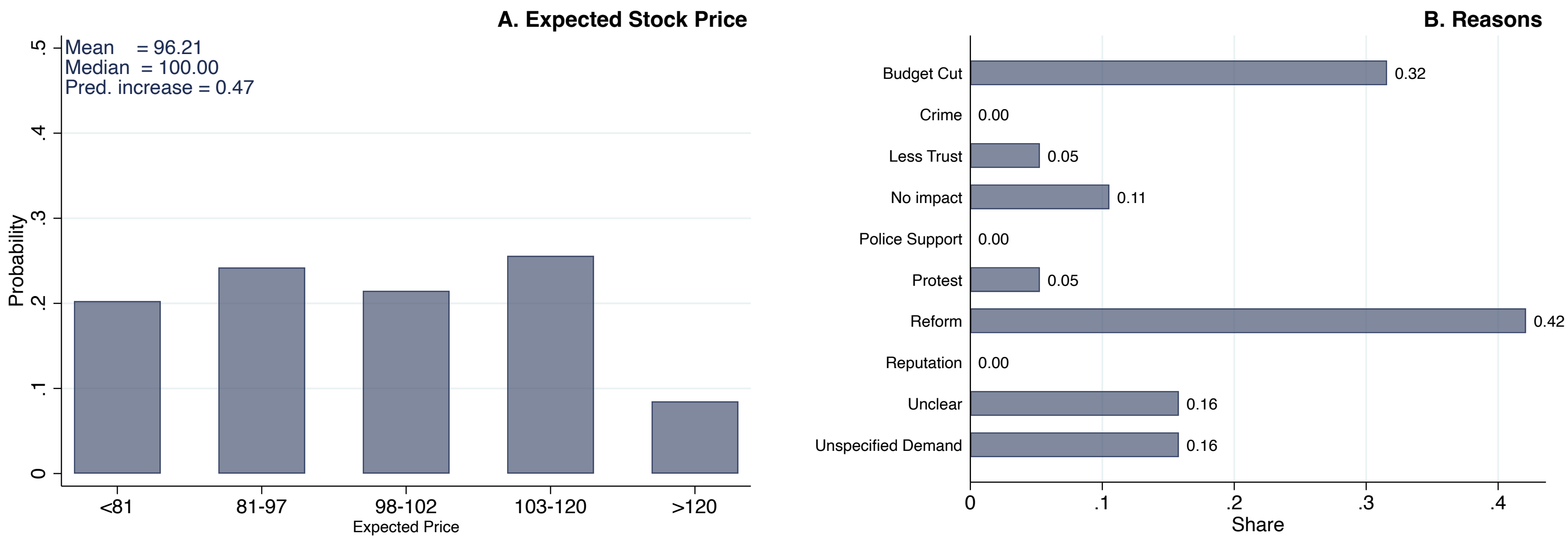
0 20 40 60 80 100 120 140 160 180 200

Portfolio of 20 companies that contract intensively with police departments

100

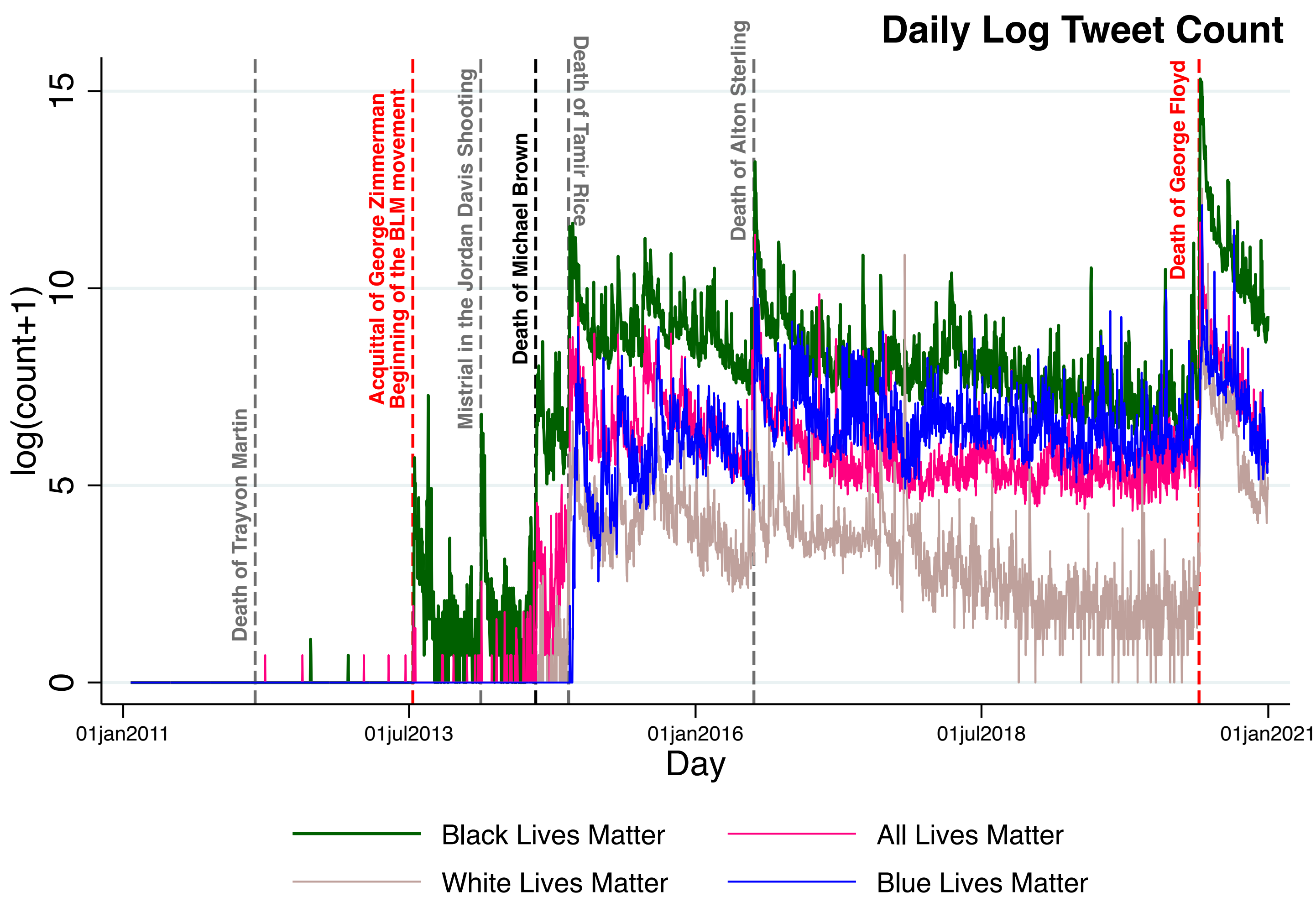
Please explain your prediction using 2 to 3 sentences.

Figure 2: Economic Expert Predictions and Explanations
of the Impact of George Floyd's Murder



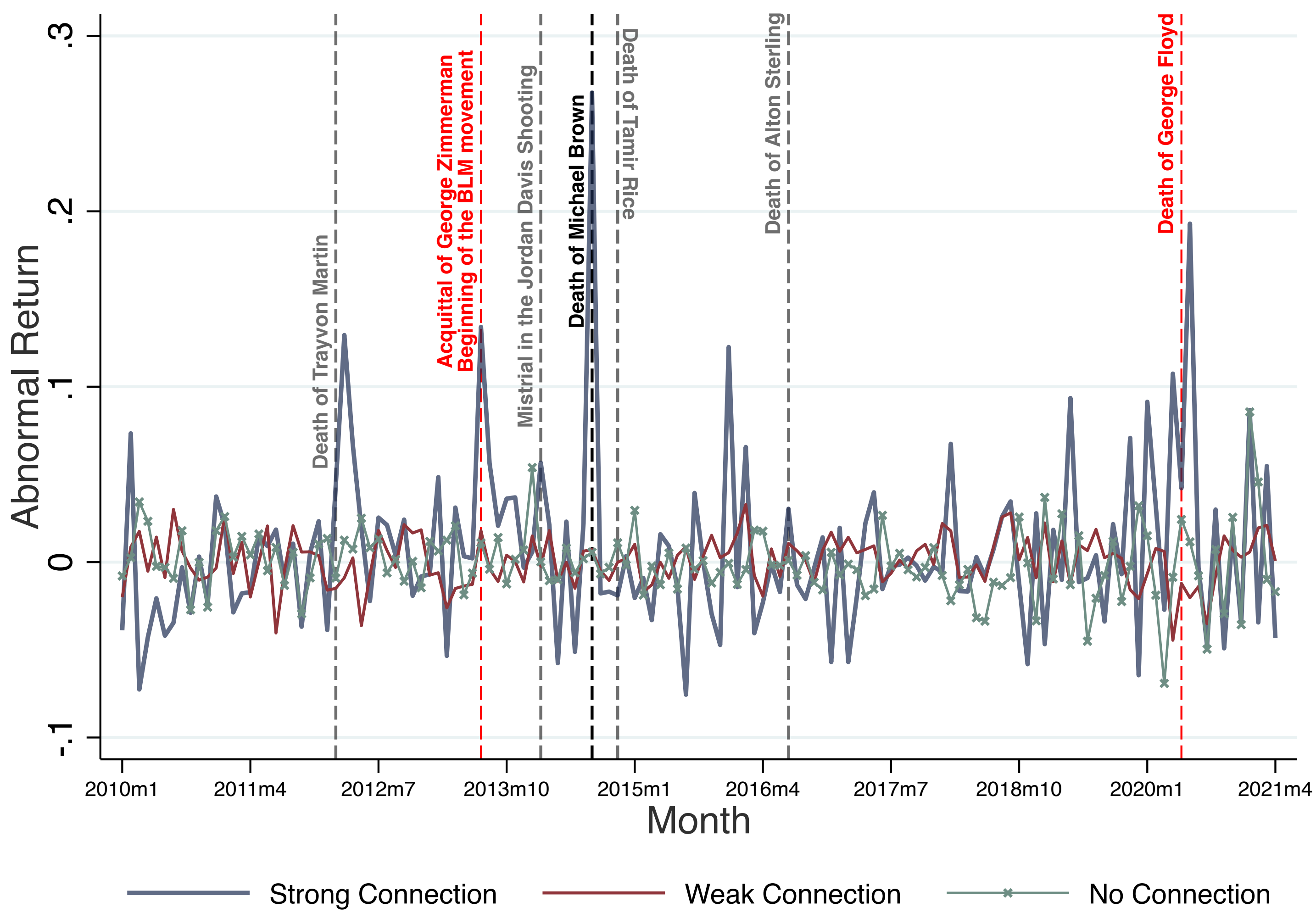
Notes: This figure presents economic experts' forecasts on the impact of George Floyd's murder on the stock performance of firms contracting with police. Each respondent provided a forecast for a portfolio of firms with ties to policing in the 21 days after the killing of George Floyd. Figure A presents the average probabilities assigned to each forecast bin. Figure B provides the share of different explanations associated with the forecast.

Figure 3: Timeline of Incidents Triggering BLM Uprisings



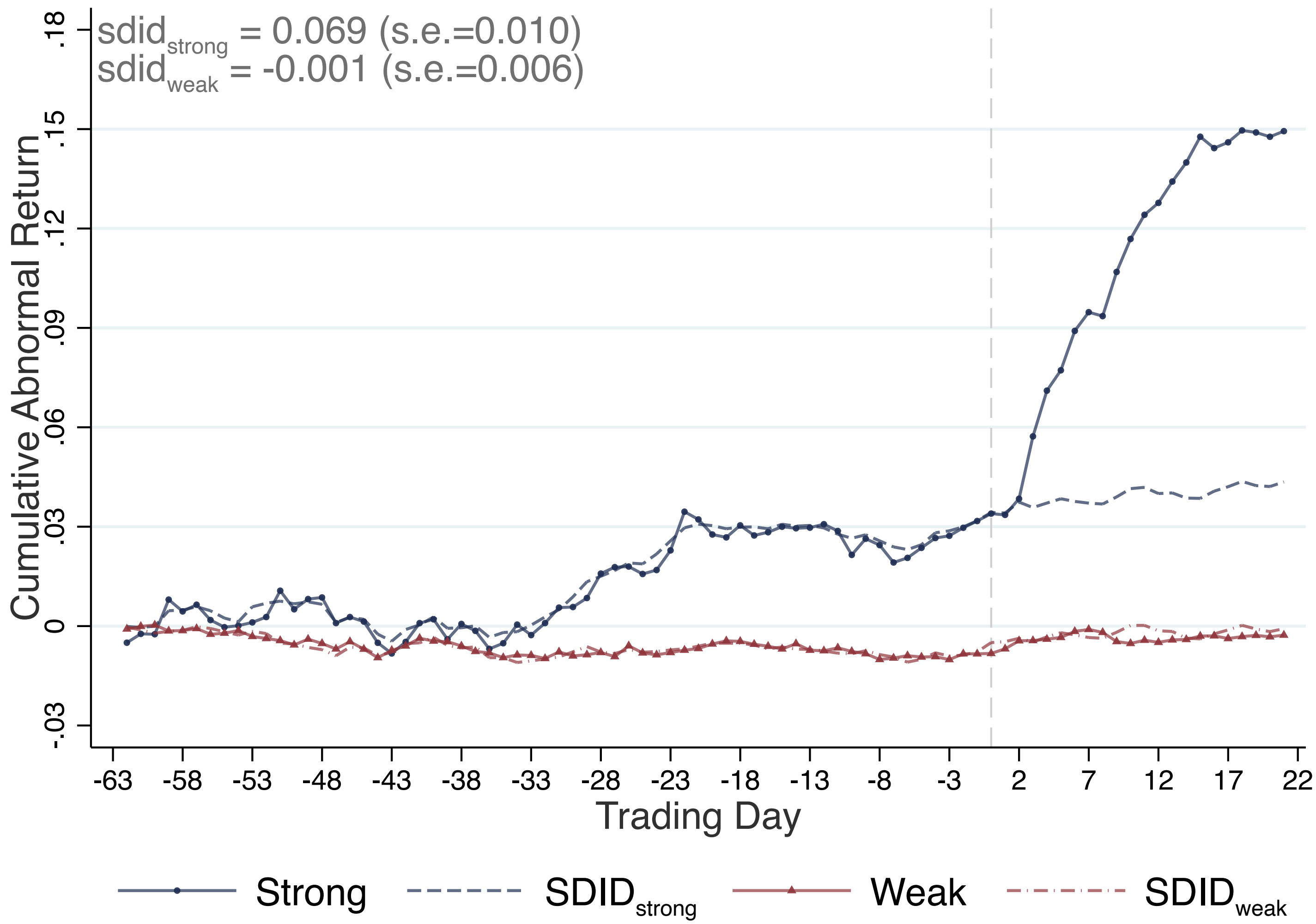
Notes: This figure reports the daily log count of tweets with the hashtags #BlackLivesMatter, #AllLivesMatter, and #BlueLivesMatter on Twitter. The vertical dashed lines represent seven high-profile incidents of interest for our analysis. The Twitter data come from Dunivin et al. (2022).

Figure 4: Monthly Abnormal Returns



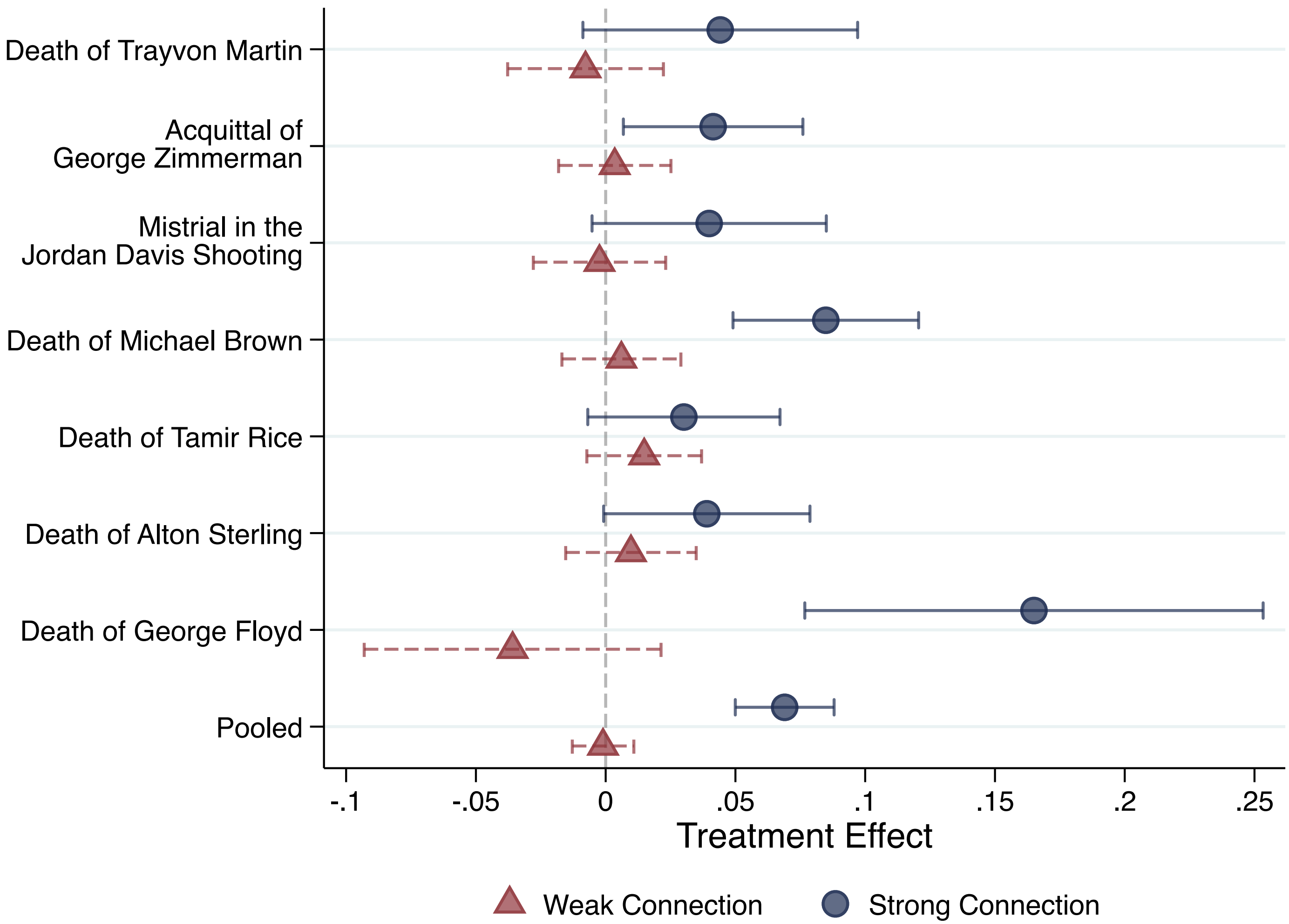
Notes: This figure shows the monthly abnormal returns (ARs) for firms connected to police and control firms. ARs are calculated with the Carhart four-factor model with an estimation window of 60 months ending 30 months before the day of interest. The vertical dashed lines represent high-profile incidents related to the BLM movement.

Figure 5: Daily Impact of High-Profile Incidents on CARs



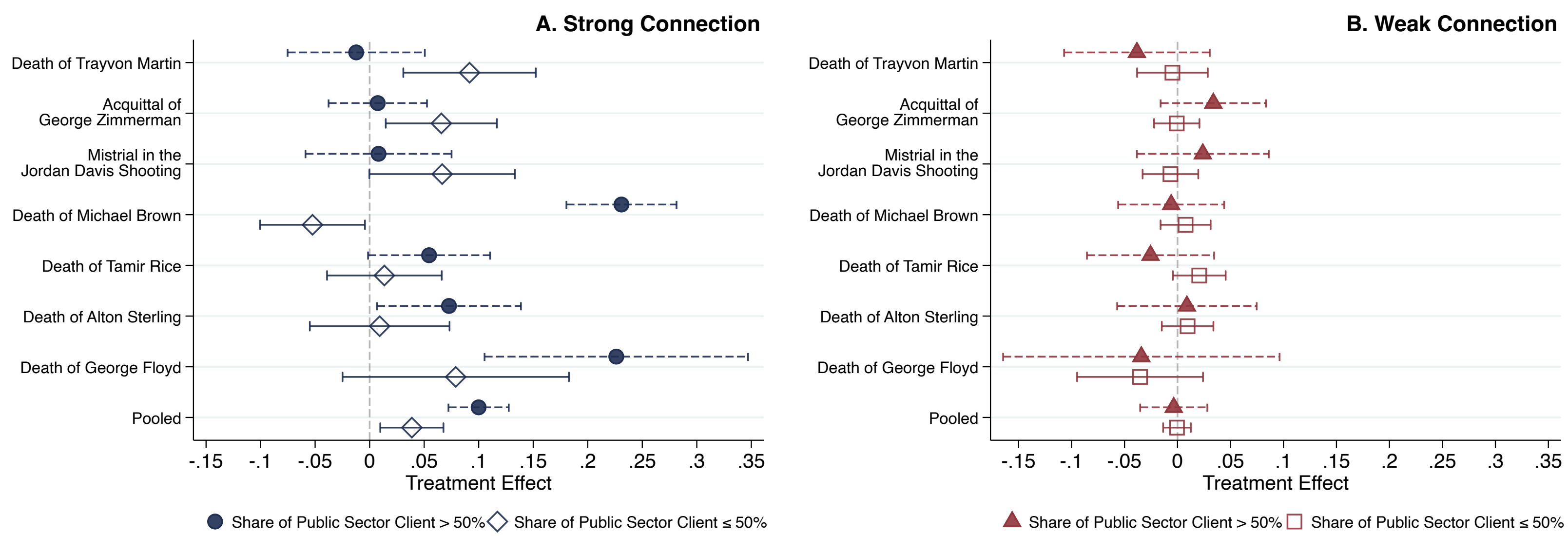
Notes: This figure presents the daily impact of high-profile incidents on the cumulative abnormal returns (CARs) of firms with weak or strong connections to the police industry. We report the CAR trends of the connected firms and their synthetic difference-in-differences (SDID) counterfactuals. The vertical dashed line represents the first trading day after the event of interest. We report SDID estimates, and standard errors are in parentheses. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest.

Figure 6: Daily Impact of High-Profile Incidents on CARs by Incident



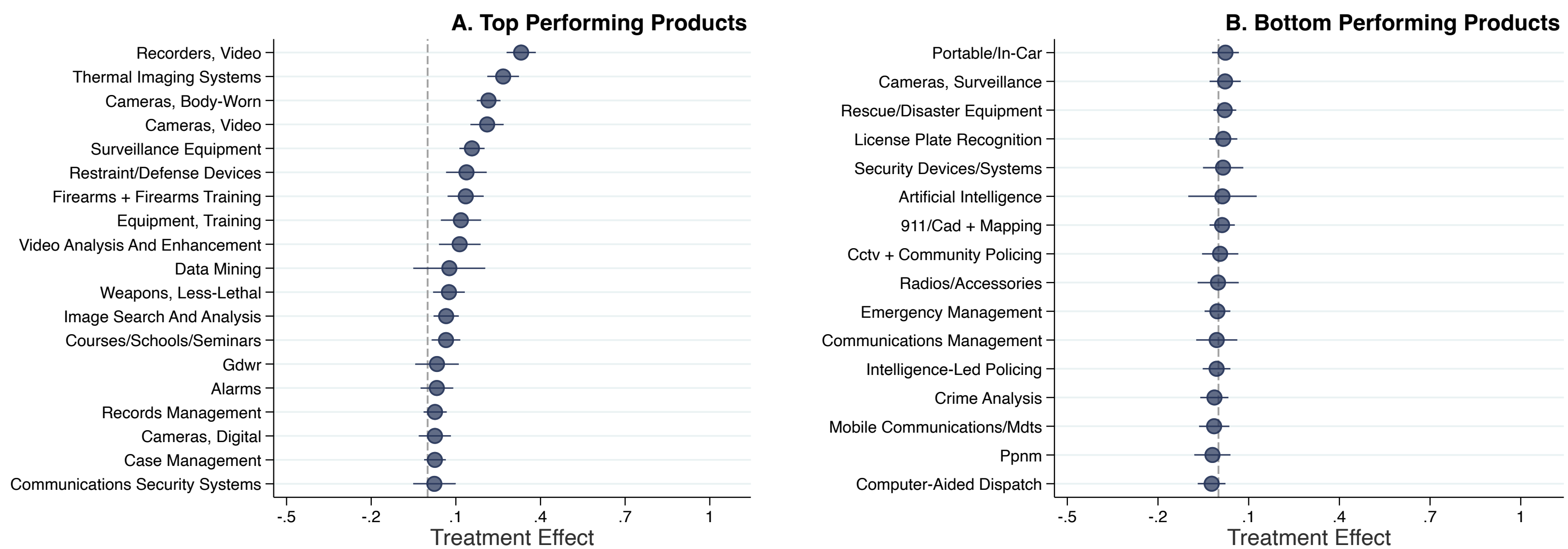
Notes: This figure provides the SDID estimates and 95% confidence intervals for each high-profile incident. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest.

Figure 7: Daily Impact of High-Profile Incidents on CARs by Firms' Level of Exposure to Government Agencies



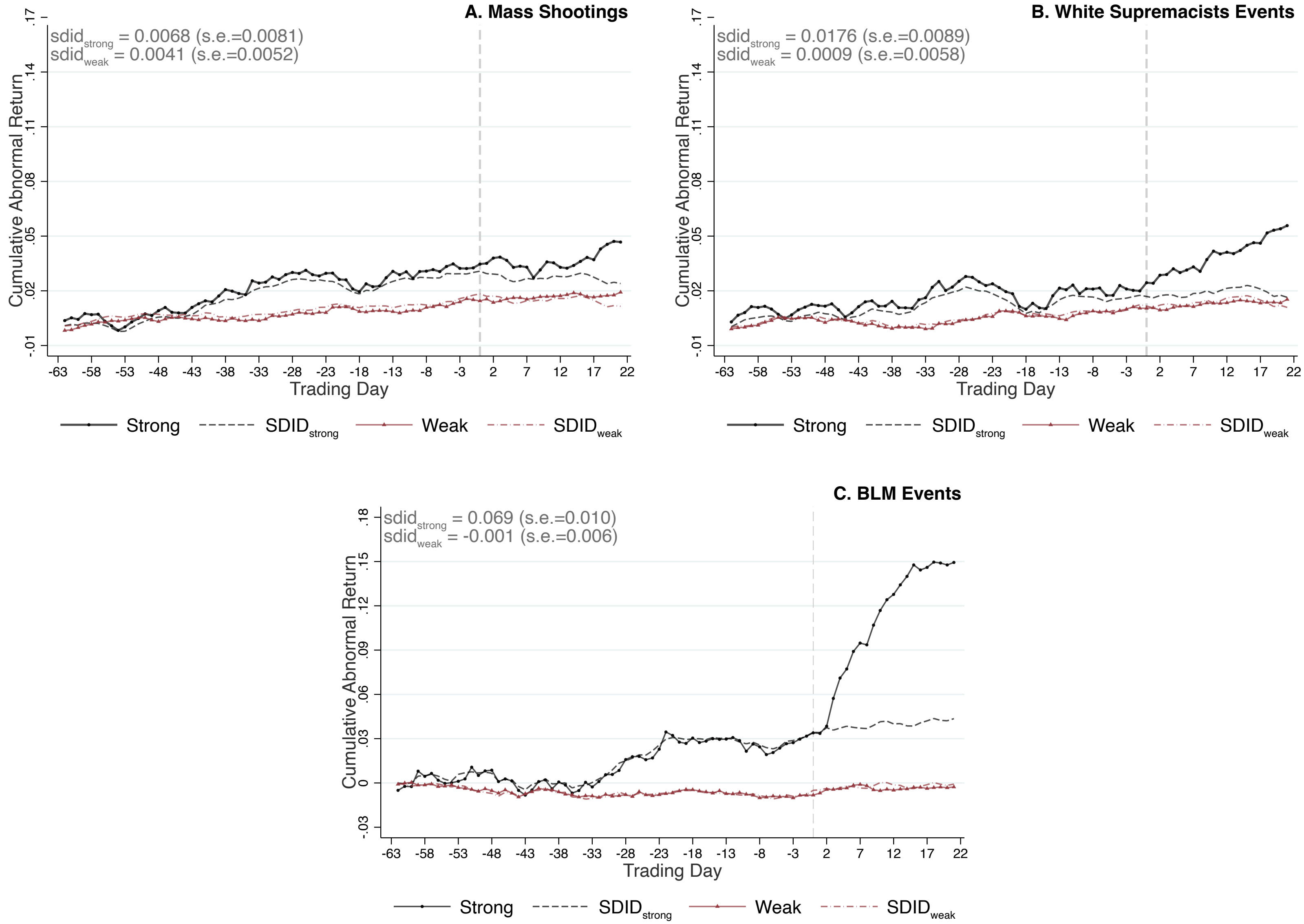
Notes: These figures present the daily impact of high-profile incidents on firms' CARs by their exposure to government agencies, i.e., whether their share of public-sector clients is below or above 50%. Figures A and B show the results for firms with strong and weak government connections. We report SDID estimates and 95% confidence intervals for each high-profile incident. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest.

Figure 8: Daily Impact of High-Profile Incidents on CARs by Type of Product and Service



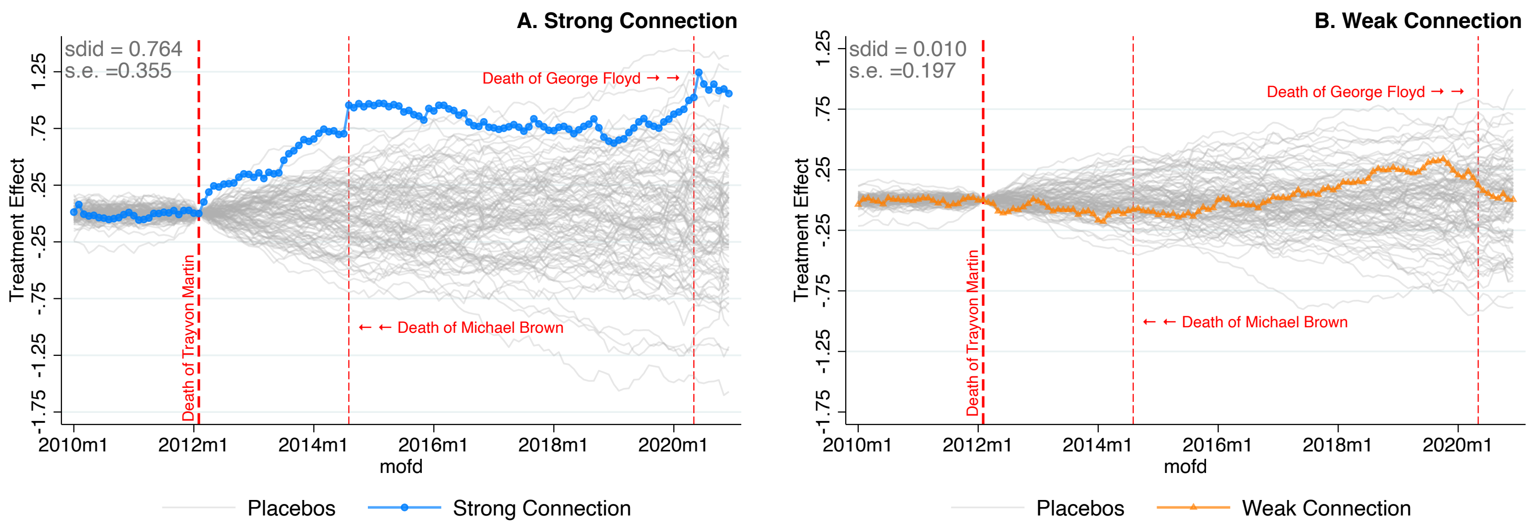
Notes: The figures present the daily impact of high-profile incidents on firms' CARs by product and service. We report SDID estimates and 95% confidence intervals. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest. GDWR: GPS + detention equipment + evidence storage + report writing. PPNM: personnel management + predictive policing + networks + mobile devices. Alarms: alarms, evacuation + public address equipment.

Figure 9: Daily Impact of Other Viral Violent Incidents on CARs



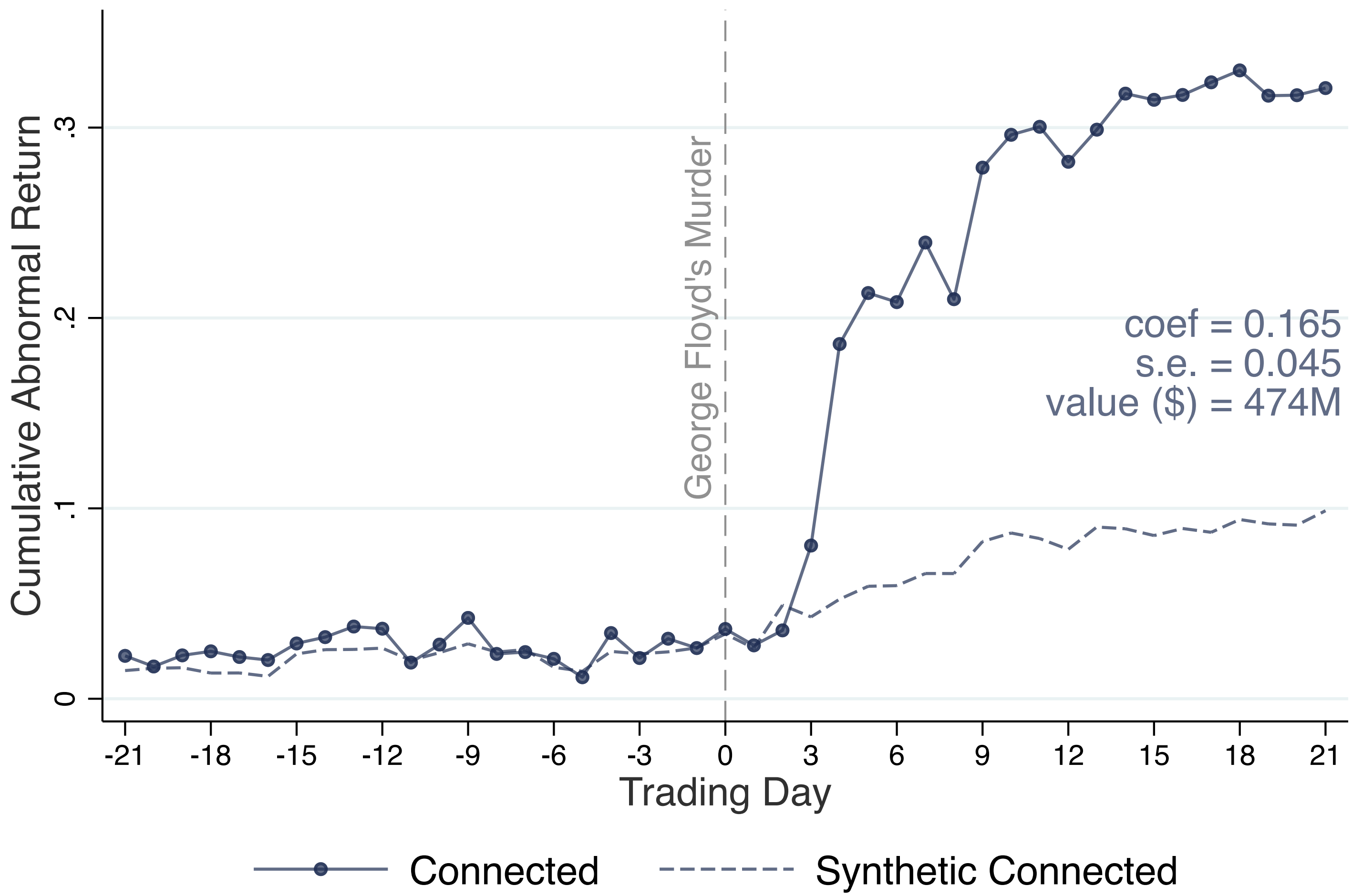
Notes: These figures present the daily impact of mass shootings, white supremacist murders, and incidents triggering BLM uprisings on the cumulative abnormal returns of firms with weak or strong connections to the police industry. We report the CAR trends of the connected firms and their SDID counterfactuals. The vertical dashed line represents the first trading day after the event of interest. We report SDID estimates, and standard errors are in parentheses. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest.

Figure 10: Long-Run Impact of BLM Uprisings on Cumulative Abnormal Portfolio Returns



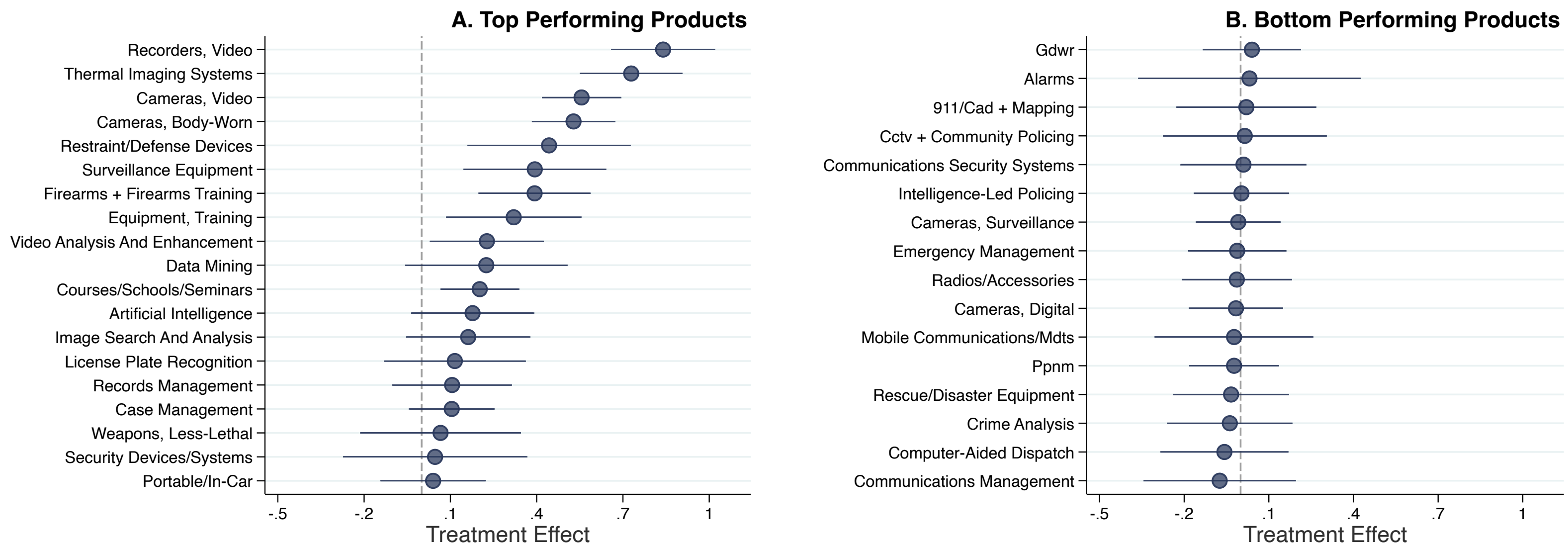
Notes: Figures A and B present the long-run impact of Trayvon Martin's death on the cumulative abnormal portfolio returns of firms with strong and weak connections to the police industry. This specification considers passive investors' portfolios with market value–weighted portfolios. We report the treatment effect of the event on the CARs of treated firms. The treatment effect is the gap in CARs between actual portfolios and their synthetic counterfactuals. The red vertical dashed line represents the month of Trayvon Martin's death. We also report the treatment effects of the placebo groups. The SDID estimates are computed from the sum of all abnormal returns since January 2010. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 60 months ending 30 months before the day of interest.

Figure 11: Impact of George Floyd's Murder on Stock Performance



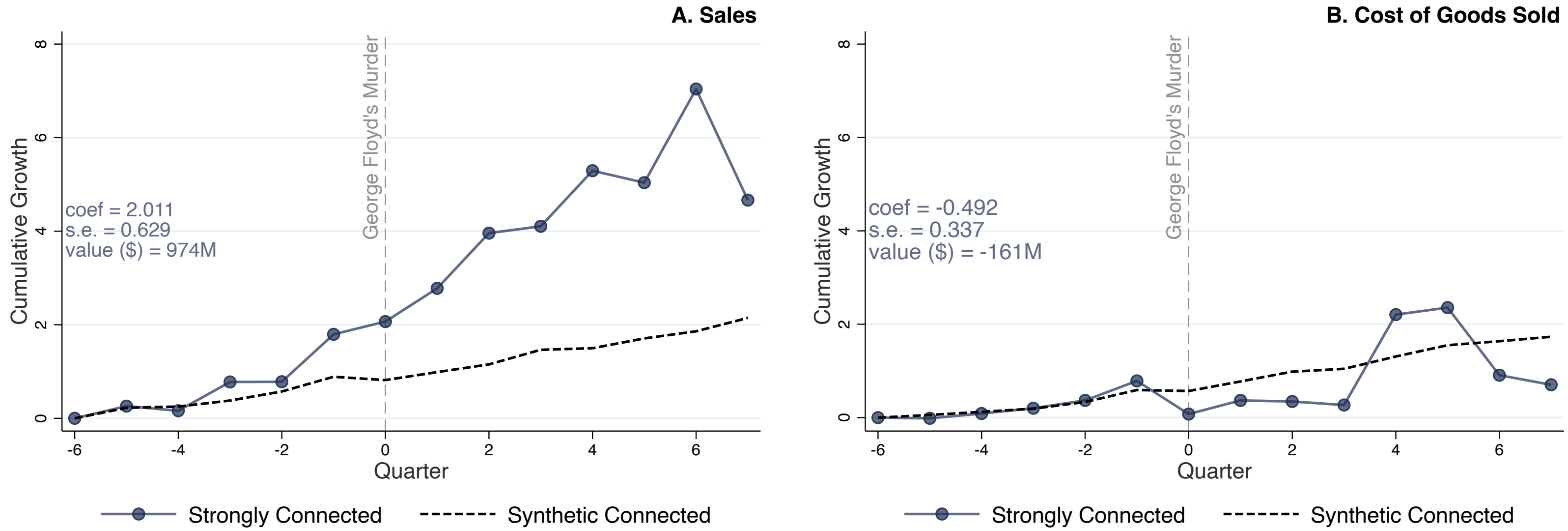
Notes: This figure presents the impact of George Floyd's murder on the cumulative abnormal returns of firms contracting intensively with police departments. We also report the dollar amount associated with the treatment effects relative to the outcomes in the first period in the analysis. We report the CAR trends of the connected firms and their SDID counterfactuals. The vertical dashed line represents the first trading day after the event of interest. We report SDID estimates, and standard errors are in parentheses. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest.

Figure 12: Daily Impact of George Floyd's Murder on CARs by Type of Product and Service



Notes: The figures present the daily impact of George Floyd's murder on firms' CARs by product and service. We report SDID estimates and 95% confidence intervals. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest. GDWR: GPS + detention equipment + evidence storage + report writing. PPNM: personnel management + predictive policing + networks + mobile devices. Alarms: alarms, evacuation + public address equipment.

Figure 13: Impact of George Floyd's Murder on Sales and Cost of Goods Sold



Notes: Figures A and B present the impact of George Floyd's murder on the cumulative growth (relative to the first period) of the sales and cost of goods sold for firms with strong ties to the police industry. The treatment effect is the gap in outcomes between the actual firms with strong connections and their synthetic counterfactuals. We report the SDID estimates and the standard errors. We also report the dollar amount associated with the treatment effects relative to the outcomes in the first period in the analysis. The vertical dashed line represents the quarter of George Floyd's death.

Table 1: Summary Statistics by Type of Connection

	(1) Strong Connection		(2) Weak Connection		(3) Donor Pool	
	Mean	SD	Mean	SD	Mean	SD
Size	5.93	2.15	8.49	2.16	6.20	2.03
Profitability	-0.01	0.15	0.03	0.08	-0.09	0.34
Leverage	0.20	1.16	1.70	8.65	0.59	7.60
Exposure to Policing	0.06	0.07	0.00	0.00	0.00	0.00
Share of Government Client	0.50	0.32	0.14	0.22		
Number of Firms	23		65		771	
Observations	114		363		3058	

Notes: The table presents descriptive statistics by level of connection to policing. We multiply exposure to policing by 100 for readability. The variables size, profitability, and leverage capture log total assets, return on equity, and the ratio between total debt and total capital, respectively. All the variables are computed on the basis of the year before the event.

Appendix

A Supplementary Materials

A.1 Alternative Empirical Strategies

A.1.1 Synthetic Control

Estimation Strategy As an alternative to synthetic difference-in-differences (SDID) for constructing the counterfactual of firms exposed to viral incidents tied to BLM uprisings, we use synthetic control (SC) (Abadie and Gardeazabal, 2003; Abadie et al., 2010; Acemoglu et al., 2016, 2018). The SC estimator captures the average effect of exposure to high-profile incidents, $\hat{\beta}^{sc}$, which can be written as

$$(\hat{\beta}^{sc}, \hat{\mu}, \hat{\gamma}) = argmin_{\mu,\gamma,\beta} \sum_i \sum_t (y_{it} - \mu - \gamma_t - Police_{it}\beta)^2 \hat{\omega}_i \tag{7}$$

where $\hat{\omega}_i$ represents the weights for each firm that align the pre-exposure trends in the outcomes of control firms with those of the treatment group. The SC approach restricts $\alpha_i = 0$ for all firms. In contrast, the SDID estimator includes firm fixed effects, α_i, and time weights, λ_t, that balance pre-exposure periods with post-exposure ones. While the SC method reweights the treated and control units to match their pre-exposure trends, the SDID estimator assumes that unit and time weights exist such that the trends of the treated firms and the weighted average of the control units satisfy the parallel trends assumption. Similarly to the procedure in the SDID approach, standard errors are computed on the basis of a placebo analysis (Arkhangelsky et al., 2021).

A.1.2 Event Study

Estimation Strategy Following Fisman and Wang (2015), we test the relationship between firms' contracting with law enforcement agencies and their cumulative abnormal returns by estimating the following equation:

$$CAR_i[n,m] = \beta_0 + Strong_i\beta_S + Weak_i\beta_W + X_i'\theta + \mu_l + \gamma_j + d_t + \varepsilon_i \tag{8}$$

The dummy variables $Strong_{it}$ and $Weak_{it}$ denote the level of connections to policing, i.e., firms with strong and weak ties, respectively. The set of firm-level covariates, X_i, includes size (log total assets), profitability (return on equity), and leverage (ratio between total debt and total capital). The variables γ_j, μ_l, and d_t denote location, industry , and event fixed effects. Finally, ε_i is an error term.

The parameters of interest are β_S and β_W, which measure how the CARs of firms with strong and weak ties to policing change relative to the CARs of firms in similar industries but not contracting with police departments.

The identification assumption requires no systematic differences between the returns of the different types of firms in the absence of high-profile cases of violence against Black civilians after we include controls for firms' fundamentals and location, event, and industry fixed effects. Standard errors are clustered at the firm level.

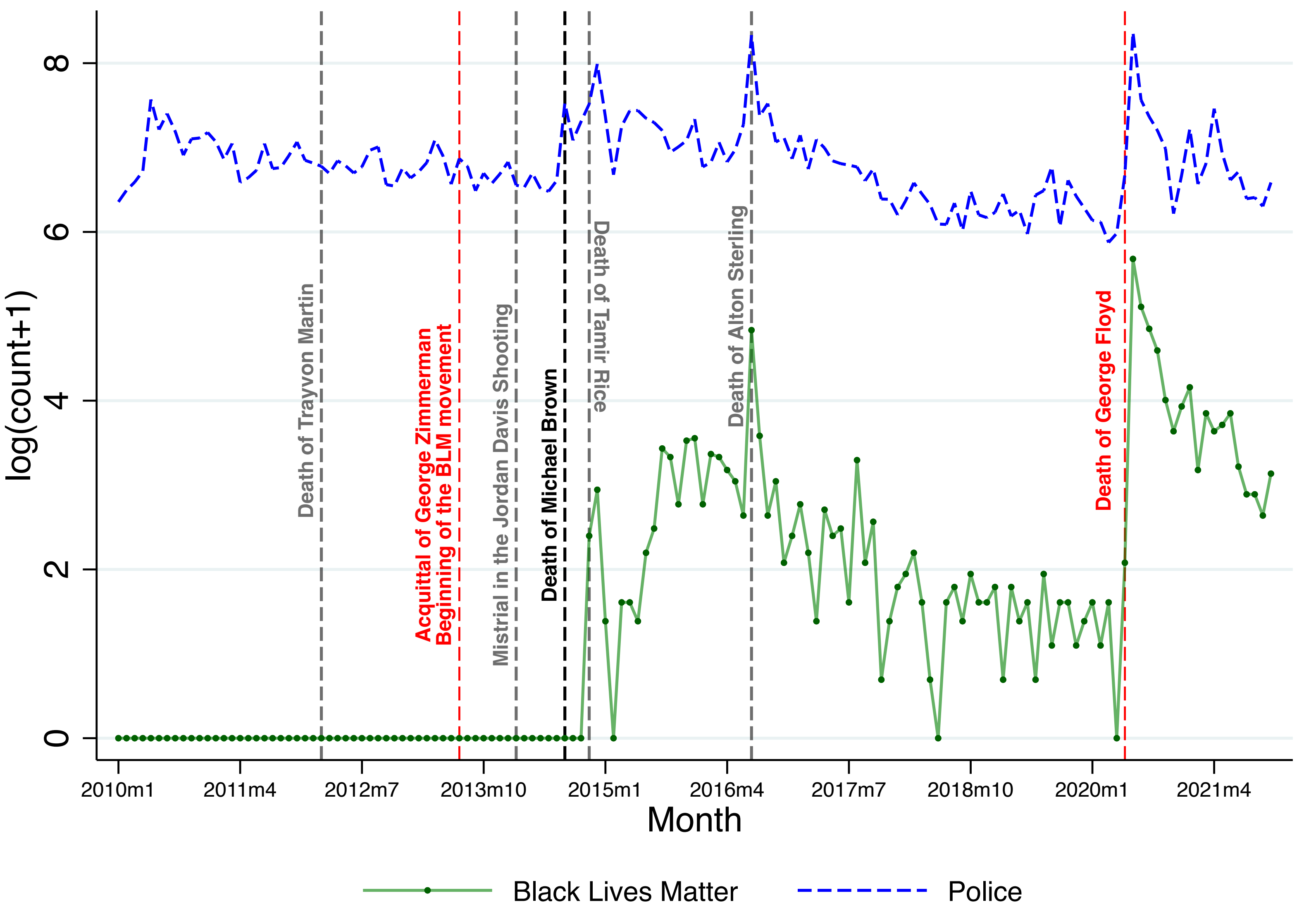
A.2 Impact of Mass Shootings on Firearms Firms

In our sample, we explore the impact of mass shootings incidents on the CARs of firearm suppliers by means of SDID. Figure A.21 reports the CAR trends of the connected firms and their SDID counterfactuals. We find that mass shootings led to no change in the performance of Smith & Wesson Brands Inc and VirTra Inc three weeks after the shootings. On the other hand, Vista Outdoor Inc experienced a drop of 9.64pp ($SE = 0.037$) in its CARs relative to those of its synthetic counterfactual three weeks after the mass shootings.

As an alternative, we use the event study approach described in Section A.1.2 to see how the effects vary over time. Tables A.3, A.4, and A.5 present the daily impact of mass shootings on the cumulative abnormal returns of each of the gun manufacturers 1, 7, 14, and 21 days after the event. Overall, visual inspection of Figure A.21 is consistent with the results from the event study tables, where the realized outcome oscillated around the counterfactuals for Smith & Wesson Brands Inc and VirTra Inc while being primarily negative for Vista Outdoor Inc.

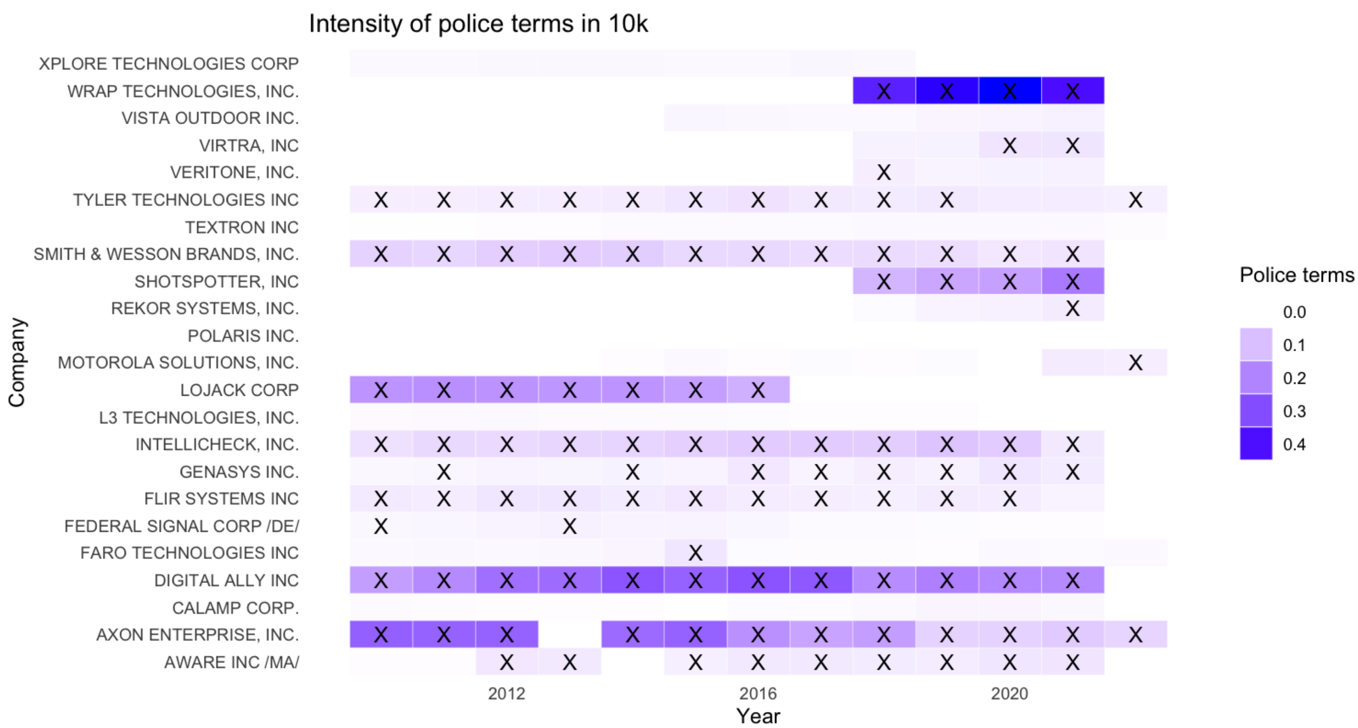
B Additional Figures and Tables

Figure A.1: Mentions of BLM and Police in the *Wall Street Journal* over Time



Notes: This figure presents the number of mentions of “Black Lives Matter”, “BLM,” and police-related terms in the *Wall Street Journal*. The vertical dashed lines represent seven high-profile incidents of interest for our analysis.

Figure A.2: Mentions of Police over Time for Firms with a Strong Connection

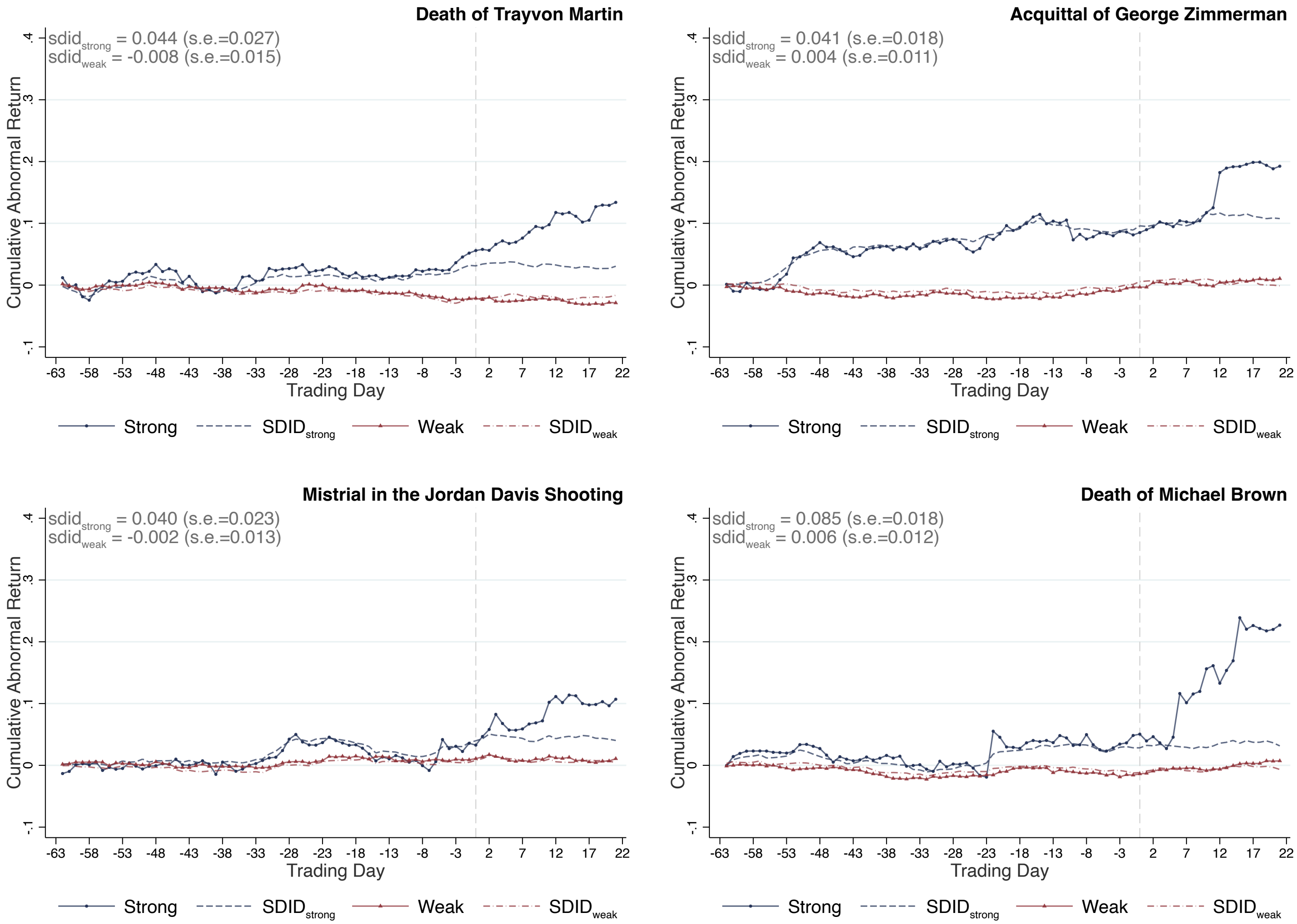


Notes: This figure plots the police exposure measures (i.e., intensity) constructed from the annual financial reports from 2010 and 2020. We report the index measure for the strongly connected firms in our sample. To compute the level of intensity, we count the number of times that words associated with the topic appear in the report. Then, we construct the intensity index by dividing this number by the total number of words in the 10-K to account for differences in document length. We multiply each exposure measure by 100 for readability. The cross symbol corresponds to firms with an exposure index above the year's median.

Figure A.3: Mentions of Police over Time for Firms with a Weak Connection

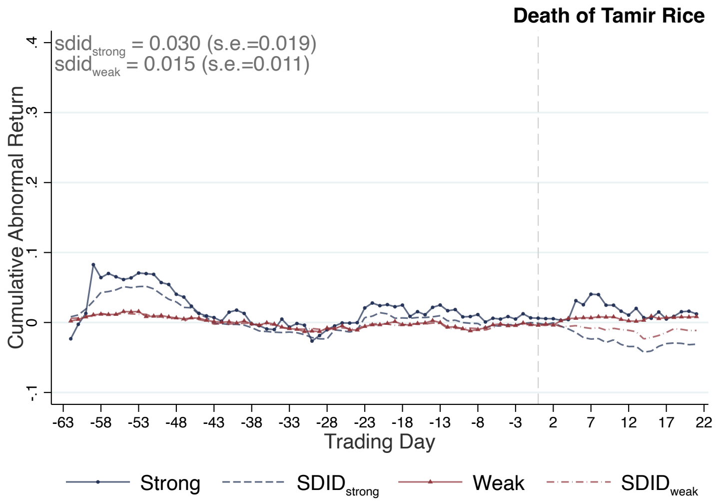
This figure plots the police exposure measures (i.e., intensity) constructed from the annual financial reports from 2010 and 2020. We report the index measure for the weakly connected firms in our sample. To compute the level of intensity, we count the number of times that words associated with the topic appear in the report. Then, we construct the intensity index by dividing this number by the total number of words in the 10-K to account for differences in document length. We multiply each exposure measure by 100 for readability. The cross symbol corresponds to firms with an exposure index above the year's median.

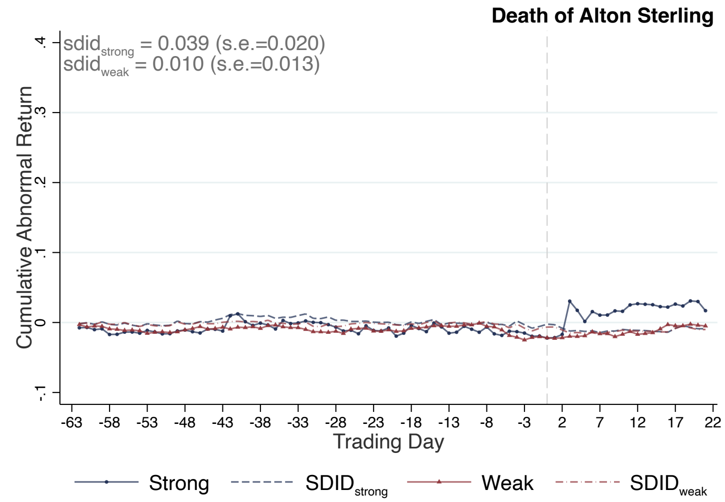
Figure A.4: Daily Impact of High-Profile Incidents on CARs of Connected Firms by Incident (Part 1)

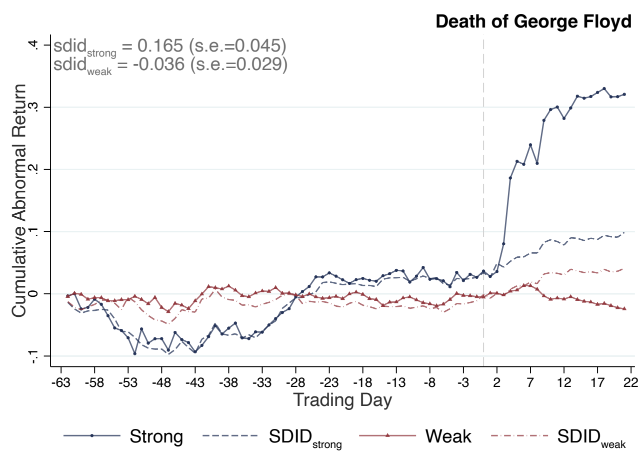


Notes: These figures present the daily impact of high-profile incidents on the cumulative abnormal returns of firms connected to the police industry. We report the CAR trends of the connected firms and their SDID counterfactuals. The vertical dashed line represents the first trading day after the event of interest. The CAR is the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest.

Figure A.5: Short-Term Impact of High-Profile Incidents on CARs of Connected Firms by Incident (Part 2)

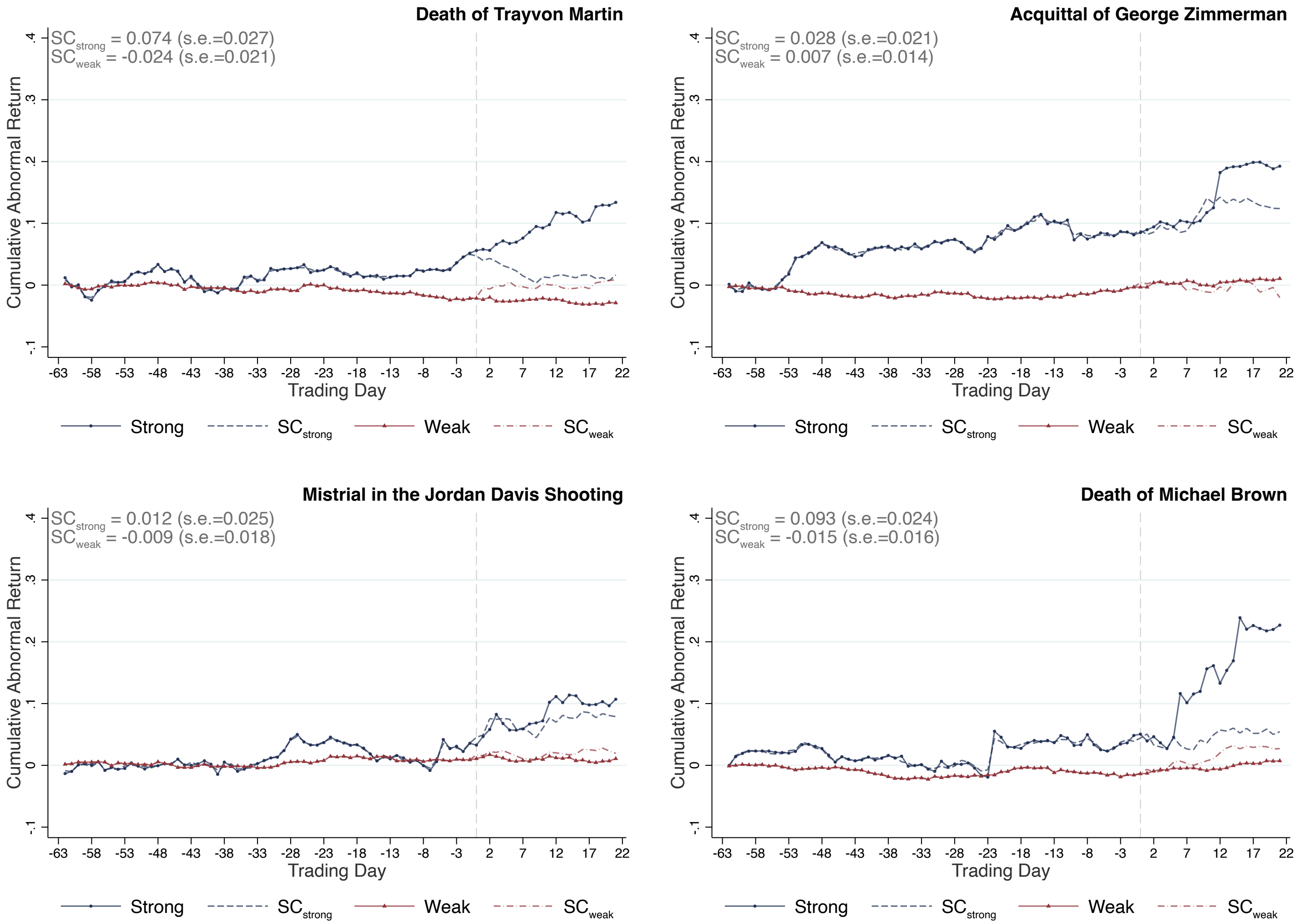






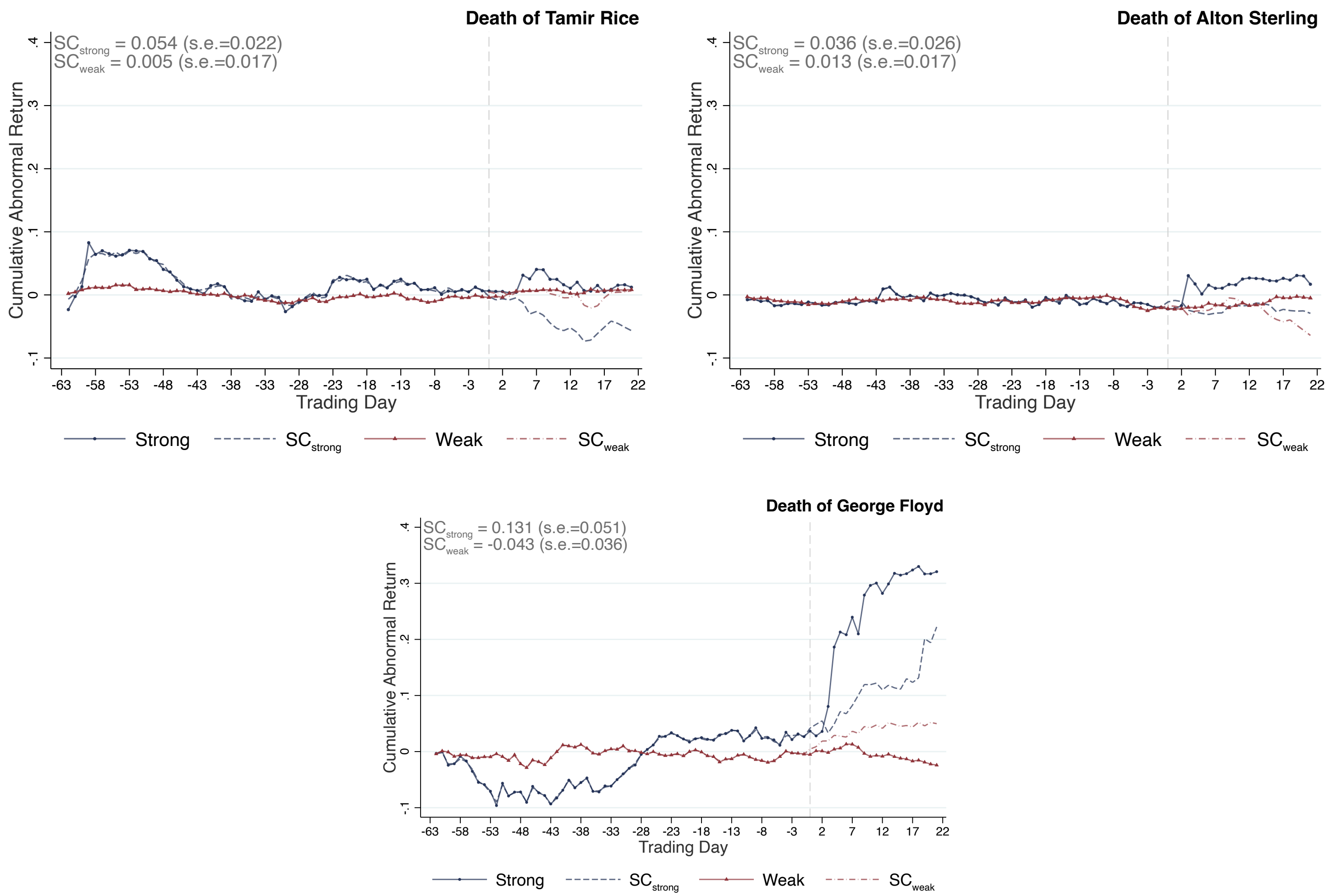
Notes: These figures present the daily impact of high-profile incidents on the cumulative abnormal returns of firms connected to the police industry. We report the CAR trends of the connected firms and their SDID counterfactuals. The vertical dashed line represents the first trading day after the event of interest. The CAR is the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest.

Figure A.6: Daily Impact of High-Profile Incidents on CARs of Connected Firms by Incident Based on SC Method (Part 1)



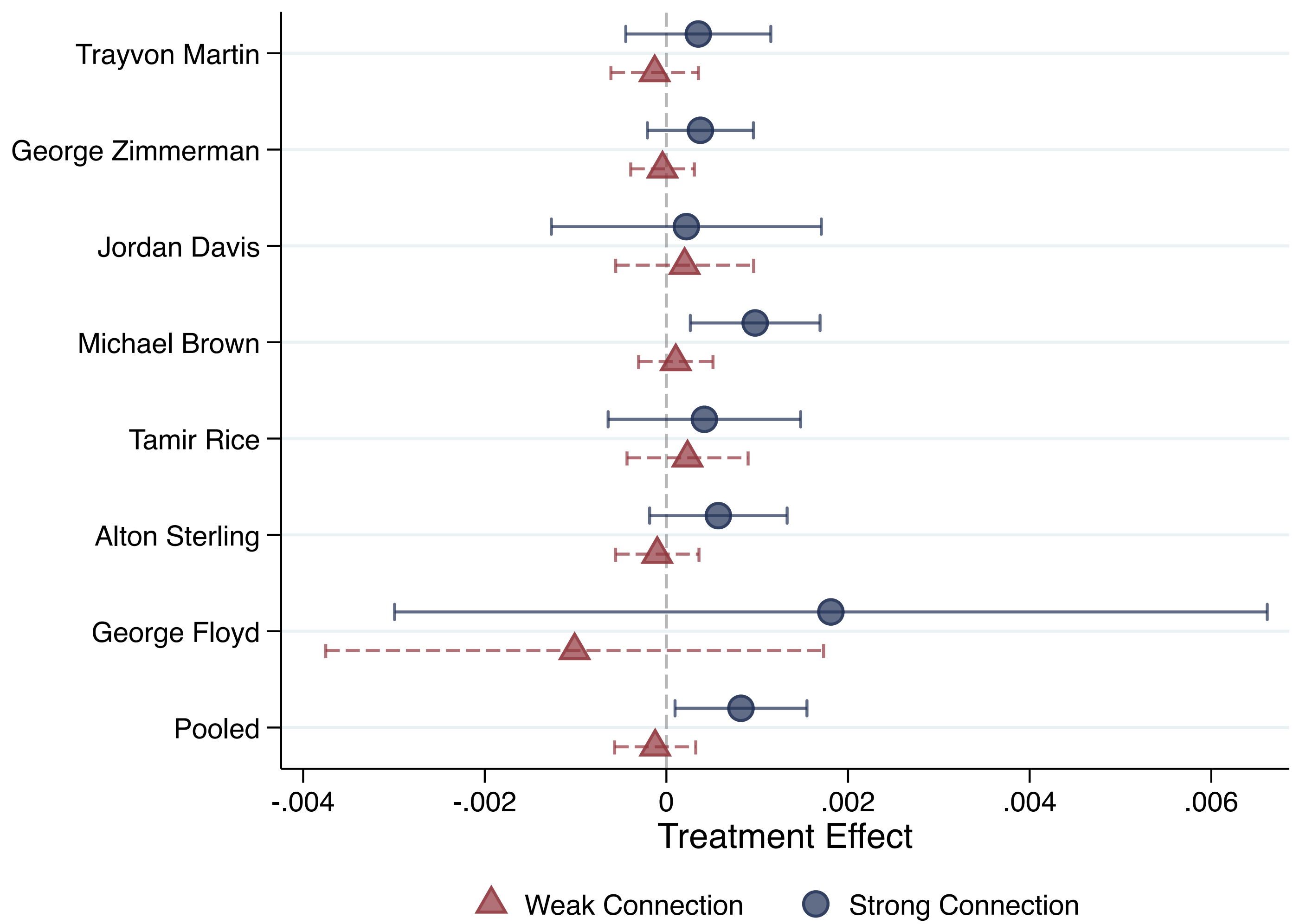
Notes: These figures present the daily impact of high-profile incidents on the cumulative abnormal returns of firms connected to the police industry. We report the CAR trends of the connected firms and their SC counterfactuals. The vertical dashed line represents the first trading day after the event of interest. The CAR is the sum of all abnormal returns since 63 trading days (i.e, a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest.

Figure A.7: Short-Term Impact of High-Profile Incidents on CARs of Connected Firms by Event Based on SC Method (Part 2)



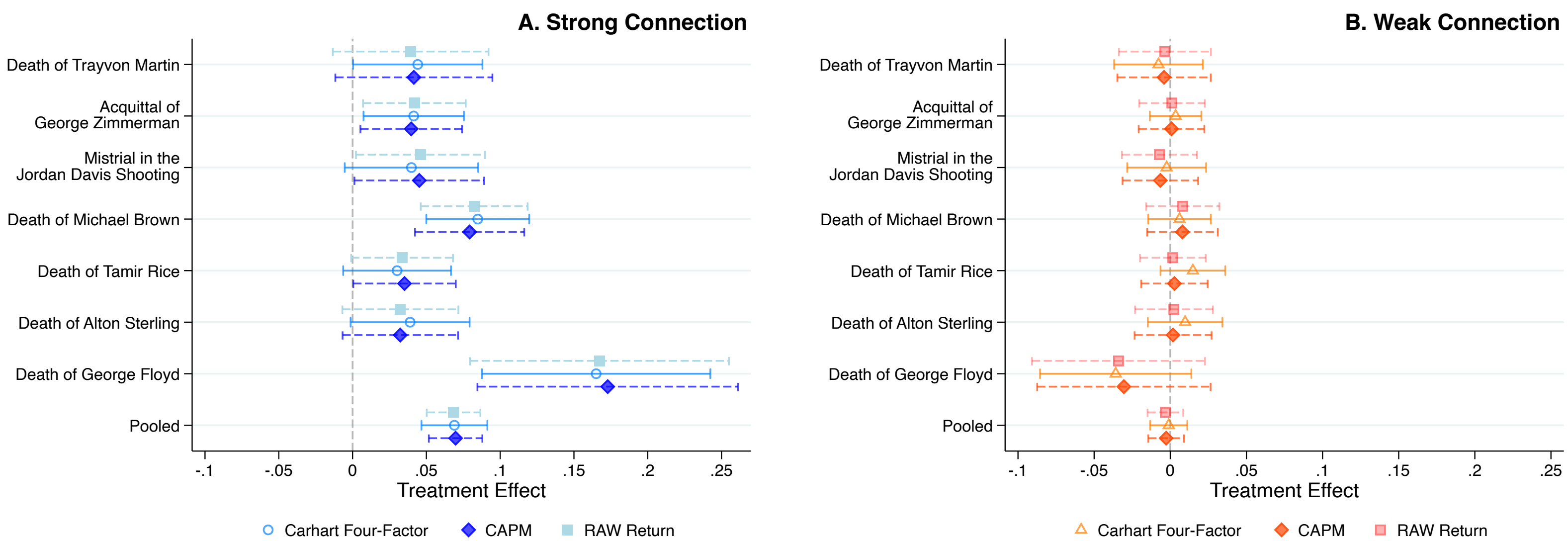
Notes: These figures present the daily impact of high-profile incidents on the cumulative abnormal returns of firms connected to the police industry. We report the CAR trends of the connected firms and their SC counterfactuals. The vertical dashed line represents the first trading day after the event of interest. The CAR is the sum of all abnormal returns since 63 trading days (i.e., a quarter) prior to the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest.

Figure A.8: Daily Impact of High-Profile Incidents on Idiosyncratic Volatility by Incident



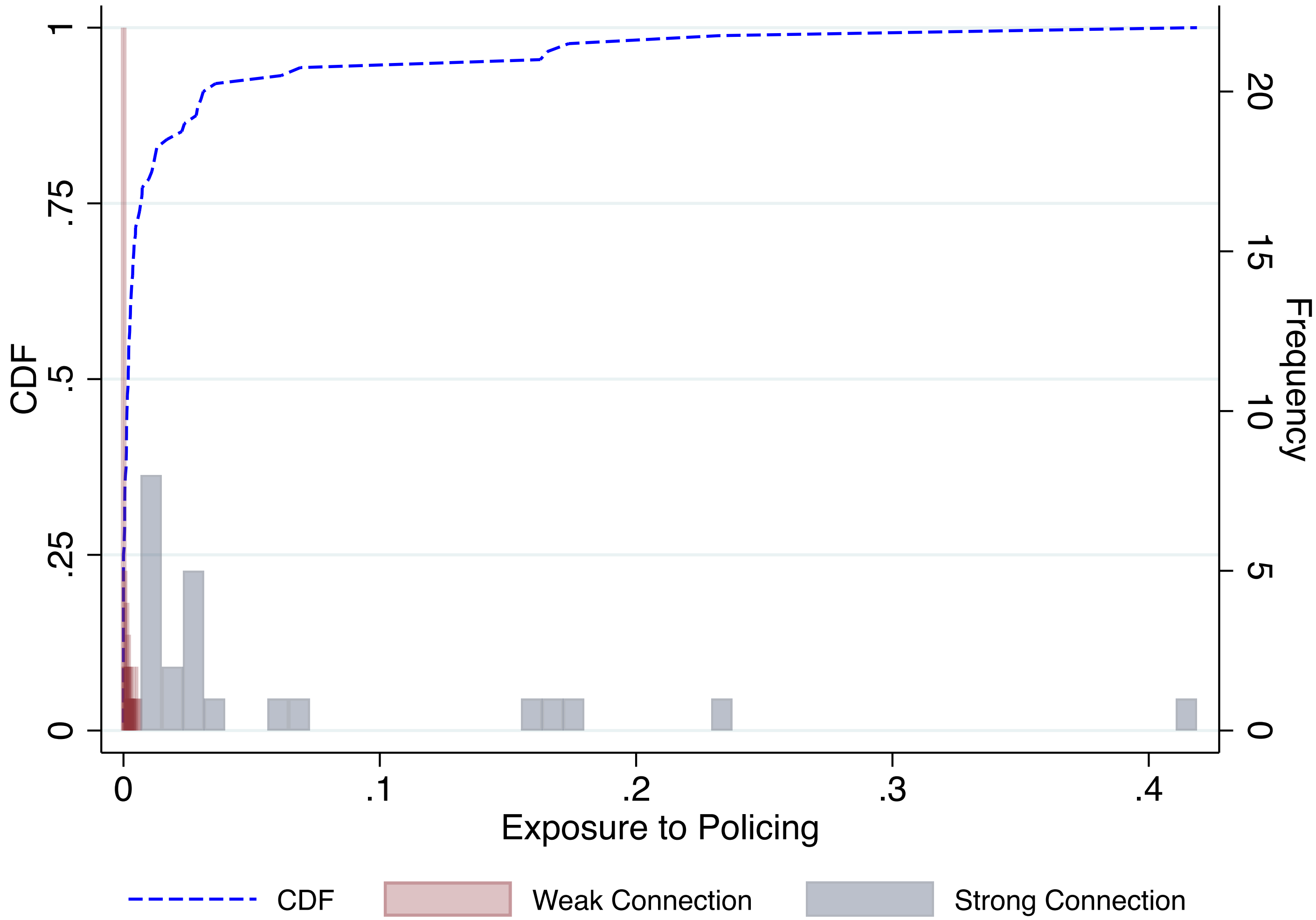
Notes: This figure provides the SDID estimates of the effect of the events on the idiosyncratic volatility and 95% confidence intervals for each high-profile incident. This idiosyncratic volatility is the difference between realized and expected returns calculated from the Carhart four-factor model. Abnormal returns are calculated with the Carhart four-factor model with an estimated 252 trading days ending 30 days before the day of interest.

Figure A.9: Alternative Specifications: Cumulative Returns and CARs Based on Carhart Four-Factor Model and CAPM



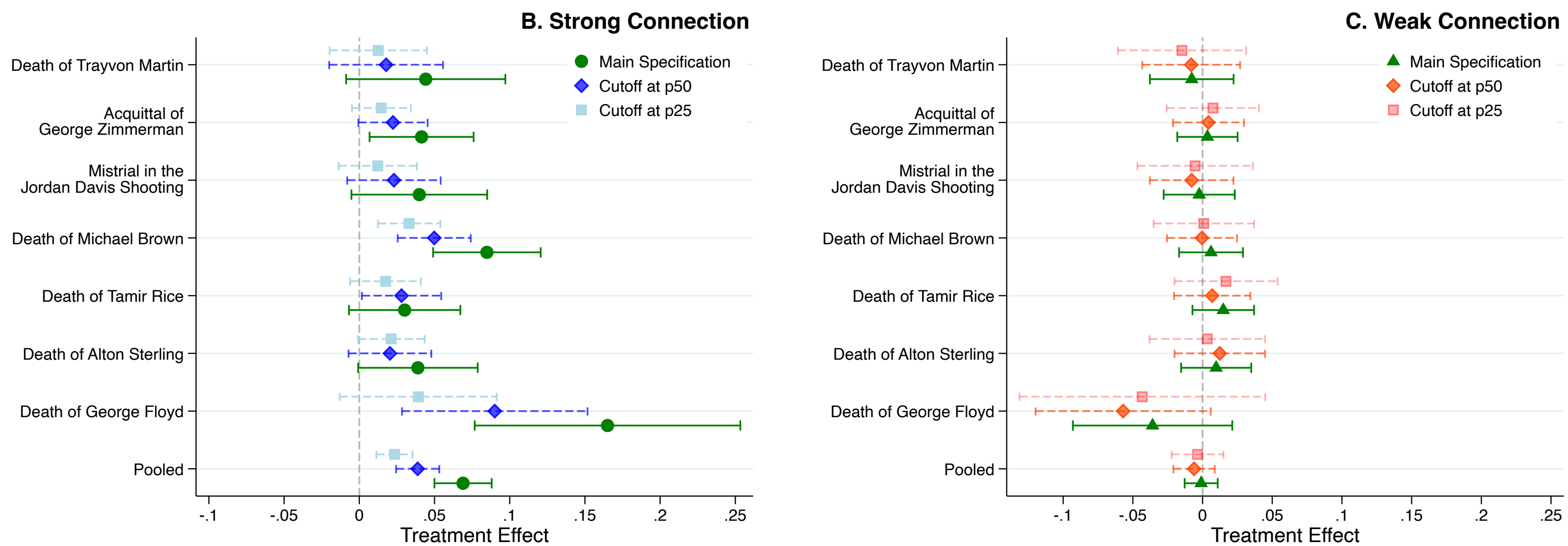
Notes: This figure provides the SDID estimates and 95% confidence intervals for each high-profile incident. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with either the capital asset pricing model (CAPM) or the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest. We also report the SDID estimates based on the cumulative returns.

Figure A.10: Distribution of Exposure to Policing



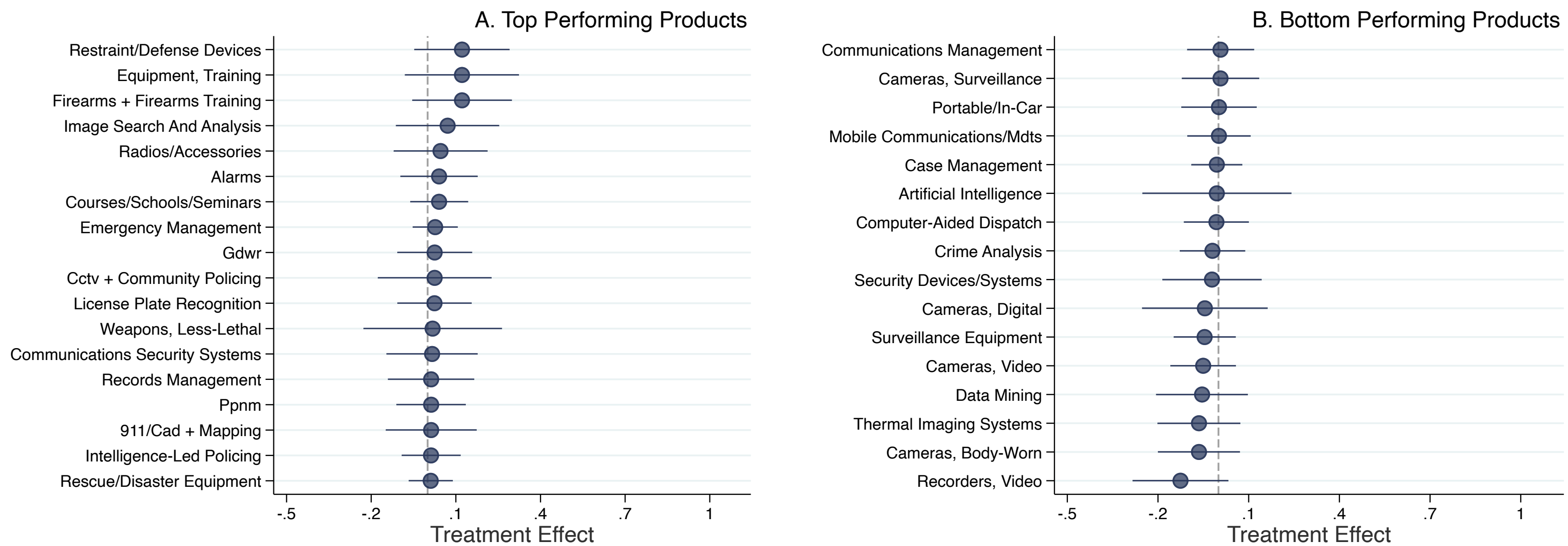
Notes: This figure presents the cumulative distribution function of the measure of exposure to policing (left y-axis) and its frequency (right y-axis) for firms with strong and weak connections to policing. We define firms as having strong connections if their police exposure is above the 75th percentile and as having weak connections otherwise.

Figure A.11: Alternative Specifications: Daily Impact of High-Profile Incidents on CARs by Incident with Different Thresholds for Defining Strong Connections



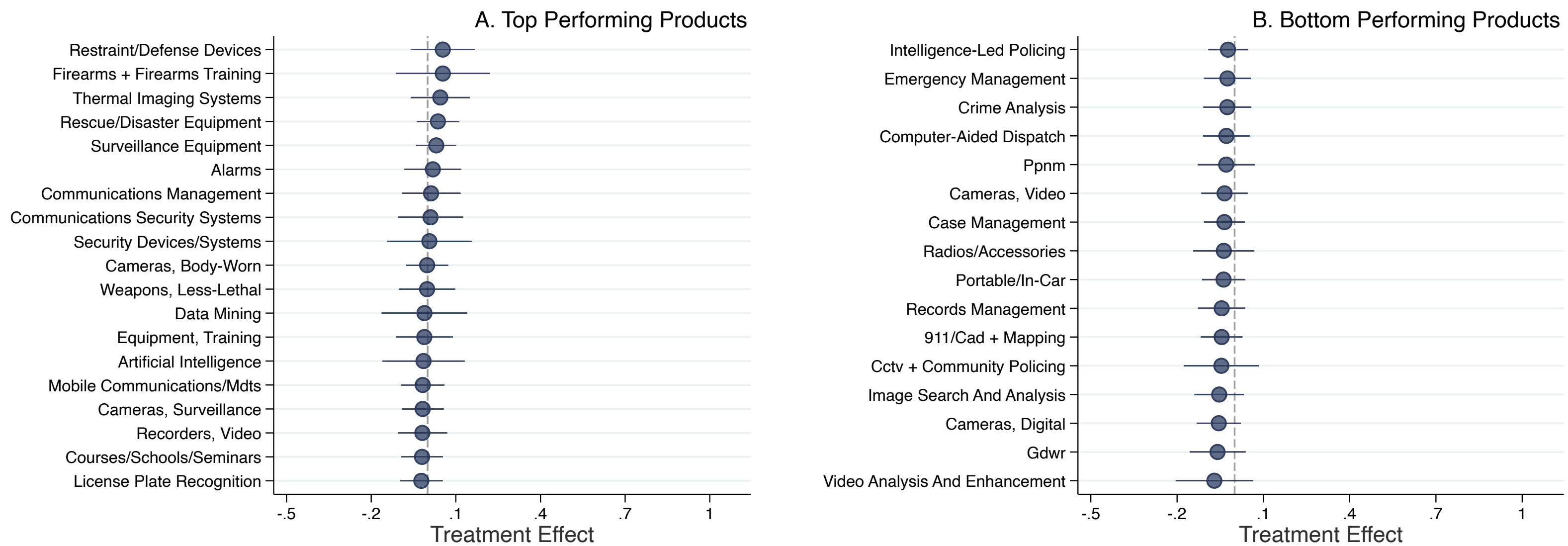
Notes: This figure provides the SDID estimates and 95% confidence intervals for each high-profile incident based on the use of thresholds at the 25th (p25), 50th (p50), and 75th (main specification) percentiles to define strong connections. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest.

Figure A.12: Daily Impact of Trayvon Martin's Death on CARs by Type of Product and Service



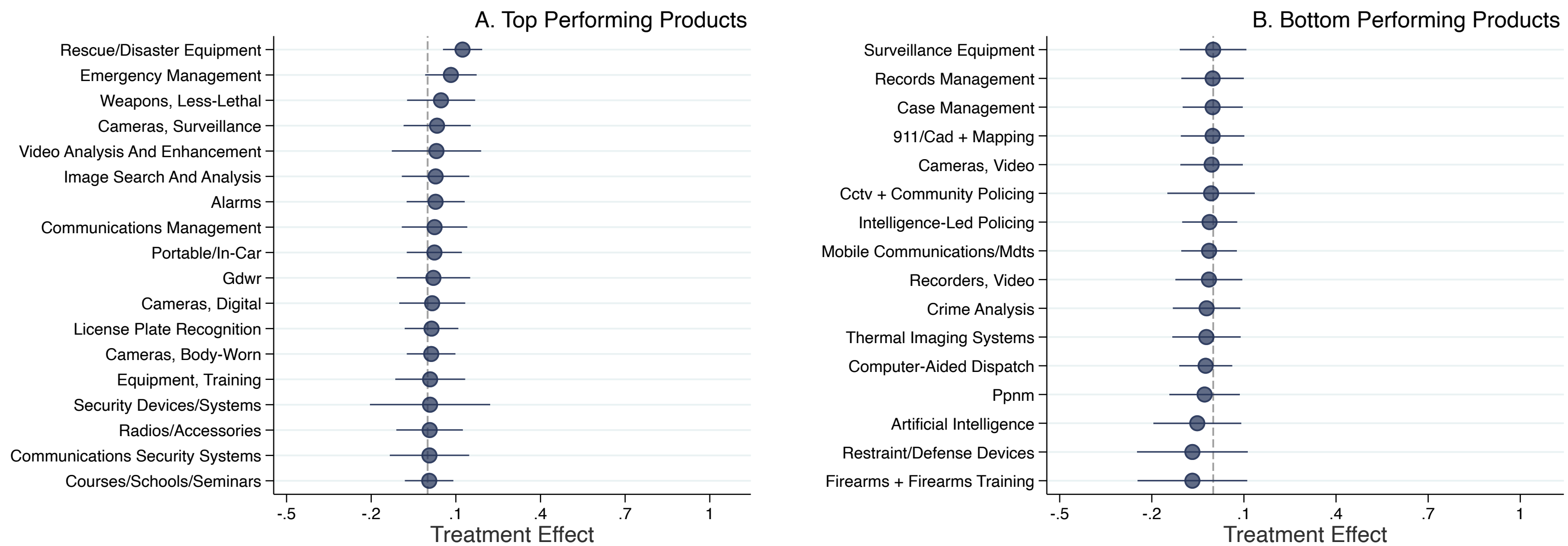
Notes: The figures present the daily impact of Trayvon Martin's murder on firms' CARs by product and service. We report SDID estimates, and standard errors are in parentheses. We report SDID estimates and 95% confidence intervals. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest. GDWR: GPS + detention equipment + evidence storage + report writing. PPNM: personnel management + predictive policing + networks + mobile devices. Alarms: alarms, evacuation + public address equipment.

Figure A.13: Daily Impact of George Zimmerman's Acquittal on CARs by Type of Product and Service



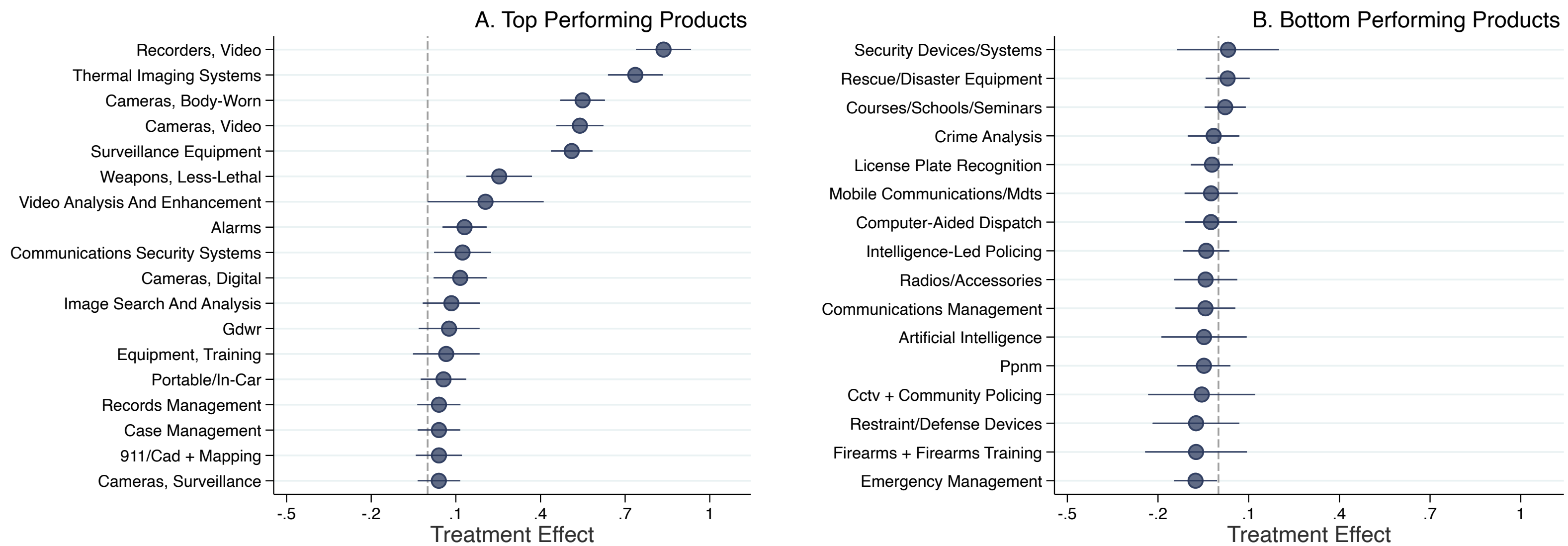
Notes: The figures present the daily impact of George Zimmerman's acquittal on firms' CARs by products and services. We report SDID estimates and 95% confidence intervals. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest. GDWR: GPS + detention equipment + evidence storage + report writing. PPNM: personnel management + predictive policing + networks + mobile devices. Alarms: alarms, evacuation + public address equipment.

Figure A.14: Daily Impact of the Mistrial in the Jordan Davis Case on CARs by Type of Product and Service



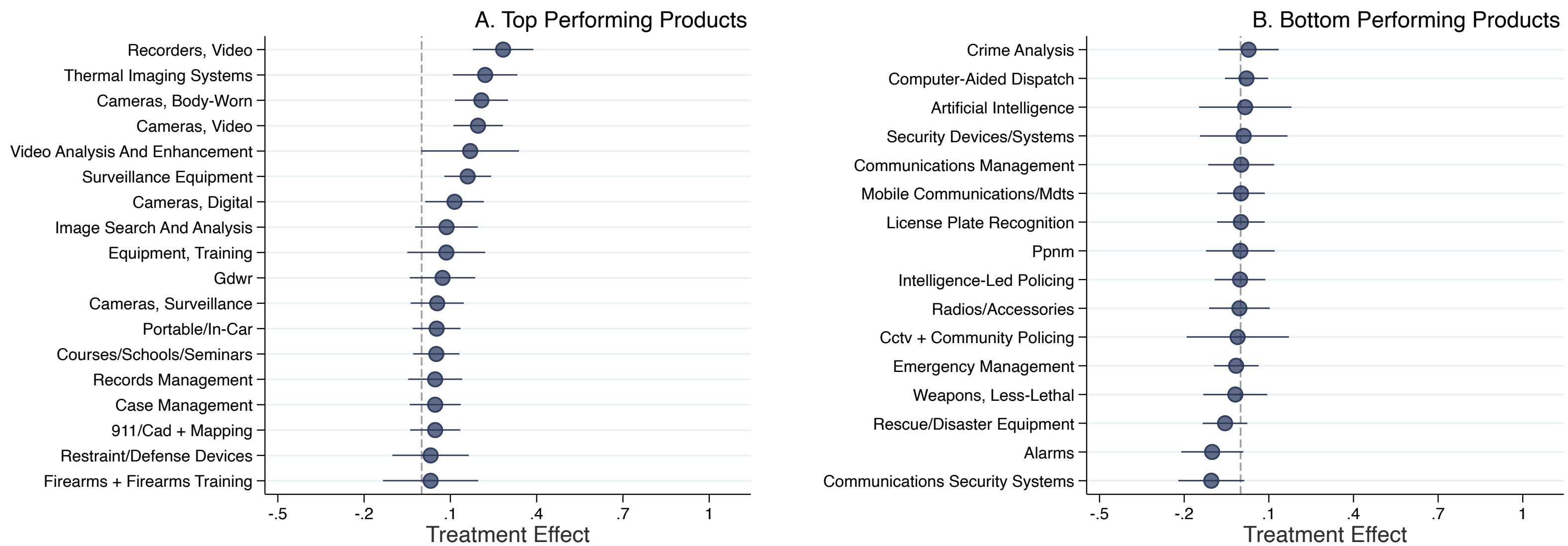
Notes: The figures present the daily impact of the mistrial in the Jordan Davis case on firms' CARs by product and service. We report SDID estimates and 95% confidence intervals. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest. GDWR: GPS + detention equipment + evidence storage + report writing. PPNM: personnel management + predictive policing + networks + mobile devices. Alarms: alarms, evacuation + public address equipment.

Figure A.15: Daily Impact of Michael Brown's Murder on CARs by Type of Product and Service



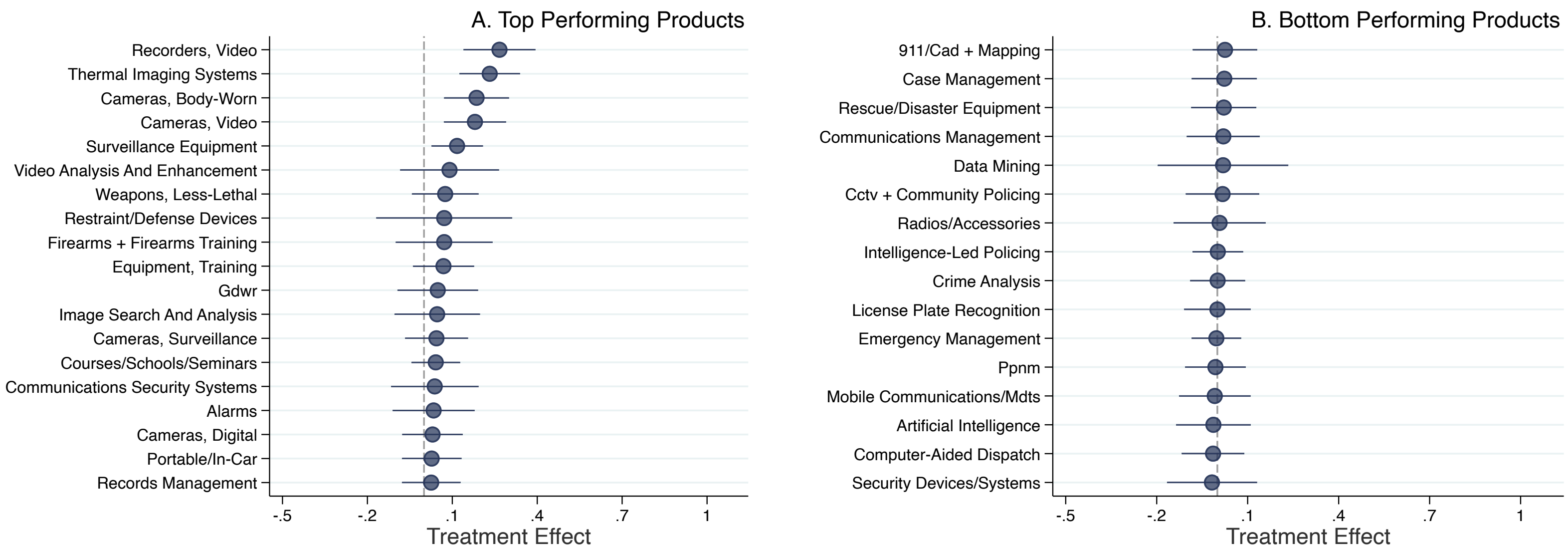
Notes: The figures present the daily impact of Michael Brown's murder on firms' CARs by product and service. We report SDID estimates and 95% confidence intervals. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest. GDWR: GPS + detention equipment + evidence storage + report writing. PPNM: personnel management + predictive policing + networks + mobile devices. Alarms: alarms, evacuation + public address equipment.

Figure A.16: Daily Impact of Tamir Rice's Murder on CARs by Type of Product and Service



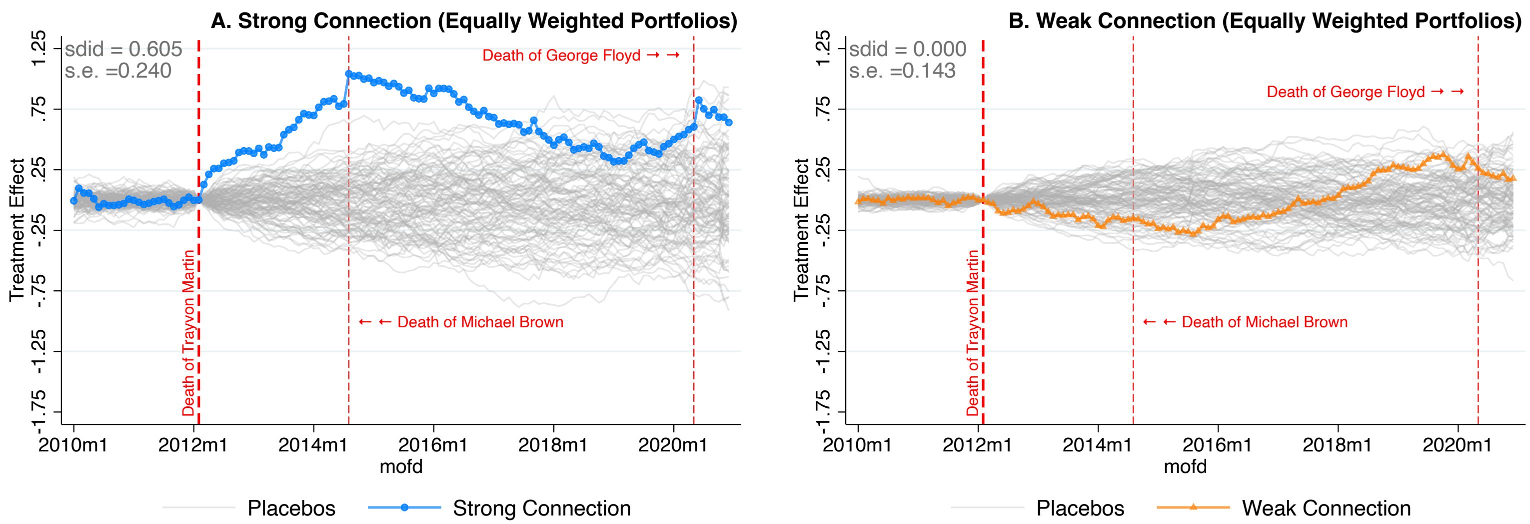
Notes: The figures present the daily impact of Tamir Rice's murder on firms' CARs by product and service. We report SDID estimates and 95% confidence intervals. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest. GDWR: GPS + detention equipment + evidence storage + report writing. PPNM: personnel management + predictive policing + networks + mobile devices. Alarms: alarms, evacuation + public address equipment.

Figure A.17: Daily Impact of Alton Sterling's Murder on CARs by Type of Product and Service



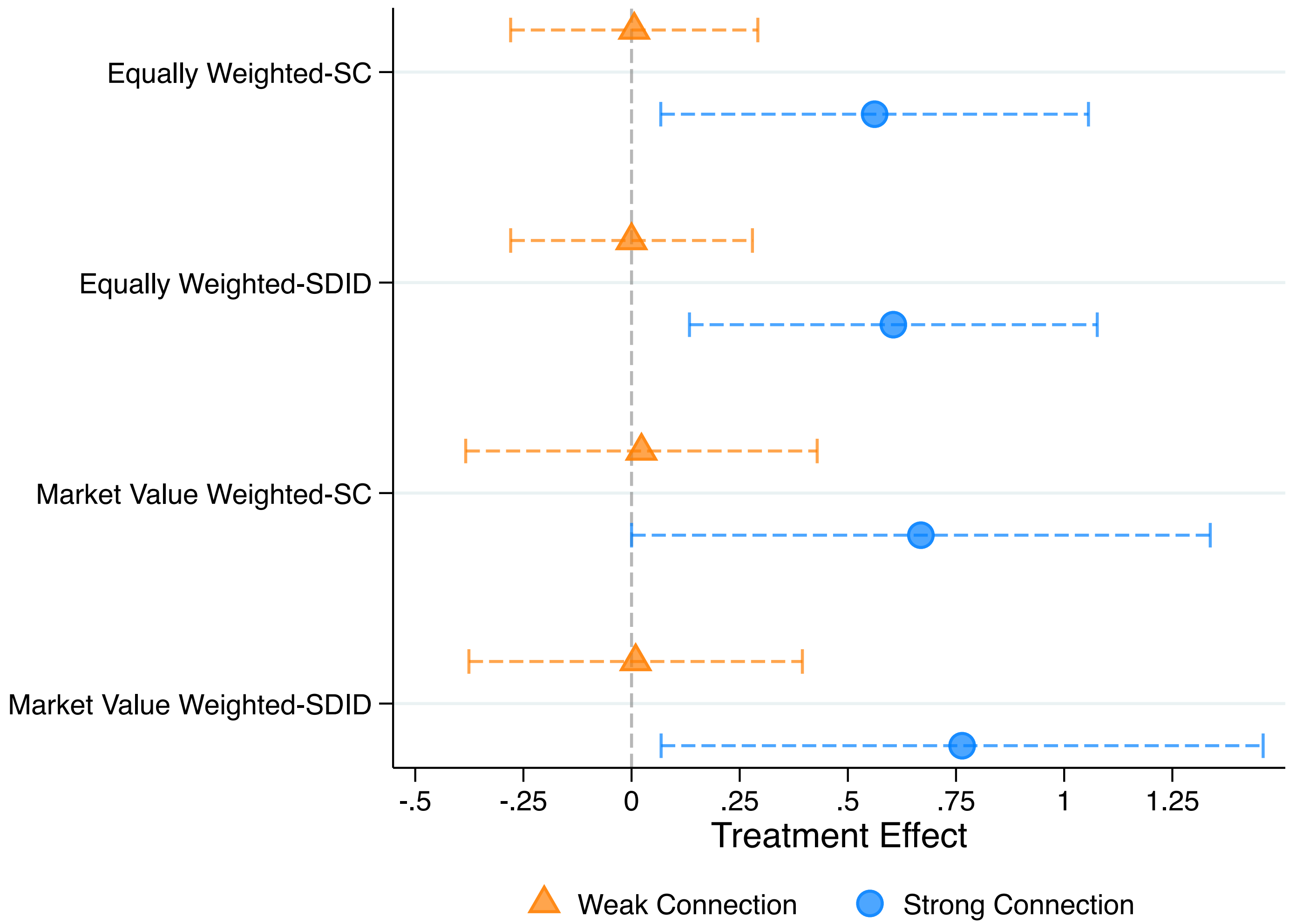
Notes: The figures present the daily impact of Alton Sterling's murder on firms' CARs by product and service. We report SDID estimates and 95% confidence intervals. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest. GDWR: GPS + detention equipment + evidence storage + report writing. PPNM: personnel management + predictive policing + networks + mobile devices. Alarms: alarms, evacuation + public address equipment.

Figure A.18: Long-Run Impact of BLM on Cumulative Abnormal Portfolio Returns (Equally Weighted)



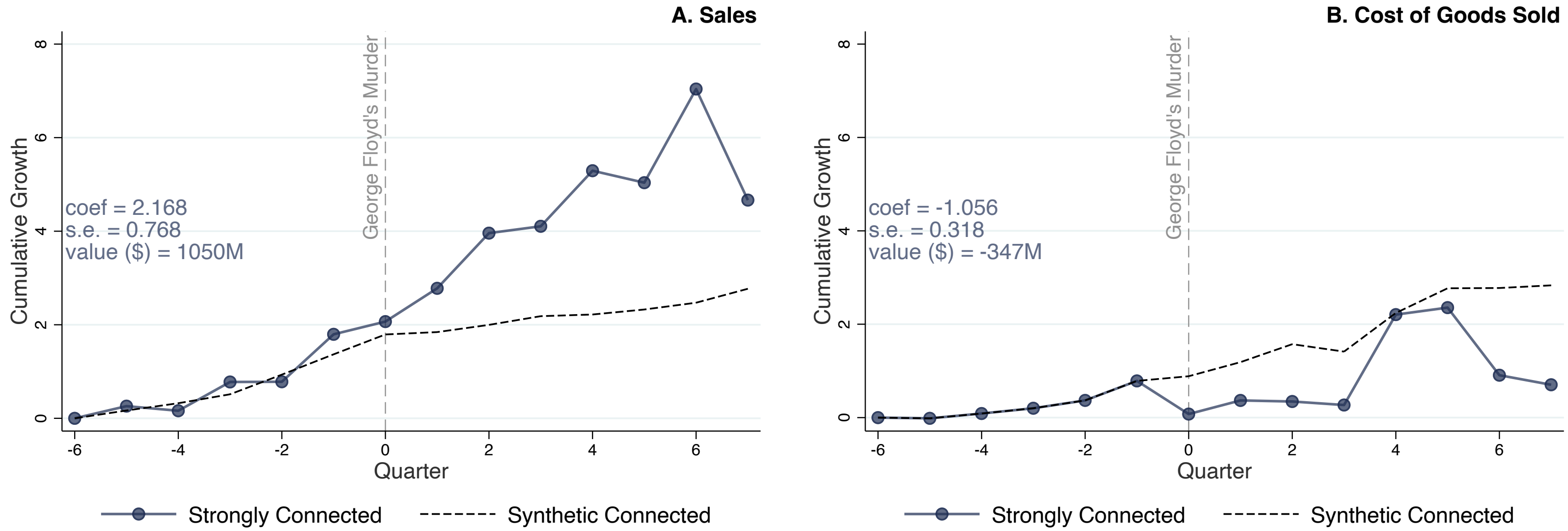
Notes: Figures A and B present the long-run impact of Trayvon Martin's death on the cumulative abnormal portfolio returns of firms with strong and weak connections to the police industry. This specification considers passive investors' portfolios with equally weighted portfolios. We report the treatment effect of the incident on the CARs of treated firms. The treatment effect is the gap in CARs between the actual portfolios and their synthetic counterfactuals. The red vertical dashed line represents the month of Trayvon Martin's death. We also report the treatment effects of the placebo groups. The SDID estimates are computed from the sum of all abnormal returns since January 2010. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 60 months ending 30 months before the day of interest.

Figure A.19: Alternative Specifications: Long-Run Impact of BLM



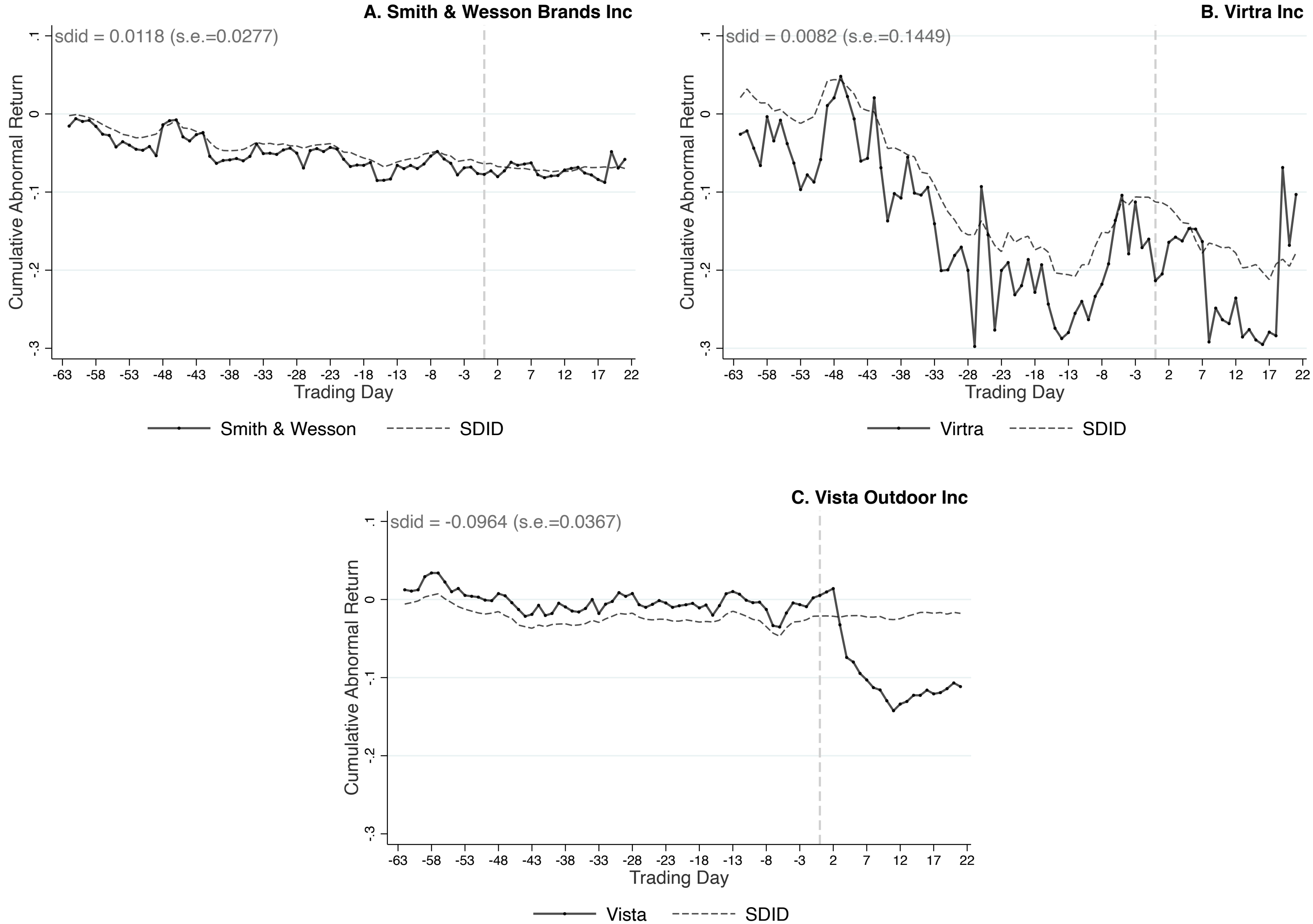
Notes: This figure provides alternative specifications of the long-run impact of the BLM uprisings. We report the SDID and SC estimates and 95% confidence intervals for each high-profile incident. These specifications consider passive investors' portfolios with either equally or market-weighted portfolios. In addition, we report the treatment effect of the event on the CARs of treated firms. The SDID estimates are computed from the sum of all abnormal returns since January 2010. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 60 months ending 30 months before the day of interest.

Figure A.20: Impact of George Floyd's Murder on Sales and Cost of Goods Sold Based on Synthetic Control Method



Notes: Figures A and B present the impact of George Floyd's murder on the cumulative growth (relative to the first period) of the sales and cost of goods sold for firms with strong ties to the police industry. The treatment effect is the gap in outcomes between the actual firms with strong connections and their synthetic counterfactuals. We report the SC estimates and the standard errors. We also report the dollar amount associated with the treatment effects relative to the outcomes in the first period in the analysis. The vertical dashed line represents the quarter of George Floyd's death.

Figure A.21: Daily Impact of Mass Shootings on Firearms Suppliers' CARs



Notes: These figures present the daily impact of mass shooting incidents on the cumulative abnormal return of firms providing firearms and firearm training. We report the CAR trends of the connected firms and their SDID counterfactuals. The vertical dashed line represents the first trading day after the event of interest. We report SDID estimates, and standard errors are in parentheses. The SDID estimates are computed from the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest.

Table A.1: Topic Keywords

Topics	Keywords
Police	police, policing, sheriff, trooper, law enforcement
Government	dod, dhs, doj, dea, cia, public, uk, united states, united kingdom, australia, canada, japan, republic of, canadian, french republic, france, israel, spain, italy, mexican, mexico, singapore, kingdom of saudi, city, baltimore, chicago, new york, university of cali, washington, enforcement, sheriff, trooper, army, armed force district of columbia, state of, county, ministry, department of, commonwealth, law

Table A.2: Event Study of the Impact of High-Profile Incidents on CARs

	(1) CAR[0,1]	(2) CAR[0,7]	(3) CAR[0,14]	(4) CAR[0,21]
Strong Tie	0.00358	0.0416**	0.0575**	0.0643**
	(0.00424)	(0.0178)	(0.0273)	(0.0298)
Weak Tie	-0.000833	0.00778*	0.00953	0.0103
	(0.00211)	(0.00471)	(0.00704)	(0.00838)
Size	-0.00113**	-0.00410***	-0.00636***	-0.00788***
	(0.000491)	(0.00104)	(0.00162)	(0.00180)
Profitability	-0.00118	0.000228	-0.00348	0.0218
	(0.00656)	(0.00939)	(0.0150)	(0.0170)
Leverage	0.000133	0.000240	0.000499	0.000667**
	(0.000117)	(0.000267)	(0.000336)	(0.000330)
Observations	3535	3535	3535	3535

Notes: The table presents the daily impact of high-profile incidents on the cumulative abnormal returns of firms connected to the police industry. Each outcome, $CAR_i[n,m]$, is the cumulative abnormal return over the window of $[n,m]$, where the event day is set to 0. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest. All the regressions include location, event, and industry fixed effects. Standard errors are clustered at the firm level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.3: Impact of Mass Shootings on Smith & Wesson's CARs

	(1) CAR[0,1]	(2) CAR[0,7]	(3) CAR[0,14]	(4) CAR[0,21]
Strong Tie	-0.0448***	0.0413	-0.0660	0.124***
	(0.0164)	(0.0341)	(0.0446)	(0.0437)
Size	0.000858	0.000393	-0.00152	-0.00197
	(0.000755)	(0.00130)	(0.00213)	(0.00214)
Profitability	-0.00359	0.0178	0.0220	0.0328
	(0.00318)	(0.0160)	(0.0227)	(0.0247)
Leverage	0.0000331	-0.00102	-0.00153**	-0.000968
	(0.000304)	(0.000624)	(0.000773)	(0.000772)
Observations	1075	1075	1075	1075

Notes: The table presents the daily impact of mass shootings on the cumulative abnormal returns of Smith & Wesson Brands Inc. Each outcome, $CAR_i[n,m]$, is the cumulative abnormal return over the window of $[n,m]$, where the event day is set to 0. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest. All the regressions include location, event, and industry fixed effects. We report bootstrap standard errors. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.4: Impact of Mass Shootings on VirTra CARs

	(1)	(2)	(3)	(4)
	CAR[0,1]	CAR[0,7]	CAR[0,14]	CAR[0,21]
Strong Tie	-0.0447***	0.0408	-0.0670	0.120***
	(0.0170)	(0.0356)	(0.0475)	(0.0418)
Size	0.000847	0.000364	-0.00154	-0.00200
	(0.000666)	(0.00139)	(0.00188)	(0.00208)
Profitability	-0.00359	0.0177	0.0218	0.0325
	(0.00315)	(0.0156)	(0.0211)	(0.0231)
Leverage	0.0000331	-0.00103*	-0.00154*	-0.000978
	(0.000291)	(0.000553)	(0.000842)	(0.000737)
Observations	1064	1064	1064	1064

Notes: The table presents the daily impact of mass shootings on the cumulative abnormal returns of VirTra Inc. Each outcome, $CAR_i[n,m]$, is the cumulative abnormal return over the window of $[n,m]$, where the event day is set to 0. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest. All the regressions include location, event, and industry fixed effects. We report bootstrap standard errors. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.5: Impact of Mass Shootings on Vista's CARs

	(1) CAR[0,1]	(2) CAR[0,7]	(3) CAR[0,14]	(4) CAR[0,21]
Strong Tie	0.00533	-0.0880	-0.104**	-0.0867*
	(0.0146)	(0.0567)	(0.0484)	(0.0517)
Size	0.000837	0.000421	-0.00157	-0.00204
	(0.000680)	(0.00149)	(0.00194)	(0.00220)
Profitability	-0.00366	0.0167	0.0222	0.0331
	(0.00368)	(0.0149)	(0.0227)	(0.0225)
Leverage	0.0000341	-0.00103**	-0.00154**	-0.000967
	(0.000286)	(0.000496)	(0.000693)	(0.000665)
Observations	1070	1070	1070	1070

Notes: The table presents the daily impact of mass shootings on the cumulative abnormal returns of Vista Outdoor Inc. Each outcome, $CAR_i[n,m]$, is the cumulative abnormal return over the window of $[n,m]$, where the event day is set to 0. Abnormal returns are calculated with the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest. All the regressions include location, event, and industry fixed effects. We report bootstrap standard errors. $***p < 0.01$; $**p < 0.05$; $*p < 0.1$.

Table A.6: Products and Services by Firm

Category	Firms
license plate recognition	federal signal corp; motorola solutions inc; veritone inc; l3 technologies inc
image search and analysis	federal signal corp; veritone inc; axon enterprise inc
alarms, evacuation + public address equipment	federal signal corp; genasys inc
emergency management	federal signal corp; motorola solutions inc; tyler technologies inc; lojack corp
radios/accessories	federal signal corp; motorola solutions inc
intelligence-led policing	federal signal corp; motorola solutions inc; textron inc; tyler technologies inc
GPS + Detention Equip + Evidence Storage + Report Writing	motorola solutions inc; axon enterprise inc
911/CAD + Mapping	motorola solutions inc; tyler technologies inc; axon enterprise inc
mobile communications/mdts	motorola solutions inc; tyler technologies inc; l3 technologies inc
crime analysis	motorola solutions inc; textron inc; faro technologies inc
portable/in-car	motorola solutions inc; l3 technologies inc; axon enterprise inc
courses/schools/seminars	motorola solutions inc; textron inc; virtra inc; smith & wesson brands inc; axon enterprise inc
case management	motorola solutions inc; textron inc; tyler technologies inc; veritone inc; axon enterprise inc
CCTV + Community Policing	motorola solutions inc; shotspotter inc
cameras, video	motorola solutions inc; axon enterprise inc; digital ally inc
communications management	motorola solutions inc; flir systems inc
computer-aided dispatch	motorola solutions inc; tyler technologies inc; faro technologies inc
communications security systems	motorola solutions inc; genasys inc
records management	motorola solutions inc; tyler technologies inc; veritone inc; axon enterprise inc
cameras, surveillance	motorola solutions inc; flir systems inc; axon enterprise inc

Table A.7: Products and Services by Firm

Category	Firms
Personnel Mgt + Predictive Policing + Networks + Mobile Devices	motorola solutions inc; tyler technologies inc
surveillance equipment	textron inc; flir systems inc; shotspotter inc; l3 technologies inc; digital ally inc
data mining	textron inc; veritone inc
artificial intelligence	tyler technologies inc; veritone inc
rescue/disaster equipment	lojack corp; genasys inc; flir systems inc; l3 technologies inc
weapons, less-lethal	genasys inc; axon enterprise inc
cameras, body-worn	flir systems inc; axon enterprise inc; digital ally inc
thermal imaging systems	flir systems inc; digital ally inc
video analysis and enhancement	veritone inc; axon enterprise inc
security devices/systems	shotspotter inc; l3 technologies inc
restraint/defense devices	wrap technologies; smith & wesson brands inc
equipment, training	virtra inc; smith & wesson brands inc; axon enterprise inc
Firearms + Firearms Training	virtra inc; smith & wesson brands inc
cameras, digital	faro technologies inc; axon enterprise inc
recorders, video	axon enterprise inc; digital ally inc

Table A.8: Deadliest Mass Shootings in the US from 2010 to 2020

Location and Date	No. of Deaths
Aurora, CO, 7/12/2012	12
Newtown, CT, 12/14/2012	27
Washington, DC, 9/16/2013	12
San Bernardino, CA, 12/2/2015	14
Orlando, FL, 6/12/2016	49
Las Vegas, NV, 10/1/2017	58
Sutherland Springs, TX, 11/5/2017	25
Parkland, FL, 2/14/2018	17
Thousand Oaks, CA, 11/8/2018	12
Virginia Beach, VA, 5/31/2019	12
El Paso, TX, 8/2/2019	22

Table A.9: White Supremacist Incidents from the Anti-Defamation League

Location and Date	Attacker	No. of Deaths	Google News Articles
Overland Park, KS, 4/13/2014	Frazier Glenn Miller	3	443
Charleston, SC, 6/17/2015	Dylann Storm Roof	9	1090
New York, NY, 3/30/2017	James Harris Jackson	1	182
Charlottesville, VA, 8/12/2017	James Alex Fields	1	86,400
Lake Forest, CA, 1/2/2018	Samuel Woodward	1	145
Shawnee, KS, 7/2/2018	Ronald Lee Tidwell	1	4840
Pittsburgh, PA, 10/27/2018	Robert Gregory Bowers	11	372
Poway, CA, 4/27/2019	John T. Earnest	1	307