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FORECASTING THE IMPACT OF RACIAL UPRISINGS, MARKET VERSUS STAKEHOLDERS' EXPECTATIONS

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ABSTRACT

Given police abolitionism's new visibility after the 2020 racial justice protests, we assess stakeholder beliefs on the protests' stock impacts on police-affiliated firms. Experts generally underestimate the firms' stock gains, except situated experts like community organizers and police experts, who link the market responses to reforms, not budget cuts. An experiment with nonexperts and finance professionals shows negatively skewed stock predictions among respondents lacking information on policing products and no effect of exposure to narratives about the protests on forecast alignment. National data show enduring support for police reform despite abolitionist advocacy and little understanding of the Defund movement's objectives.

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1 Introduction

Over the past decade, the Black Lives Matter (BLM) movement has illuminated the pervasive racial injustice in America (Akbar, 2020). The movement has also drawn attention to the significant impact of public policies and funding allocation on racial minorities (D'Acunto et al., 2020; Alesina et al., 2021; Cook et al., 2022). Incidents of police violence, in particular, have catalyzed the largest and longest-lasting protest movement in U.S. history (New York Times (2020)). In response to this violence, BLM advocacy has helped bring into the mainstream the longstanding calls of Black prison and police abolitionists to defund the police (Gilmore, 2007; Davis, 2011; Kaba et al., 2021).[1] Despite this, there is evidence that the police industry benefitted from the BLM movement (Ba et al., 2023). This paper assesses the beliefs held by various stakeholders on how this new visibility of abolitionist arguments is likely to have impacted the police industry in the aftermath of the summer 2020 protests.[2]

We survey experts and members of the public on how they expect the market to have been impacted by the 2020 racial uprisings. Finance experts and other nonspecialists consistently underestimate the stock gains experienced by police-related firms in the wake of George Floyd's murder. In contrast, on-the-ground experts, including community organizers and police specialists, accurately predict these gains and attribute them to public demand for police reform. To understand why various experts and nonexperts systematically underestimate the stock gains, we run an experiment where we randomize the provision of narrative and product information. We find that respondents not exposed to information about the products marketed by police-connected firms have more negatively skewed stock predictions than those treated with this information. Moreover, narrative information does not substantially improve forecasts and, in some cases, makes them worse. By coding and analyzing free text responses, we suggest that this is because experts and nonexperts overestimate the influence of arguments related to police budget cuts (*budget cuts*) and decreasing levels of trust in the police (*less trust*). Finally, we use data from the Cooperative Congressional Election Study (CCES) to provide further evidence that the emphasis experts and nonexperts place on *less trust* and *budget cuts* does not reflect the preferences of voters in the United States. Abolitionists' "defund the police" campaign has boosted support for budget cuts but has not shifted the existing strong backing for reforming the police by means of costly accountability measures, suggesting that Defund's increased visibility may have distorted perceptions of the relative purchase of

[1] One of the main argument of abolitionists is that "reformist reforms" (body-worn cameras, training, etc) continue or expand the reach of policing without reducing harm and violence against marginalized groups (Gilmore (2007); Vitale (2017); Critical Resistance (2020))

[2] A variety of stakeholders with nonpecuniary motivations (Bénabou and Tirole, 2010; Broccardo et al., 2022) influence policies related to police funding. For instance, in the context of the Defund movement or support for police abolition, the role of social pressures cannot be overlooked. Preference falsification (Kuran, 1995) or social cover (Bursztyn et al., 2022) can influence public willingness to express dissenting views on defunding. These factors add complexity to how stakeholders such as voters, law enforcement, community organizers, and academics influence policies on police funding.

police abolitionist and reformist arguments in public opinion.

Navigating the complexities of how expertise interacts with public opinion and policy in the realm of racial justice presents both opportunities for innovation and challenges. Our study fills three gaps in the scholarship on racial justice expertise: it explores underexamined advocate perspectives on reducing the scope of policing in our society (Akbar, 2020; Davies et al., 2021), evaluates which types of expertise are valuable for yielding social insights, and identifies factors affecting expert consensus (DellaVigna and Pope, 2018; DellaVigna et al., 2019). However, a key limitation is the lack of a comprehensive survey capturing diverse expert opinions, which has constrained rigorous analysis to date.

We address this challenge and deliver these innovations in several steps. First, we surveyed experts and nonexperts on their predictions of the impact on police-related firms' stocks following George Floyd's murder, providing them with comprehensive background information. We then compared these forecasts to those in Ba et al. (2023), which shows a 16.5-percentage-point (pp) boost in the return of police-tied stocks three weeks after the event. This method allows us not only to gauge stakeholder beliefs against an empirical baseline but also to inform policy debates on police funding by highlighting the stock market's role in aggregating information on the impacts of social movements on firm performance.

Second, we surveyed 372 experts from various fields—finance, law, policing, community organizing, and academia—and 139 nonexperts to gauge their predictions on the stock performance of police-related firms after George Floyd's murder. Our analysis reveals that both nonexperts and experts without on-the-ground knowledge underestimated these firms' gains. On the other hand, community organizers and police experts offered forecasts more closely aligned with the firms' actual performance, suggesting less bias and a better understanding of the dynamics behind market reactions to such events among these groups. However, we also find that all groups underestimated the actual rise in stock values. Prediction variability is highest among nonexperts and community organizers, indicating less consensus within these groups. In contrast, finance and law experts show the least variability, with both groups anticipating a more modest market response.

Next, we investigate the influence on stock forecasts of an information treatment in which we randomly assigned over 2,300 nonexperts and nearly 500 finance professionals to one of four groups, each with exposure to different types of information. The first group was provided with minimal information along with a prompt for the forecast. The second group received the comprehensive background information provided to respondents in the first expert survey, including both narrative information and details on the products offered by policing-connected firms. The remaining two groups were exposed to either narrative information about the aftermath of George Floyd's murder—namely, details on the calls for police defunding and reform as well as crime rates—or details about the products offered by police-related firms.

Prior to the treatment, over 70% of survey respondents predicted little or no change in portfolio value following George Floyd's murder. The product information treatment shifted this share, with over 50% predicting an increase in value, though uncertainty remained. Finance professionals and nonexperts processed information differently: nonexperts' forecasts improved when they received full information, while those of finance professionals were more accurate when they were given product details rather than narrative information.

As a complement to respondents' forecasts, we also delved into the reasoning behind their predictions. Furthermore, the randomized information treatment allows us to identify how knowledge of policing products and narratives associated with summer 2020 influences respondents' thought processes. We manually code the content of respondents' explanations of their predictions into various categories that include reasoning associated with "defund the police" (*budget cuts*), police *reform*, or a general decline in public trust of the police (*less trust*), to name a few.

In the nonexpert survey, the number of references to *reform*-related arguments decreased substantially in the absence of product information. We suspect that this is because exposure to this information causes participants to consider investment in police reform-related technologies such as body-worn cameras. We find a similar, albeit smaller, effect in our survey of finance professionals. Among nonexperts and finance professionals, *budget cut*–related arguments are prevalent when narrative information is provided. This might be because the Defund slogan evokes strong emotions. Among finance professionals, *budget cut*–related arguments remain prevalent even when narrative information is absent. This may explain the respondents' underestimation of the performance of police-related firms.[3]

In the last part of the experimental data analysis, we explore what drives the divergence in perspectives among nonexperts, finance professionals, and experts on pivotal events such as George Floyd's murder. A key factor is the information environment. This section examines how information treatments can either amplify or mitigate these differences. Our findings reveal that exposure to only limited information widens the reasoning gap between nonexperts and experts, especially police specialists. Conversely, finance professionals' reasoning aligns more closely with that of police when they are exposed to only product-specific information (i.e., when the narrative information is removed). Thus, the type and amount of information play a critical role in shaping belief disparities among these groups.

Finally, we investigate whether the emphasis in the reasoning of experts and nonexperts on *budget cuts* and *less trust* reflects voters' preferences in the United States. We use nationally representative survey data from the Cooperative Congressional Election Study (CCES) to examine how the Defund movement influences public sentiment on police reform.[4] We use an event-study

[3]Arguments related to *less trust* in the police are also prevalent among nonexpert respondents in the absence of product and narrative information. This suggests that arguments turning on *less trust* are a prevalent "inattentive" response. A comparison of the outcomes under the narrative-only treatment to those under the limited-information treatment suggests that exposure to narrative information shifts respondents' attention from rationales related to *less trust* to rationales related to *budget cuts* and policing-related products (*reform*).

[4]While most research has overlooked CCES's policing-related questions, they are highly relevant, as shown by Chyn et al. (2022).

analysis to show that areas with more Defund-related Google searches saw increased support for reducing police budgets, although not enough to sway the median voter. We also find significant support for accountability measures such as body-worn cameras in areas with higher search intensity. However, 80% of respondents in low-search areas still feel safe due to police presence. While the Defund movement aims to shift funds away from law enforcement, public understanding of this goal is limited. The murder of George Floyd did not lead to increased support for budget cuts in other sectors, suggesting the campaign's emotional and visible nature may cause an overestimation of its impact, consistent with salience-based explanations of overreaction (Bordalo et al., 2022).

Literature Review Our paper intersects with multiple research areas. It relates to studies on factors affecting support for policies impacting marginalized groups (Cascio and Washington, 2013; Alesina et al., 2021; Cook et al., 2022; Derenoncourt, 2022). Amid debates on police funding and reforms (Bursztyn et al., 2022),[5] and calls for police abolition (Gilmore, 2007; Davis, 2011), our analysis highlights the views of a wider range of experts than considered in prior literature, focusing on the perspectives of both police and community organizers (Davies et al., 2021). This differs from research that primarily considers either police or academic viewpoints (Bell, 2021).[6]

Second, our work adds to the literature on how expert opinions shape policy (Sapienza and Zingales, 2013) and how policy insights can be drawn from stock market data (Wolfers and Zitzewitz, 2004; Snowberg et al., 2007; Wolfers and Zitzewitz, 2009). We quantify experts' forecast accuracy with respect to the stock impacts of social movements, aligning with studies on financial decision-making (Hanspal et al., 2021; Stroebel and Wurgler, 2021; Giglio et al., 2021a,b). We also explore the role of narratives or stories (Shiller, 2017; Bénabou et al., 2018; Eliaz and Spiegler, 2020; Schwartzstein and Sunderam, 2021) in shaping beliefs, using expert surveys and information experiments similar to those featuring in prior research (DellaVigna et al., 2019; Andre et al., 2021; Alsan et al., 2022).

Our paper extends the existing literature on the role of attention, memory, and salience in decision-making (Bordalo et al., 2012, 2013, 2020, 2022).[7] We focus on how salient information influences forecasting overreactions (Bordalo et al., 2020; Afrouzi et al., 2023). This is especially pertinent in the wake of exposure to crime-related news (Philippe and Ouss, 2018; Mastrorocco and Ornaghi, 2023) and in police-civilian interactions following incidents involving officer injuries or fatalities (Holz et al., 2023; Cho et al., 2023). Our work also aligns with studies examining the significance of memory and preferences in information processing (Bordalo et al., 2020; Andre

[5] See Owens and Ba (2021) for a review.

[6] Other research has underscored the value of domain-specific expertise in research (DellaVigna and Pope, 2017, 2018; DellaVigna et al., 2019),finance (Ljungqvist et al., 2009; Patton et al., 2015), housing (Rutherford et al., 2005; Levitt and Syverson, 2008), the purchase of medicine or health insurance (Bronnenberg et al., 2015; Handel and Kolstad, 2015; Finkelstein et al., 2022), health outcomes (Johnson and Rehavi, 2016), and the legal system (Fisman et al., 2015; Fishbane et al., 2020).

[7] See also the critical role of salience in decision-making for consumer choices (Chetty et al., 2009; Finkelstein, 2009; Haggag et al., 2018) and political decisions (Bordalo et al., 2020).

et al., 2021, 2022; Graeber et al., 2022), particularly in the realm of corporate social responsibility (Colonnelli et al., 2022). Overall, our work provides insights for policymakers, corporations, and community organizers on crafting effective communication strategies around public safety policies.

Plan The remainder of this paper is structured as follows. Next, we provide a brief overview of the influence of the summer 2020 uprisings on the stock performance of firms contracting with the police. Section 3 presents an analysis of the surveyed experts' beliefs and preferences concerning the impact of the events of 2020 on investment in the policing industry. Section 4 examines the impact of an information treatment on the forecasts of nonexperts and finance professionals. Section 5 focuses on the forecasts' underlying reasoning and the mechanism whereby the information treatment shapes this reasoning. To complement the survey analysis, Section 6 explores salience-driven mechanisms using the nationally representative sample from the CCES. Finally, we conclude and discuss the implications of our findings in the last section.

2 Background

The Murder of George Floyd On May 25, Minneapolis police officer Derek Chauvin killed George Floyd. This event is the most high-profile police killing in recent memory and sparked massive protests in the U.S. and worldwide. Moreover, it was one of the most salient and important developments of 2020, in the midst of the throes of the pandemic era in the US. For instance, the top panel of Figure 1 presents pageviews for Wikipedia articles on "Black Lives Matter", "George Floyd protests", "COVID-19", and "Donald Trump" from January 2020 to September 2020. Shortly after the murder of George Floyd, "George Floyd protests" and "Black Lives Matter" overtook "Donald Trump" and "COVID-19" in their number of Wikipedia views, peaking at approximately 200,000 views in a single day in June of 2020. Interest in BLM remained elevated, with the BLM entry having some half the number of views of the COVID-19 entry for months following the murder.

A prolonged debate over policing reform accompanied these protests. In the weeks that followed Floyd's murder, many policymakers and activists advocated reforming the police by investing more in accountability tools (e.g., training or body-worn cameras). Other stakeholders supported defunding the police by shifting funds from police departments to nonpolicing alternatives (e.g., housing or mental health resources). However, many opponents of Defund argued that some of their demands would lead to more unrest and increase crime, particularly homicide rates, and that more, not less, resources should be invested in the police to control crime.

As an example, the bottom panels of Figure 1 track the frequency of articles related to "defund the police" and police-related products in the *New York Times* and the *Wall Street Journal* span from January 2010 to September 2023.[8] The figures indicate a notable difference in the frequency of

[8]The *New York Times* primarily attracts a readership interested in in-depth reporting on a variety of topics, while the

articles discussing Defund and that of articles covering police-related products. Specifically, articles on Defund saw a significant increase in both publications starting in mid-2020, while articles on police-related products remained relatively constant. This contrast suggests that the press's focus, as represented by these outlets, lay more on the broader policy and budgetary aspects of policing than on specific technologies or products used in law enforcement.

Stock Performance Stock prices aggregate information about market expectations for firms' performance and revenue streams. Hence, we compare our survey respondents' forecasts against the abnormal stock returns of firms contracting with police departments after George Floyd's murder as our index of the market's anticipation of changes in demand for policing products. We rely on results from Ba et al. (2023) that estimate the effect of George Floyd's murder on the returns of firms with strong ties to the police relative to those of similar firms without police connections over the 21 days after the event.[9]

Figure 2 presents the main results of Ba et al. (2023) showing the daily impact of George Floyd's murder on the cumulative abnormal returns (CARs) of firms contracting with police.[10] The figure indicates that the return of a portfolio composed of stocks tied to police was 16.5 pp higher than that of a portfolio of the firms' nonconnected peers three weeks after the viral event triggering the mass protests. In other words, a portfolio of firms contracting with police worth $100 a day before the murder of George Floyd would have a value of $116.5 three weeks after the event (assuming no other market fluctuations affecting firms similar to policing firms). This result indicates that the financial market anticipated increased demand for products and services tailored for law enforcement agencies.[11]

3 Who Are the Experts?

3.1 Survey Design

To motivate our analysis and to quantify expert views and beliefs about the impact of George Floyd's murder, we surveyed various constituencies of experts who impact policy-making in these spheres. We also recruited respondents from an online platform, whom we refer to here as "nonexperts", to compare their responses to those of our sample of experts.

Wall Street Journal caters to a more business-oriented audience focused on financial and corporate news.

[9] The set of nonconnected firms includes publicly traded firms in the same states and 4-digit SIC codes as policing-connected firms. The effects are estimated with synthetic difference-in-differences (Arkhangelsky et al. (2021)), which compares policing-connected firms with their synthetic counterfactual constructed from firms in a donor pool.

[10] 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 returns.

[11] Ba et al. (2023) also document that policing firms' fundamentals, such as sales, improved after George Floyd's murder. This suggests that the stock movements reflected positive expectations based on policing firms' realized performance following the George Floyd protests.

Structure of the Survey The survey started with an example exercise to ensure that participants understood what was expected of them. This exercise also served as an attention test. If respondents failed the test, the survey was terminated. Next came a "warm-up" prediction in which the participants made a forecast related to the returns of a traveling company at the beginning of the COVID-19 pandemic.

We then provided information about George Floyd's murder and products related to policing. Next, we asked participants how they expected stock prices to have moved after the killing of George Floyd for a portfolio of firms contracting intensively with police and to provide the rationale behind their reasoning. The respondents were also asked to predict price movements for five firms within the portfolio and were offered the opportunity to revise their forecasts for the portfolio. Finally, we collected data on the participants' views on ethical investing, investment experience, and demographics.

Implementation For the sample of experts, participation in the survey was solicited via email in November and December 2022. One of the challenges in conducting this survey was that the research agenda of the researchers on this project primarily focuses on policing and, in turn, knowledge of the researchers' identities could have a priming effect on the survey participants. Moreover, the principal investigator has a Black-sounding name, which could impact the survey response rate (Jowell and Prescott-Clarke, 1970; Bertrand and Mullainathan, 2004). To overcome these challenges, initial communications with survey participants were sent on behalf of The Social Capital Research Team in the Duke Economic Analytics Laboratory through an email account created for this project. We also sent personalized follow-up emails in December 2022 to individuals from whom we had not received responses by November 30, 2022. We contacted only individuals who had not opted out of communication. Personalized emails were sent by Duke undergraduate students from the study's email address.

Respondents We surveyed various stakeholders with expertise relevant to our topic. First, community organizers and police specialists themselves tend to have expertise on the externalities of policing. Moreover, we investigated the views of other relevant stakeholders, such as professional and academic experts in finance, law, and other academic fields.

Our study relates to the impact of police violence incidents and the Black Lives Matter movement. Understanding the views of individuals connected to affected communities is vital. Our primary experts are tied to nonprofit organizations working on racial justice, climate change, LGBTQ+ rights, and other grassroots movements.[12] We sourced experts from mailing lists, such as commu-

[12]The inclusion of these experts provides a multifaceted perspective on systemic inequities that intersect with racial justice, climate change, and LGBTQ+ rights. For instance, the Black Lives Matter movement, which primarily focuses on racial justice, has had instances of collaboration with the Sunrise Movement on environmental issues and with organizations advocating for LGBTQ+ rights. These collaborations suggest an interconnectedness of various social issues, particularly in how they relate to systemic inequities affecting marginalized communities.

nityresourcehub.org and sunrisemovement.org. Police specialists constitute the second group of experts, given their relevance for racial justice. We collected email addresses from *Police Chief Magazine* from 2010 to 2021 to engage law enforcement personnel. We also surveyed finance professionals using Discovery Data and invited top 100 finance department faculty.[13] We reached legal practitioners via usalawyerlist.com[14] and emailed faculty from U.S. law schools. We also contacted African-American studies, political science, sociology, and social work faculty from 36 U.S. universities.

Finally, we surveyed nonexperts drawn from a sample recruited from Prolific, an online survey platform frequently used in social science research and marketing. Our sample of nonexpert respondents was recruited on November 8, 2022. Participants were required to reside in the United States and to be adults fluent in English.

Sample Selection We sent invitations to 131,325 email addresses for the expert sample and received 1,204 responses. We excluded individuals who failed the attention checks, did not complete the comprehension question, or did not provide their demographic information. The final sample for our analysis includes 511 responses, with 45 community organizers, 26 police experts, 143 finance and 104 law experts, 54 other academics, and 139 nonexperts.[15] We provide a discussion of the response rates and sample attrition in Section and Table A.1 in the appendix.

3.2 Experts' and Nonexperts' Forecasts

Summary Statistics Table 1 presents demographic summary statistics across expertise groups: nonexperts, community organizers, police experts, finance experts, law experts, and other academics. The gender distribution varies, with approximately 37% women on average, with this share rising to 53% for nonexperts and 73% for community organizers. The different expert groups also show varying proportions of white respondents, with finance and law experts having the highest shares at 77% and 88%, respectively. Additionally, the community organizers are generally younger and are the least likely to report checking investments weekly or daily (9%), followed by the police specialists (12%).

Relationship between Expertise and Forecasts The top panel of Figure 3 presents various summary statistics for our experts' forecast of the value of a portfolio of policing-connected firms three weeks after the killing of George Floyd. We benchmark the respondents' forecasts against the actual portfolio value presented in Figure 2.

[13] See the ASU ranking here.

[14] For both finance professionals and legal practitioners, we randomly selected 50,000 individuals from this dataset and invited them to participate in the study.

[15] Only participants on Prolific received a payment of $1.58 for participation. The payment was conditional on participants' completing the study and not failing the attention checks.

On average, all groups predicted an increase in the policing portfolio value. However, the significant heterogeneity and wide tails of the forecasts make the median prediction a helpful statistic. Community organizers performed best, with mean and median forecasts slightly below the correct value. Police and other academics have lower mean and median forecasts than community organizers, but the distribution of their forecasts is much tighter. Among the experts, law and finance experts show the least accurate forecasts, with relatively tight distributions around a small predicted increase. Overall, nonexperts performed worst, with mean and median forecasts near 100 (i.e., no change) and the widest distribution in terms of the 10th and 90th percentiles.

The forecast precision differences across experts are displayed in the bottom panel of Figure 3, which contains the cumulative distribution functions (CDFs) of the negative absolute difference between the predicted and actual returns. Notably, community organizers and nonexperts have long tails on this measure of accuracy. However, while the CDF for community organizers converges with the CDFs of other experts above 40%, the predictions of nonexperts are much less precise, and the corresponding CDF converges above 80%. Finally, the p-value of a Kolmogorov–Smirnov test of equality of the community organizer and nonexpert distributions rejects the null, while the test fails to reject the hypothesis of equality of the community organizer and finance expert distributions.

Overall, our results illustrate the important heterogeneity across categories of experts and particularly the strong predictive performance of groups generally excluded under the definition of an "expert" in the economics survey literature, namely, practitioners (police specialists) and affected community members (community organizers). Despite being the least likely to report having high investment experience among all the expert and nonexpert groups, community organizers and police specialists were the most likely to correctly predict an increase in portfolio value, and their mean and median predictions are closest to the actual value. This is also despite the high imprecision of the predictions of community organizers, much like those of nonexperts.

4 What Kind of Information Shapes Forecasts?

Given the differing levels of public discourse on Defund as opposed to specific law enforcement products, this section describes an online experiment that engages two distinct audiences: nonexperts and finance professionals. As pivotal stakeholders, these groups can influence both public policy and market performance through their support or investment choices. The study explores how their perceptions of the police industry are shaped in the aftermath of George Floyd's murder, depending on whether they are presented with narrative accounts related to the event, including discussions on "defunding the police", or information about industry fundamentals.

4.1 Research Design

Overview and Logistics We conducted an online experiment using Prolific from December 20 to 28, 2022. The baseline survey took place from December 20 to 23, 2022, and the follow-up survey took place from December 27 to 28, 2022. Our hypotheses, research, and analysis design were registered on the AEA registry (AEARCTR-0010670) and AsPredicted (#117117). Participants were required to reside in the United States, to be of voting age and to be fluent in English.

In the baseline survey, each participant received a payment of $0.36 for completing a survey, with the median completion time being less than 3 minutes. In the follow-up survey, each participant received a payment of $1.20 for completing a survey, with a median completion time of approximately 8 minutes. A participant who completed both surveys was paid $1.56 in total and spent 10 minutes and 26 seconds on the survey. The payment was conditional on the participant's completing the study and passing the attention checks.

Survey Structure To mitigate the experimenter demand effect, we followed Haaland and Roth (2020, 2021) and designed the Prolific survey in two parts: a baseline survey and a follow-up survey performed one week later. The randomized information treatments were applied in the follow-up survey. Where possible, we hid the connection between the two surveys to address concerns about demand effects. For example, the second survey was styled differently (e.g., with different fonts and backgrounds).

We discuss the structure of each part of the survey below, and Figure 4 presents the flow of the experiment design. We collected information on participants' demographics and beliefs in the baseline survey. Specifically, we collected data on their views on ethical investing, investment experience, political leanings, and demographics (age, gender, and race).[16] One week following the baseline survey, participants were contacted again to complete another survey, in which randomization was applied and respondents were tasked mainly with some forecasting exercises.[17]

The follow-up survey is designed as follows and is similar to the expert survey. Respondents started with a comprehension check and warm-up prediction. Next, using a 2x2 factorial experimental design, we randomly assigned participants to four groups: $\{$Narratives, No Narrative$\}$ $\times$ $\{$Product, No Product$\}$. We discuss the various treatment arms below. After the randomization, we asked participants to forecast how stock prices moved after the killing of George Floyd for the portfolio and the five firms within the portfolio. Afterward, respondents were offered the opportunity to revise their portfolio predictions.

In the last part of the survey, respondents were offered the opportunity to donate to a nonprofit organization. This outcome allows us to measure respondents' support for various policies related to policing, namely, policies focused on police welfare, police reform, and police abolition. Sur-

[16] The full set of questions from the baseline survey can be found here.

[17] The full set of questions from the follow-up survey can be found here.

vey participants were offered the chance to donate to one of the following organizations: (1) an organization that aims to improve officer safety as well as health and wellness in police, (2) an organization that advocates reforming the police by increasing accountability, for example, through officer training, and (3) an organization that aims to reduce the scope of policing in society by providing vetted alternatives to policing to support public safety.

In addition to the Prolific survey, we conducted a parallel survey of professionals in the finance sector. Over 300,000 individuals in this industry were invited via email to participate in a Qualtrics survey. The final sample size depended on the response rate. Unlike the Prolific survey, this survey was administered in a single phase, rather than in a baseline and a subsequent survey.

Incentives to Provide Accurate Answers Each prediction received an accuracy score, and participants were randomly selected to receive a bonus payment depending on the accuracy of their predictions. Moreover, we followed Alesina et al. (2018); Bursztyn et al. (2020) by using an incentive-compatible outcome, i.e., donation, to minimize possible experimenter demand effects. Hence, we told respondents that randomly selected participants who earned the bonus would also be able to give up to $10 to a charity. If selected, a respondent could choose to divide the $10 charity payment between herself and a nonprofit organization. Finally, we asked respondents whether they would like to donate the money to their choice of one of the nonprofit organizations.

Treatment Arms and Randomization Ex ante, the impact of protests following George Floyd's murder on the market valuations of firms heavily contracting with police is ambiguous. This uncertainty stems from the interplay of various factors, including calls for police reform, concerns about rising crime, and the Defund movement, in shaping market expectations.[18] Figure 1 indicates that public discourse leans more toward discussion of broad policy and budgetary issues than toward discussion of applications of specific law enforcement technologies or products. This narrative focus could shape both market expectations and policy debates.

To disentangle these effects, we designed treatments to assess how different types of information influence participants' perceptions and attitudes related to the summer 2020 protests. We employed a 2x2 factorial experimental design to examine the effects of two key variables: narrative information and product information. The randomization was implemented with Qualtrics's "evenly present elements" functionality. Following Figure 4, participants were first randomly assigned to one of the two narratives conditions, which emphasizes various views of various stakeholders:

- **No narratives:** *"On May 25th, police specialists killed George Floyd, an event that led to massive protests across the country starting on May 26th."*

[18] For potential narratives associated to viral police killing in economics see Rivera and Ba (2018); Devi and Fryer (2020); Premkumar (2019); Ang et al. (2021)

- **Narratives:** *"On May 25th, police specialists killed George Floyd, an event that led to massive protests across the country starting on May 26th. In particular, local policymakers and activists advocated 'reforming the police' by investing in more accountability tools such as training, body-worn cameras, or early-warning systems to detect police misconduct. However, many opponents argued that some of these demands would lead to more unrest and a rise in crime, particularly homicide rates. Finally, some activists and policymakers advocated 'defunding the police' by shifting funds from police departments to nonpolicing alternatives (e.g., investment in housing, mental health resources)."*

Then, participants were randomly assigned to one of the two product conditions, which emphasize technologies and products used by police:

- **No product:** *"We constructed a portfolio consisting of twenty publicly traded companies that contract intensively with police departments."*
- **Product:** *"We constructed a portfolio consisting of twenty publicly traded companies that contract intensively with police departments. Companies in this portfolio sell various products to police departments, including training, body-worn cameras, surveillance equipment, firearms, etc."*

The interaction of the treatment arms[19] results in participants' being randomly assigned to one of four conditions:(1) *No Information*, (2) *Narratives* (exposed only to narrative information), (3) *Products* (exposed only to product information), and (4) *FullInformation* (exposed to both types). This design enables us to isolate the separate impacts of narrative and product information on public opinion and market expectations.

Empirical Specification We analyze the impact of the information treatments on various outcomes using the following OLS specification:

$$y_i = \alpha_0 + \beta_1 Product_i + \beta_2 Narratives_i + \beta_3 NoInformation_i + \gamma X_i + \epsilon_i \tag{1}$$

where outcome y_i of respondent i is a function of each treatment condition. The variable $Narratives_i$ is a binary variable that equals one if the respondent received the narrative treatment and zero otherwise. The variable $Product_i$ is a binary variable that equals one if the respondent received information about the products in the portfolio and zero otherwise. The variable $NoInformation_i$ designates respondents who did not receive either narrative or product information. The reference group comprises respondents receiving both the narrative and product information treatments. We also refer to the omitted group as the reference or full information group. The selection of this

[19] i.e., $\{$Narratives, No Narrative$\} \times \{$Product, No Product$\}$

reference group enables a more streamlined comparison with the nonexperimental sample, given that experts in the initial part of the study were allocated to the *FullInformation* condition. Hence, each treatment arm is designed to assess the impact of withholding specific types of information, rather than introducing additional information. In addition, in X_i, we control for the individual covariates collected in the baseline survey. We use robust standard errors as we randomized at the individual level.

4.2 Results

4.2.1 Descriptive Statistics

In our study, we included in the nonexperts sample respondents who met our eligibility criteria and completed both the baseline and follow-up surveys. For individuals in the finance industry, we combined the two surveys. We excluded participants who failed the attention checks or did not complete the comprehension question from our analysis. Summary statistics categorized by treatment condition are presented in Table 2 with Panel A focusing on nonexperts and Panel B focusing on finance professionals. We recruited a total of 2,346 nonexperts and 467 finance professionals. The tables display the mean level of each variable for the entire sample in column (1), while columns (2) to (5) show the mean level of each variable for each treatment arm. The last column indicates the p-value of a test evaluating whether the means are the same across all experimental conditions.

In terms of demographics, 44% of respondents in the nonexpert sample are female, whereas only 20% of the finance experts are female. The vast majority (90%) of the respondents in our analysis were born in the U.S. Both the nonexpert and expert groups are mostly white, with the share of white respondents being approximately 72% among nonexperts and 84% in the finance sample. Additionally, the nonexperts tend to be younger and to have completed the survey at a faster pace. Moreover, over two-thirds of the financial experts reported checking their financial investments on a weekly basis, whereas only one-third of the nonexpert sample did so. We observe a balance in individual characteristics across the experimental conditions, with some exceptions. For instance, in the nonexpert sample, the "$NoInformation$" treatment arm has lower percentages of women and respondents born in the US.

4.2.2 Main Results

Accuracy of Portfolio Predictions Table 3 presents the results for the effect of the information treatments on prediction accuracy (equation 1) in columns (1) and (2) for the nonexperts and finance experts, respectively. Among the nonexperts, the absence of information about products significantly decreases respondents' likelihood of predicting an increase in stock prices. The effects are substantial: the likelihood of predicting an increase in the portfolio value declines in the no-information treatment by 34.4 pp ($SE = 0.0257$), while the narratives-only treatment reduces the likelihood of predicting an increase by 31.1 pp ($SE = 0.0261$). This is a pronounced effect relative to the outcome in the full information group, where 50% of nonexperts predicted an increase in the portfolio value. In contrast, exposure to product information does not significantly influence the likelihood of predicting an increase only for nonexperts. Similarly to the effects on nonexperts, for finance experts, the no-information and narratives-only treatment significantly reduce the likelihood of predicting an increase, by 24.1 pp ($SE = 0.0630$) and 30.1 pp ($SE = 0.0616$), compared with a mean of 53%. However, finance experts exposed solely to product information perform better in terms of the prediction error and are 10.9 pp ($SE = 0.0656$) more likely to predict an increase than nonexperts.

Columns (3) and (4) display the effects of the treatments on prediction errors. The no-information and narratives-only treatments significantly increased the prediction error among nonexperts (both $p < 0.01$) by roughly half their mean and similarly increased the error among finance experts, albeit by less than one-third the mean error for this group (both $p < 0.05$). In contrast, the product information treatment only slightly increased the error for nonexperts by approximately 10% of the mean and actually decreased error among finance experts by approximately 15% of the mean.

Our findings also indicate that the absence of information about policing products leads respondents to believe that the murder of George Floyd negatively affected publicly traded firms contracting with the police. In the nonexpert experiment, over 80% of respondents in the no-information condition predicted no increase in the portfolio value. However, exposure to product information attenuated this effect, leading to a shift whereby close to 50% of respondents predicted an increase. Furthermore, there are differences in how finance professionals and nonexperts processed the product and narrative information. While full information improved the forecast accuracy among nonexperts, finance professionals demonstrated greater accuracy only when exposed to product, not narrative, information.

Heterogeneity by Type of Forecast Table 4 examines how the respondents' forecasts vary with the types of products sold by firms, where the dependent variable is a respondent's likelihood of predicting a portfolio increase. We report the results from Table 3 in column (1) to facilitate comparison with the portfolio forecast. Among nonexperts, 60% of those exposed to full information predicted an increase in individual stocks. Columns (2) to (7) of this table indicate that respondents exposed solely to narratives or product information no longer differ from their peers provided with full information in their likelihood of predicting an increase. Respondents who did not receive any information have a 6 pp ($SE = 0.0274$) higher likelihood of predicting a stock decline for Axon (a seller of body-worn cameras and less-than-lethal products) than the group exposed to full information.

In contrast, similarly to what we found in the previous section, finance professionals exposed solely to product information are more likely to predict an increase in individual stocks than respondents in the group treated with full information (14.8 pp, $SE = 0.044$). However, there is no strong evidence that finance professionals exposed to no information or only to narratives are more or less likely to predict an increase in individual stocks than respondents in the reference group. Our findings suggest that, while respondents' knowledge of product information influenced their beliefs about the impact of George Floyd's murder, nonexperts and finance professionals process information about products differently.[20]

4.2.3 Additional Analysis

Willingness to Change Forecasts Utilizing the exposure of survey participants to information on various products associated with the policing industry, we investigate in Table 5 whether respondents were willing to revise their portfolio forecasts based on this information. In revising their main forecast, nonexperts exposed solely to narratives or to no information show a significantly higher likelihood of changing their prediction than their peers treated with full information. Specifically, the respective increases are 6.64 pp ($SE = 0.0228$) and 11.3 pp ($SE = 0.0235$), which are substantial relative to the reference group mean of 17%. However, nonexperts who received information about products do not exhibit a propensity to revise their predictions that is significantly different from that of respondents provided with full information.

On the other hand, finance professionals provided with less information proved more likely to adjust their forecasts than their peers treated with information about both products and narratives. The likelihood of revising one's forecast among finance experts exposed to no product information is higher by 8.85 to 12.8 pp ($p < 0.1$), with the reference group average being 12%. In contrast, compared to the reference group, finance professionals who received only product information show a modest increase of 5 pp in their likelihood of revising their forecasts. However, the standard errors are relatively large, making it difficult to rule out moderate-sized effects.

The results presented in columns (2) to (6) of Table 5 align with the findings from Table 3, supporting the notion that having less information about products and narratives corresponds to lower forecast accuracy. Additionally, the results suggest that product information, rather than narrative information, plays a crucial role in improving forecast accuracy. Furthermore, the coefficients in Table 5 are relatively smaller in magnitude than those in Table 3. This implies that respondents tend to update their beliefs after being exposed to product information, as observed in the results from Table 4. This updating process helps to reduce, but does not close, the accuracy gap between respondents with more and less information.

[20] Table A.6 presents the effects of the negative absolute forecast error outcome. Generally, nonexperts not exposed to information about products or narratives tended to exhibit lower accuracy in their forecasts than their peers treated with full information. On the other hand, finance professionals exposed to full information did not consistently demonstrate greater accuracy than their peers.

Support for Policies We investigate the impact of information on nonexperts' support for various policing-related policies in Table 6. In general, we do not find significant effects of the information treatment on support for the different policing-related policies (including support for the nonprofits advocating police wellness, police reform, or police abolition initiatives), the likelihood of donating, or the donation amount. We exercise caution in interpreting these results given the large standard errors, which prevent us from drawing informative conclusions.

Heterogeneity Analysis In the appendix, Tables A.2 to A.4 report the analysis results for different subsamples across various demographics, political affiliations, investment patterns, and preferences related to the ethics of investment in policing and regulation.

The findings from the heterogeneity analysis align with the main results, indicating that the absence of product information leads to less accurate forecasts. However, it is important to note that we cannot definitively rule out statistical differences between the results for the main sample and those from the subsample analysis. Among nonexperts, we confirm that respondents not exposed to product information are less likely to predict a portfolio increase than their counterparts treated with full information. However, we note that the effects are smaller for male respondents, younger respondents, nonwhite respondents, and those who check their investments on a weekly basis.

Regarding finance professionals, we observe differences in the likelihood of predicting a portfolio increase between men and women who are exposed to product information. Specifically, men are significantly more likely to predict a rise in the portfolio value when narratives are removed, with an increase in this likelihood of 18.3 pp ($SE = 0.0737$). On the other hand, although the estimate is less precise, there is suggestive evidence that female finance professionals exposed to only product information are less likely to predict a portfolio increase compared to if they were shown both narratives and products. Furthermore, we find suggestive evidence that finance professionals exposed exclusively to product information have a higher likelihood of predicting an increase than their peers treated with full information if they check their investments on a weekly basis, view investing in policing as ethical, and prefer less regulation.

Decomposing the Variation in Beliefs We follow Giglio et al. (2021a) and employ a variance decomposition analysis to understand the factors influencing beliefs about the impact of George Floyd's murder on the policing industry in Section B.1.3 in the appendix. Individual fixed effects account for the majority of this variation—55.5% for nonexperts and 53.8% for finance professionals—while prediction fixed effects contribute minimally. Observable characteristics such as demographics have limited influence. However, specific treatment arms do significantly affect forecasts. For example, nonexperts in the "No Information" or "Narratives" arms are less optimistic about the industry, while finance professionals in the "Products" arm are more optimistic. Overall, individual predispositions are the primary drivers of beliefs, but treatment conditions also matter.

5 What Are the Reasons Behind the Forecast?

5.1 Coding Procedures

We exploit the fact that our surveys asked respondents to explain their main prediction to analyze their reasoning qualitatively (Stantcheva, 2023; Andre et al., 2021, 2022). We opted to hand-code the responses rather than use large-language models as the reasons were often subtly embedded and included in open-ended responses. We manually coded more than 3,300 respondents' answers using a tailored coding procedure that fits our context. We identified ten common themes in the open-text explanations for the main prediction and tagged them as follows: (1) *less trust*, (2) *budget cuts*, (3) *reputation*, (4) *protests*, (5) *crime*, (6) *reform*, (7) *police support*, (8) *unspecified demand*, (9) *no impact*, and (10) *unclear*. Each response could be classified into more than one category. Table 7 displays all the categories in our coding scheme alongside the examples provided to the coders.

Human coding has several limitations, including unintentional human error or lack of concentration. Moreover, human inference on open-ended responses is subjective. To mitigate these risks, five coders hand-coded each open-text answer into ten categories independently.[21] Given a free text response and a reason, the final categorization was taken by a majority vote across the classifications. While the coders had some knowledge of the goals of the overall research project, they did not have access to the respondent covariates associated with each open-text response (aside from a randomly generated identifier). For example, for the expert survey, coders were unaware of the type of expert responding to each answer. For the experimental samples, coders were unaware of the treatment assignment. We offer further discussion in Section A.3 of the Appendix regarding our evaluation of the classification procedure's quality. We show a high level of agreement among coders in classifying the open-text responses.

5.2 Reasoning, Information, and Forecasts

Relationship between Information, Reasoning, and Forecasts Before delving into the overall results on the impact of the information treatment on respondents' reported reasoning in our experiment, we conduct a visual inspection of the relationship between information and the reasoning and forecasts of nonexperts and finance professionals.[22]

Figure 5 demonstrates the effects of exposure to narrative and product information on forecasting within the nonexpert group. The impact of exposure to different types of information on forecasting and narratives varies significantly. With no information exposure, 80% of respondents

[21] The coders were Duke graduate and undergraduate students and participated in a training session where they were required to complete some sample tasks and received feedback. The coders also received instructions that included up to six examples for each categorization.

[22] In Section B.2.2 of the appendix, we report the relationship between respondents' reasoning and the forecast by type of expertise using the sample from the expert survey.

forecast a decrease in the portfolio price. When respondents were presented with narrative information alone, there is minimal change in the forecasts but a 9% increase in the percentage of respondents citing budget cuts as a reason for their forecasts. In contrast, among the group provided with product information, 48% predict an increase in the policing portfolio value, compared to only 16% in the no-information group. Notably, the mention of police reform as an explanation for forecasting an increase in the portfolio value substantially increases from 2% in the no-information group to 18% in the group provided with product information. Moreover, respondents treated with product information cited trust and reputation far less frequently. Similar trends are observed in the group with access to both narrative and product information, as their forecasts closely resemble those of respondents exposed only to product information. The group with complete information cited protests, diminished trust, and budget cuts more frequently than the group treated with only product information.

Furthermore, Figure 6 illustrates the impact of the information treatment on forecasts and reasoning among finance professionals. In contrast to Figure 5, where we observe that the narrative information treatment slightly increases the percentage of respondents predicting a portfolio increase, finance professionals provided with narrative information are actually less likely (24%) to predict a portfolio increase than those provided with no information (29%). This trend is also observed between finance professionals treated with both narrative and product information and those treated with only product information. Among finance professionals with complete information, only 53% predict an increase in the portfolio value, whereas 63% of those treated with only product information do so. The key distinction between these two groups is a significant decrease in the mention of reform as a justification for the forecast among respondents exposed to narrative information, for whom instead a higher percentage of unclear reasons is reported. The product information treatment has an effect similar to that observed in Figure 5, increasing the respondent's likelihood of predicting an increase in the portfolio price.

Impact of Information on Reasoning Having established that reasoning correlates with respondents' belief about whether George Floyd's murder negatively impacted the policing industry, we explore how exposure to product and narrative information impacts reasoning in Tables 8 and 9 for nonexperts and finance professionals, respectively. For each explanation category (*less trust*, *budget cuts*, etc.), we regress whether a participant mentions the respective category on the treatment condition (exposure to product information, no exposure to narrative information, and no exposure to information of either type).

Nonexperts The results for nonexperts are presented in Table 8. An overarching observation for the nonexpert sample is that which narratives a participant mentions are sensitive to exposure to both types of information. In the nonexpert sample, mentions of seven of the ten narrative categories change by a statistically significant amount in the absence of product information. Mentions of four of the ten narrative categories change by a statistically significant amount in the absence of narrative information. When both types of information are absent, mentions of six out of the ten narrative categories change by a statistically significant amount. The absence of narrative information increases the chance of a participant explaining her forecast by mentioning *protests*, *less trust*, and *reputation* by 9.6, 6.2, and 3.3 pp, respectively. Meanwhile, the no-narratives treatment decreases the chance of a participant's mentioning *budget cuts* by 8.8 pp. These changes are all significant at the 5% level. Removing product information increases the chance of a participant's mentioning *less trust*, *reputation*, and *no impact* by 10.7, 6.5, and 4.1 pp, respectively. Meanwhile, the no-product-information treatment decreases the chance of a participant's mentioning *reform*, *unspecified demand*, *protests*, and *crime* by 16.1, 8.0, 2.9, and 1.8 pp, respectively. Again, these changes are all significant at the 5% level. The absence of both product and narrative information increases the chance of a participant's mentioning *less trust*, *reputation*, and *no impact* by 21.0, 12.1, and 2.8 pp, respectively. Meanwhile, the no-information treatment decreases the chance of a participant's mentioning *reform*, *unspecified demand*, and *budget cuts* by 20.2, 9.0, and 7.3 pp, respectively. These changes are all significant at the 5% level.

Finance Professionals The results for nonexperts are presented in Table 9. The absence of narrative information (i.e., exposure to product information only) increases the chance of a participant's mentioning *reform* and *protests* by 17.2 and 7.0 pp, respectively. Meanwhile, this treatment decreases the chance of a participant's mentioning reasons coded as *unclear* by 18.5 pp. These changes are all significant at the 5% level. The no-product-information treatment decreases the chance of a participant's mentioning *protests* by 3.9 pp. This change is significant at 5%. We find some evidence that the absence of both product and narrative information increases the chance of a participant's mentioning *reputation*, *no impact*, and *protests*. We also find some evidence that the absence of both product and narrative information decreases the chance of a participant's mentioning reasons coded as *unclear* and reasons related to *unspecified demand*. These changes are significant only at the 10% level.

5.3 The Role of Information in Shaping Group Disagreements

What drives the differing perspectives among various groups—such as nonexperts, finance professionals, and on-the-ground experts—on significant events such as George Floyd's murder? One crucial factor could be the information environment that shapes their perspectives. Information treatments not only inform but also polarize, serving as a critical mechanism that can either widen or narrow gaps in reasoning and beliefs among these groups. This section explores the dynamics of belief divergence and the role that information plays in either fostering or bridging divides between groups.

Defining Dissimilarity We explore how the information treatment impacts disagreement between the respondents in the experimental sample and those in the expert survey sample. To achieve this goal, we construct a measure of dissimilarity using Jaccard differences for each individual in the experimental sample. The Jaccard distance between individual i in the experimental sample $s = \{\text{nonexperts, finance}\}$ and individual $-i$ in the expert survey $J(-i) = \{\text{community organizers, police, nonexperts, law, other academics}\}$ is given by

$$d_i(s, J(-i)) = 1 - \frac{|R_s \cap R_{J(-i)}|}{|R_s \cup R_{J(-i)}|} \tag{2}$$

where R_s and $R_{J(-i)}$ correspond to the list of reasons provided by i and $-i$, respectively. The symbol $|\cdot|$ denotes the number of elements in a set. The Jaccard difference takes a value between zero and one, such that $d_i(s, J(-i)) = 0$ for identical reasoning ($R_s = R_{J(-i)}$) and $d_i(s, J(-i)) = 1$ for completely distinct explanations ($|R_s \cap R_{J(-i)}| = 0$). In other words, higher values of $d_i(s, J(-i))$ correspond to greater dissimilarity between i and $-i$. Finally, we compute the average dissimilarity for each i, such that $d_i(s, J) = \frac{1}{J}\sum_{-i=1}^{J} d_i(s, J(-i))$. We analyze the impact of the information treatments on the variable $d_i(s, J)$ using equation 1. We use bootstrap standard errors to account for the sampling variation when constructing the dissimilarity index.

Results Figure 7 and Table 10 present the impact of information on the dissimilarity between the explanations offered by the respondents in the experimental and expert survey samples. To assess the significance of the estimates, we focus on the mean dissimilarity between the two groups of interest among respondents who received full information. For nonexperts, the average dissimilarity index with respect to the reference group ranges from 0.83 when the nonexperts are compared to community organizers or experts to 0.86 when they are compared to academics. In comparison, finance professionals with full information exhibit a dissimilarity index ranging from 0.80 when compared to law experts to 0.87 when compared to police experts.

Nonexperts The top panel of Figure 7 shows that exposure to less information leads to greater dissimilarity in reasoning between nonexperts and other groups. However, the effect of exposure to less information remains consistent across the treatment arms when we examine the dissimilarity between nonexperts and law experts (3 to 5 pp ($p < 0.01$)) and that between nonexperts and academics (1.6 to 2.9 pp ($p < 0.01$)). This indicates that the treatment effects do not neutralize the differences in participants' stated reasoning for their forecasts across the treatment arms. On the other hand, the dissimilarity in reasoning between nonexperts and police or community organizers increases as less information is provided to respondents. Nonexperts exposed only to product information have dissimilarity indexes with community organizers and police that are approximately 2.2 to 2.6 pp ($p < 0.01$) higher than the dissimilarity indexes of their peers treated with full information. These gaps widen to 4.75 pp ($p < 0.01$) for community organizers vs. nonexperts and 6.6 pp ($p < 0.01$) for police vs. nonexperts among nonexperts exposed only to narratives. The gaps widen further for participants who are exposed to the no information-treatment. Specifically, the gap is 6.4 pp ($p < 0.01$) between community organizers and nonexperts and 9.01 pp ($p < 0.01$) between police and nonexperts, respectively.

These findings suggest that disagreements between nonexperts and police specialists regarding the impact of George Floyd's murder on the policing industry increase as less information is provided to nonexperts. The effect is more pronounced when we compare the reasoning of nonexperts with that of police specialists than when we compare the reasoning of nonexperts with that of community organizers. Finally, exposure to narratives appears to widen the disagreement more than exposure to product information.

Finance Professionals The lower panel of Figure 7 highlights results for finance professionals that largely contrast with those for nonexperts above. In general, the effect sizes for the information treatment arms are modest compared to those that we observe for nonexperts. Only respondents not exposed to any information tend to exhibit higher dissimilarity indexes than their peers treated with full information. It is uncertain whether these effects differ among police specialists, community organizers, law experts, and academics. Conversely, we do not observe differences in the dissimilarity indexes of respondents exposed solely to narrative information and the reference group. However, we find compelling evidence that finance professionals exposed exclusively to product information experience an increase in the similarity of their reasoning with that of police specialists by approximately 5.28 pp ($p < 0.01$). Exposure solely to product information also decreases the reasoning dissimilarity between finance professionals and community organizers; however, the results are less definitive and show smaller effects. This suggests that informational treatments, in particular narratives, can widen the gaps in beliefs between groups.

6 Do We Expect the Police to Be Defunded?

Our surveys reveal a connection made by respondents between the murder of George Floyd and the push to defund the police. Notably, as many as 80% predict a decline in stock values for companies tied to law enforcement[23]. Additionally, reasoning related to *less trust*, *budget cuts*, and *reputation* resonate more for respondents than rationales related to police *reform*. Given the outsized emphasis placed on Defund in the portfolio predictions, this section delves into the possibility of salience-driven explanations for our results (Bordalo et al., 2022) using a nationally representative survey.

[23] In the no information condition in the nonexpert experiment

6.1 Sample and Data Sources

We use the post-election wave of the Cooperative Election Study, a nationally representative survey conducted every election year from 2014 to 2022 in November (Kuriwaki, 2023; Schaffner et al., 2023). Notably, our surveys discussed in the previous section were conducted at the time of the 2022 CCES wave. The CCES gathers data on political perspectives, demographics, and, crucially, respondents' stance on state legislature decisions to adjust funding for sectors such as law enforcement, education, infrastructure, healthcare, and welfare. For a deeper understanding of the underlying factors, we also refer to the pre-election CCES waves from 2020 and 2022, carried out from late September to late October (Schaffner et al., 2021, 2023). These surveys delve into questions concerning support for police reform and the public's sense of safety in relation to the police (Mazumder, 2019; Chyn et al., 2022).

Complementing the CCES data, we incorporate Google Trends information on searches for "defund the police" by designated market area (DMA) spanning May 1 to August 31, 2020. This provides insight into the public's engagement with the movement during that summer. For each DMA, Google Trends offers a normalized index ranging from 0 to 100, reflecting search intensity.

6.2 Descriptives

6.2.1 Salience of "Defund the Police"

Figure 8 offers a nuanced view of the prominence of the "defund the police" slogan. The top-left panel shows a spike in Wikipedia searches for the phrase starting in June 2020 and eclipsing topics such as "police reform", while "police brutality" remained consistently searched. The top-right panel indicates public curiosity about the term, with leading queries such as "what does defund the police mean" and notes its association with political figures and the Black Lives Matter movement. The bottom panel reveals regional search variations, with high interest in areas such as Portland–Auburn and New York and lower engagement in places such as Albany, Georgia.

Overall, the phrase "defund the police" quickly gained public attention in June 2020, as seen in Wikipedia and Google searches. Simultaneously, "police brutality" remained a consistent concern. Most searches sought to understand the slogan's meaning, with the geographical data revealing varying regional interests. Overall, the slogan's rapid rise in salience occurred in a context of complex and regionally diverse public understandings.

6.2.2 Summary Statistics

In Table 11, we display the summary statistics for the control variables derived from the CCES survey, spanning the years 2014 to 2023, which are utilized in our analysis. Column (1) offers an overview of the entire sample, while Columns (2) through (5) delineate the summary statistics corresponding to varying levels of Google searches related to the term “defund the police”—namely, no search, low search, medium search, and high search.

Overall, the demographic and socioeconomic characteristics are fairly consistent across different levels of search interest, although there are some variations. The majority of the sample is white and middle-aged across all search interest levels, but there are slight increases in the proportion of white and older individuals in the high-search category. Education and employment status are also relatively stable across categories, but there is a slight increase in postgraduate education and full-time employment in the high-search group. Political orientation shows a trend where the high-search category has a higher proportion of individuals identifying as liberal, suggesting that search interest in Defund may correlate with political leanings.

6.3 Support for Police Funding

6.3.1 Empirical Strategy: Event Study

We analyze the effect of George Floyd’s murder on support for reducing police funding by estimating the following equation:

$$\begin{aligned} Defund_{idt} = \beta_0 + \sum_t D_t \cdot Low_d \cdot \beta_t^L + \sum_t D_t \cdot Medium_d \cdot \beta_t^M \\ + \sum_t D_t \cdot High_d \cdot \beta_t^H + X_i\delta + \alpha_d + \gamma_t + \epsilon_{idt} \end{aligned} \tag{3}$$

where $Defund_{idt}$ denotes the viewpoint of respondent i in DMA d during year t. This dependent variable reflects whether the respondent endorses action by her state legislature to decrease law enforcement funding. The variables $\{None_d, Low_d, Medium_d, High_d\}$ represent the quartile of search intensity related to “defund the police” on Google Trends, with $None_d$ being the omitted group. We interact this search intensity with D_t, which are the year dummies, with 2018 as a reference year. Additionally, we control for the respondent characteristics denoted by X_i.[24] Year and DMA fixed effects are captured by α_d and γ_t. The error term is captured by ϵ_{idt}, and standard errors are clustered at the DMA level.

The key parameters, β_t^L, β_t^M, and β_t^H, capture the temporal variations in average outcomes relative to 2018 and benchmarked against the lowest quartile of search intensity. This baseline is established using search patterns observed from May 1 to August 31, 2020, encompassing the period before and after George Floyd’s murder. The validity of our identification strategy rests on the parallel trends assumption. Specifically, we assume that, absent the 2020 events, regions with different levels of search intensity for “defund the police” would have exhibited similar trends in

[24] The controls are demographics, marital status, education, income, and employment status. We provide the details in 11.

support of police budget reductions. This implies that areas with higher search intensity in 2020 were not inherently different in their historical support for budget cuts, as evidenced by data from 2014, 2016, and 2018, from areas with lower search intensity.

6.3.2 Results

Figure 9 depicts the evolving sentiment toward reducing police funding from equation 3. We report the 95% confidence interval. We provide the mean of the dependent variable for the omitted category in 2018, corresponding to the lowest quartile of Google searches.

Leading up to George Floyd's death, endorsement of such reductions remained relatively restrained. Before 2020, sentiment across regions with varying levels of interest was consistent relative to that of the baseline group, implying similar trends. Notably, only 7% of respondents in areas with the lowest interest supported police budget reductions. The pivotal shift occurred in 2020. Support for budget cuts surged across all interest levels, rising by 3 pp on average. The surge was particularly pronounced in high-interest DMAs, increasing by over 6 pp (SE=0.0116). By 2022, sentiment toward police funding reductions stabilized across DMAs, remaining notably higher than the pre–Gorge Floyd incident levels, with an increase of 2–3 pp ($p < 0.01$).

The aftermath of George Floyd's death amplified the calls for budget cuts. Although this momentum waned somewhat the following year, it remained significantly above pre-incident levels, and uniformly so across interest gradients. However, even in areas where "defund the police" searches were most prominent, support reached a maximum of 13%,[25] a share far smaller than one that could incorporate the median voter. In other words, while there was indeed a certain increase in support for budget reductions, the majority of surveyed respondents still endorsed maintaining or increasing law enforcement funding, as indicated by their views on related state legislature actions.

6.4 Public Understanding of the Defund Movement's Implications

As illustrated in Figure 8, the spike in Google searches for "defund the police" indicates a marked increase in public curiosity. However, the new prominence of police abolitionism and the Defund movement may have sown confusion regarding the movement's true objectives. This section explores this mechanism by delving into the relationship between this search activity and public perspectives on law enforcement and associated policy reforms.

6.4.1 The Defund Movement, Support for Reforms, and Attitudes toward Police

We present the correlation between the Google search intensity of "defund the police" and support for various police reforms and attitudes toward law enforcement in Table 12. All specifications

[25] This number corresponds to adding the baseline mean of the reference group in 2018 to the estimate of β^H_{2020}, i.e., $0.1344 = 0.07 + 0.0644$

control for demographics, marital status, education, income, and employment status and include year fixed effects. Standard errors are clustered at the DMA level.

Table 12 offers a nuanced analysis of the relationship between Google search frequency for "defund the police" and public attitudes toward law enforcement and policy reforms. While the increased search activity does not significantly alter the general perception of safety around the police, it does indicate a shift in resource allocation preferences. Specifically, areas with medium to high search intensity show a statistically significant inclination toward reallocating resources away from policing to other services. Moreover, there is robust support across all levels of search intensity for specific reforms, such as banning chokeholds and demilitarizing the police. This support extends to accountability measures such as body-worn cameras, misconduct registries, and lawsuits against police, particularly in areas with higher search intensity. These findings are statistically significant and account for controls for various demographic factors and year fixed effects, thereby enhancing their reliability. Overall, the results suggest that while the Defund movement may not necessarily be impacting perceptions of safety, it does appear to be influencing public opinion on resource allocation and specific police reforms, highlighting the role of public discourse in shaping attitudes toward law enforcement.

However, it is relevant to discuss the mean of the dependent variable linked to the bottom quartile of Google search activity, i.e., regions with no "defund the police" searches. These means shed light on the prevailing sentiment vis-à-vis different police reforms in areas with the most minimal "defund" search activity. Among the respondents in this bottom quartile, 80% express a sense of safety attributed to the police. Alongside this sentiment, a substantial majority (over three-quarters) of the respondents in the reference group are in favor of policies bolstering police accountability, such as the prohibition of chokeholds, adoption of body-worn cameras, the creation of a registry to track police misconduct, and the right to initiate lawsuits against police specialists. Notably, the implementation of some of these measures, especially the adoption of body-worn cameras (Williams et al., 2021), establishing a misconduct registry (Ba, 2018; Rivera and Ba, 2018), and enabling lawsuits (Schwartz, 2016), could result in augmented expenditure on policing.

We observe a mixed picture of public sentiment toward certain police policies. While some policies garner a clear consensus, others, such as police demilitarization, evoke a broader range of opinions. Notably, demilitarization does not necessarily translate to increased police funding. As referenced by (Bove and Gavrilova, 2017; Mummolo, 2018), police departments might access surplus military equipment instead. Moreover, the debate intensifies with respect to funding reallocation between police forces and other public services. For instance, in areas where "defund" searches are absent, nearly half of respondents are inclined to support expanding the police force even if doing so compromises other public services. However, the ambiguous correlation between the intensity of "defund" searches and public preferences on police staffing complicates the interpretation of how the Defund movement influences perceptions of police funding trade-offs.

6.4.2 Additional Evidence

Activists in the Defund movement also advocate for a strategic reallocation of government funds from law enforcement to community-based services such as housing and mental health (Kaba et al., 2021; Fegley and Murtazashvili, 2023). This policy stance carries empirical implications, suggesting that we should observe increased public support for sectors other than law enforcement. However, our data, as shown in Figure A.11 and Table A.9, indicate that the public's response to the murder of George Floyd did not extend to advocating for budget cuts in other sectors such as education, infrastructure, healthcare, or welfare. This finding suggests that the public may not be fully aware of the broader goals of the Defund movement, as evidenced by the Google search trends shown in Figure 8. Were the public more informed, we would expect to see not just a rise in support for reducing police budgets but also an increase in advocacy for boosting funding in other critical areas such as healthcare and education. These findings suggest that the broader objectives of the Defund movement, which promotes reallocation of police resources to other alternatives, may not be fully understood by the general public.

7 Conclusion

Our research evaluates how stakeholders perceive issues related to police funding and the stock performance of police-affiliated firms in the wake of George Floyd's murder. On-the-ground specialists, including police specialists themselves and community organizers, are the only group to accurately predict stock gains, in contrast to what not only nonexperts but also even finance experts expect. We also reveal that exposure to incomplete product information distorts respondents' stock forecasts. While the Defund campaign has garnered support for budget reductions, it has failed to fragment the existing (politically determinant) majority that supports costly accountability measures associated with police reform rather than abolition. While the Defund protests achieved significant scale and reach, their net impact on the political economy of policing remains ambiguous. The stock (and real) performance of policing-connected firms remains robust, and our analysis suggests that the purchase of abolitionist arguments with political majorities—despite their outsized salience in forecasts for the policing industry—remains limited.

Our paper underscores the complexity of stakeholder perspectives on debates about racial justice and policing and their broader implications for firm performance and public policy. As social movements gain traction, their influence becomes increasingly hard for governments, corporations, and voters to ignore (Ba et al., 2023; Cantoni et al., 2023). Our research adds to the understanding of the dynamics and outcomes of social movements, both globally and in the U.S. (Mazumder, 2018, 2019; Cunningham and Gillezeau, 2019; Wasow, 2020). [26] We find that while social move-

[26]See also the growing literature examining the origins and outcomes of global protests, including those in Egypt (Acemoglu et al., 2018), China (Bursztyn et al., 2021; Beraja et al., 2021), Russia (Enikolopov et al., 2020), and Nigeria

ments such as BLM may increase support for activist demands among a subset of the population, market dynamics and the opinions of political majorities may reflect considerable status quo bias even after a pronounced shock such as the murder of George Floyd. Nonetheless, our nuanced findings suggesting the salience of Defund in forecasts could imply that a spike in support among political minorities could prove to be a crucial factor in long-term political shifts.

(Archibong et al., 2022), to name a few. We focus on a modern mass movement protesting incidents of police violence against Black individuals in the U.S. (DiPasquale and Glaeser, 1998; Cunningham and Gillezeau, 2019) and its antecedents in Black abolitionism.

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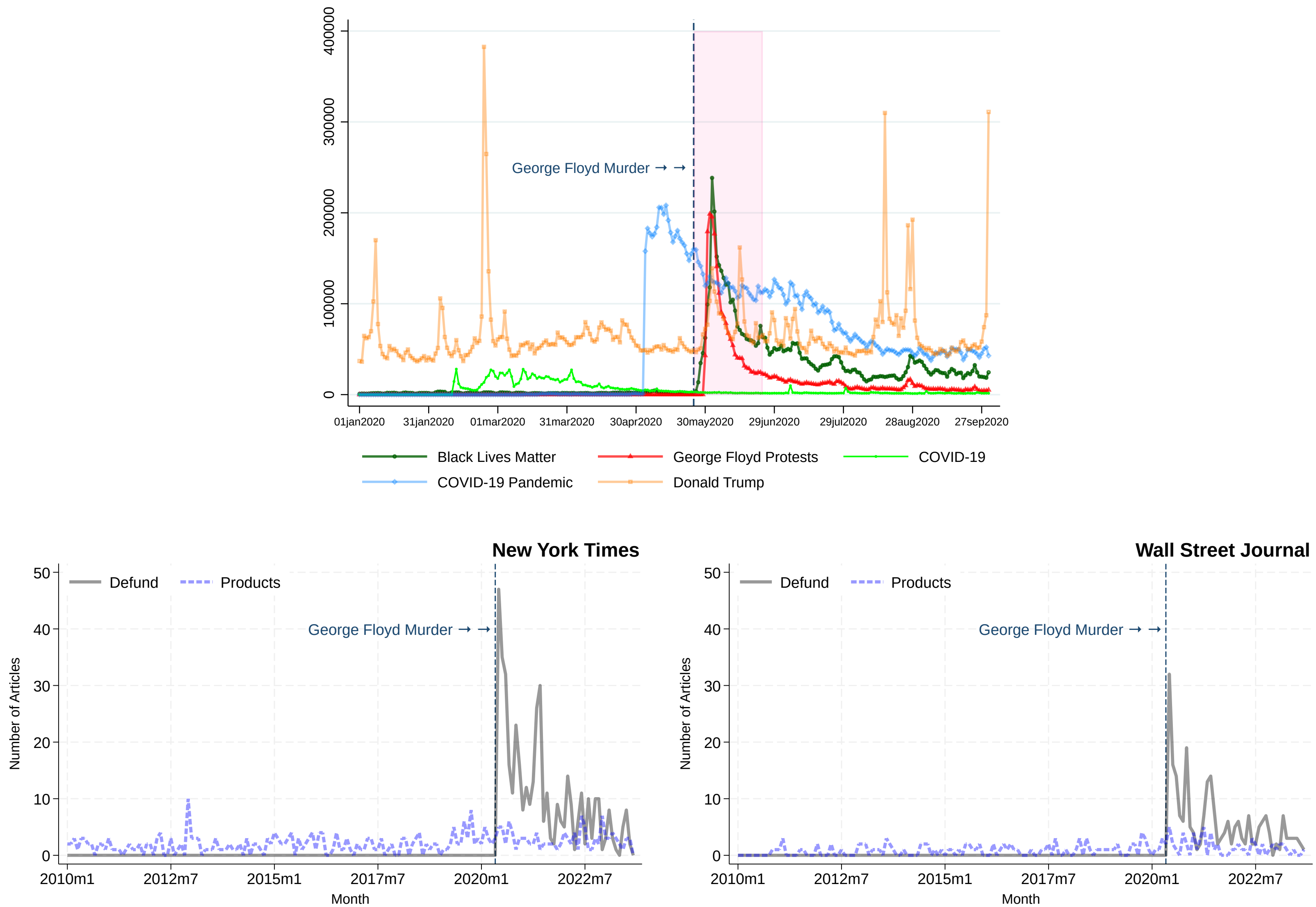
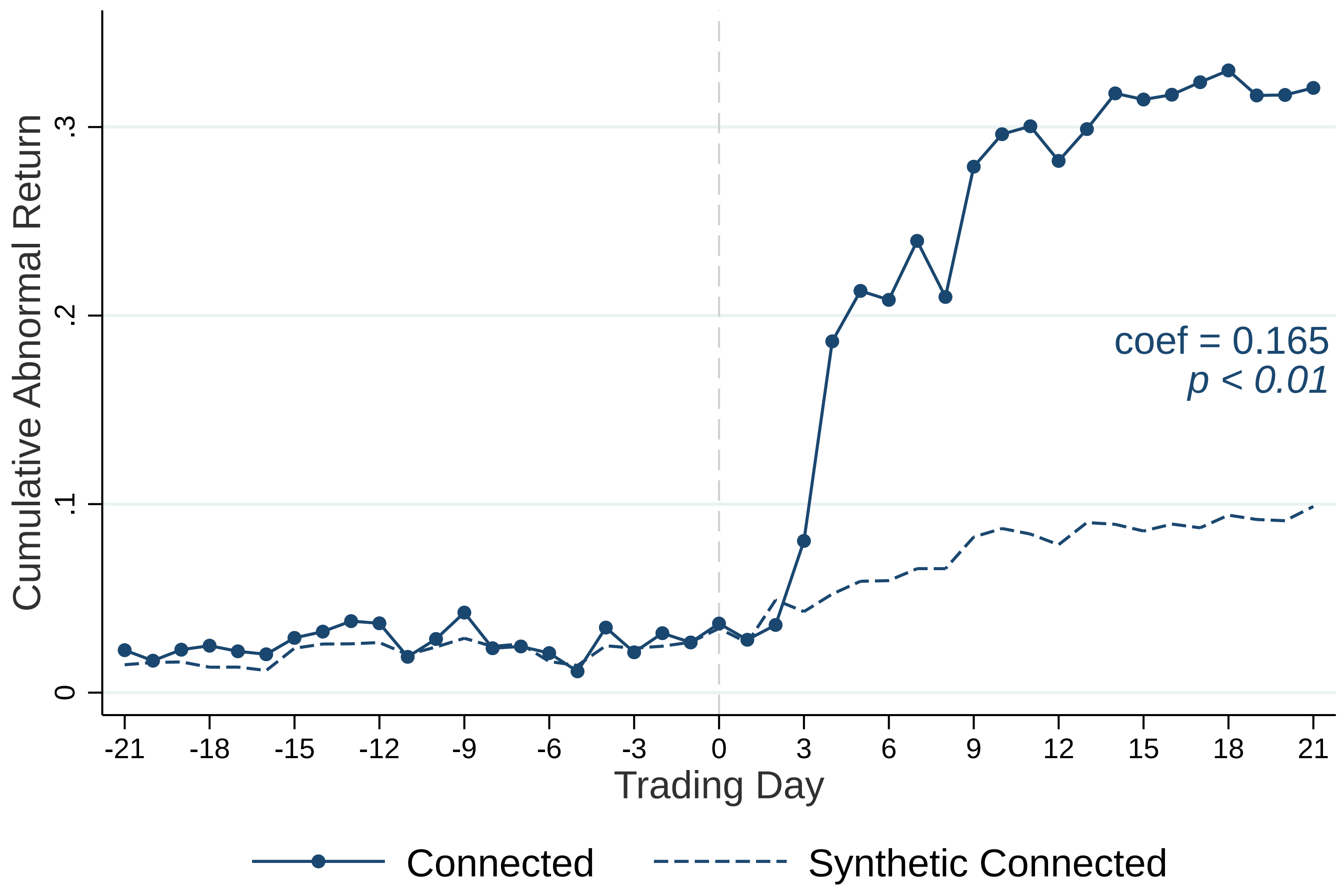
Figure 1: Discussion Associated with George Floyd's Murder



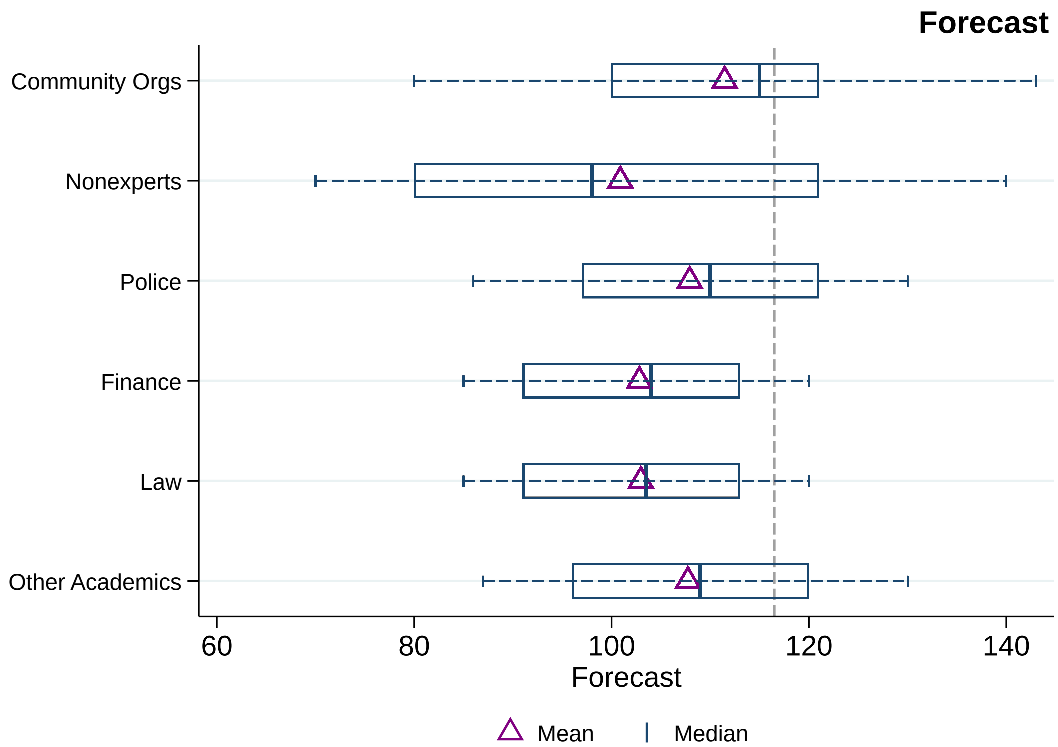
Notes: The top figure presents the daily views for Wikipedia articles on "Black Lives Matter", "George Floyd Protests", "COVID-19", and "Donald Trump" from January 2020 to September 2020 (Pageviews Analysis (2023)). The shaded vertical sections on the graph represent the 21-day period following the murder of George Floyd. In the lower panels, we display the monthly frequency of articles from the *New York Times* and *Wall Street Journal* that feature terms related to both "defund the police" and specific police-related products. For police-related products, we include a range of terms such as "body-worn camera", "simulation-based training", "gunshot location", "less lethal", "surveillance systems", "thermal imaging systems", "dispatch systems", "firearms training" and "tactical training". In the context of "defund the police," we consider variations such as "defund the police", "defund police", "defunding police", "defunding the police", "police defund", and "funding from police".

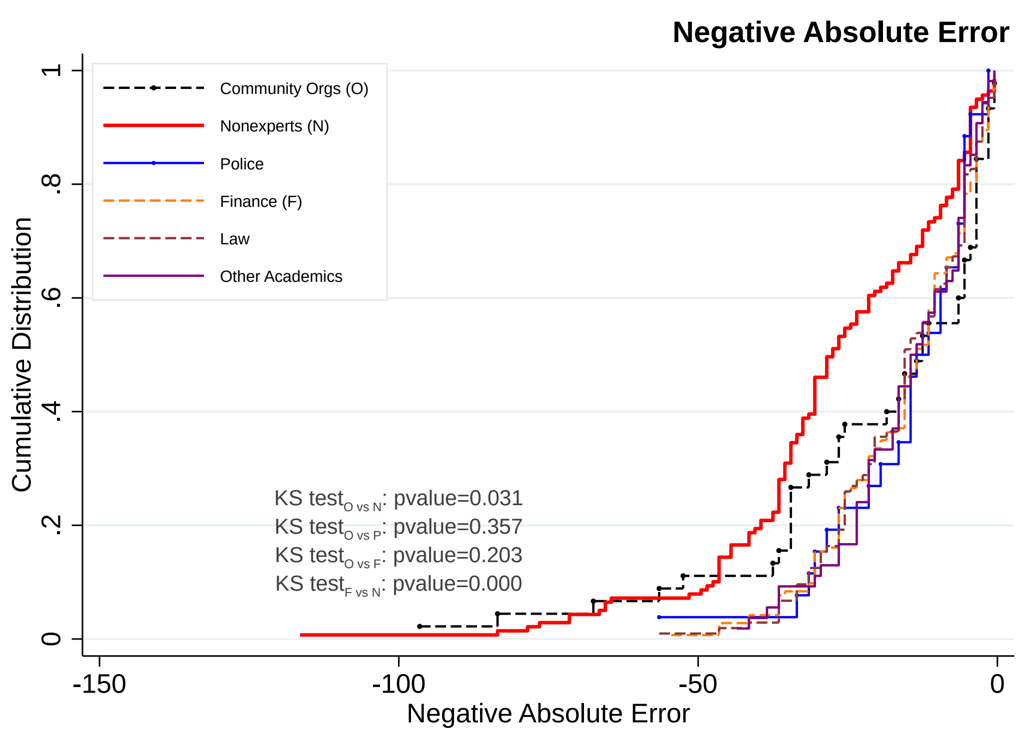
Figure 2: Impact of George Floyd's Murder on Stock Performance



Notes: This figure presents the impact of George Floyd's murder on the cumulative abnormal returns (CARs) of firms contracting intensively with police departments. 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 the p-values. The SDID estimates are computed on the basis of the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated on the basis of the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest.

Figure 3: Distribution of Forecasts and Negative Absolute Error by Category by Expertise





Notes: The top figure presents the distribution of the portfolio forecast by category of expertise. The box plots show the distribution means and 10th, 25th, 50th, 75th, and 90th percentiles. The bottom figure presents the cumulative distribution functions (CDFs) of the negative absolute error (accuracy) by type of expertise. Respondents provided a forecast of the price of a portfolio of firms with ties to policing 21 days after the killing of George Floyd. We also report the *p*-value of a Kolmogorov–Smirnov (KS) test of equality of the different pairs of the distributions of community organizers (O), nonexperts (N), and finance experts (F).

Figure 4: Flow of the Experiment Design

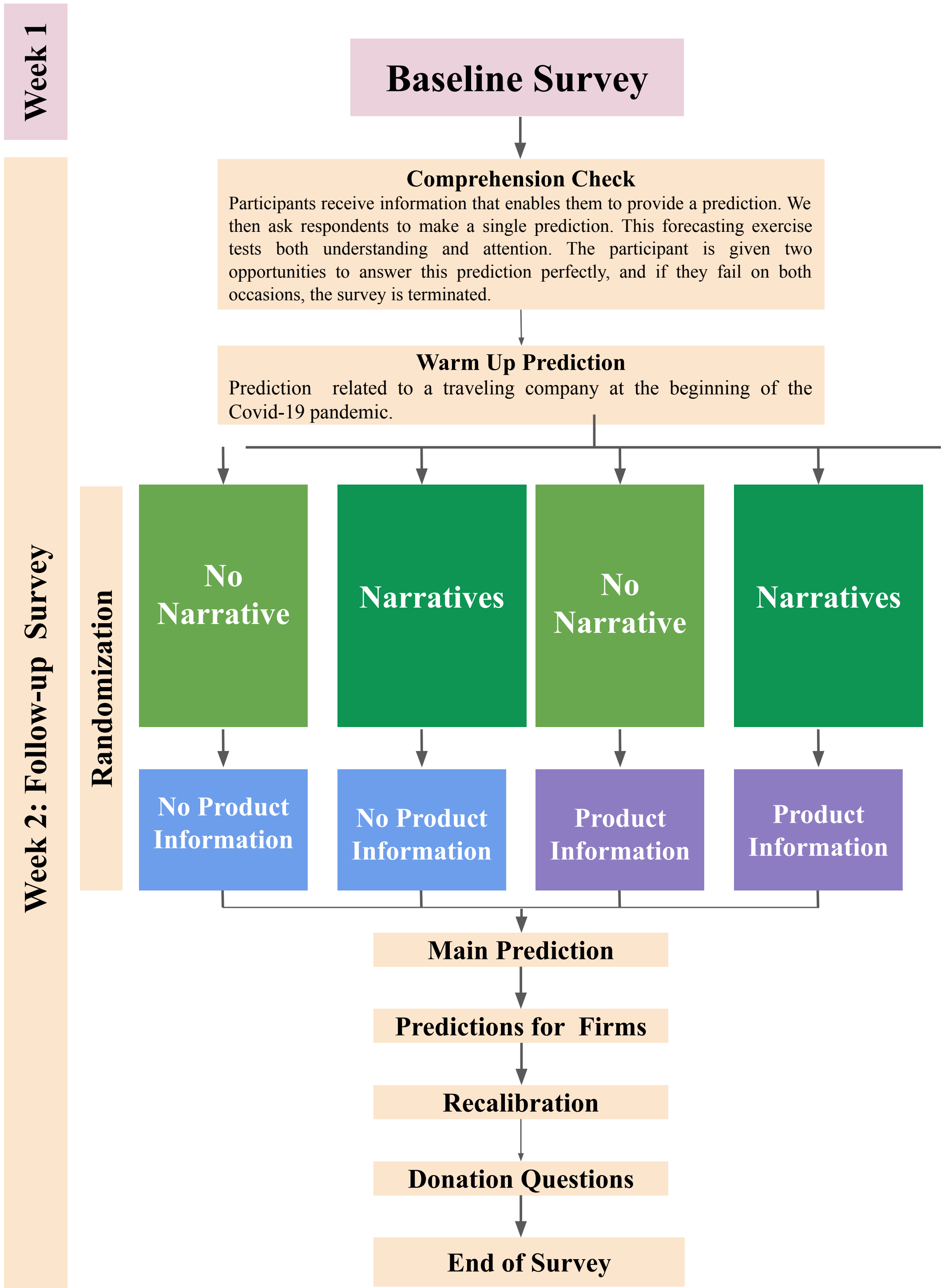
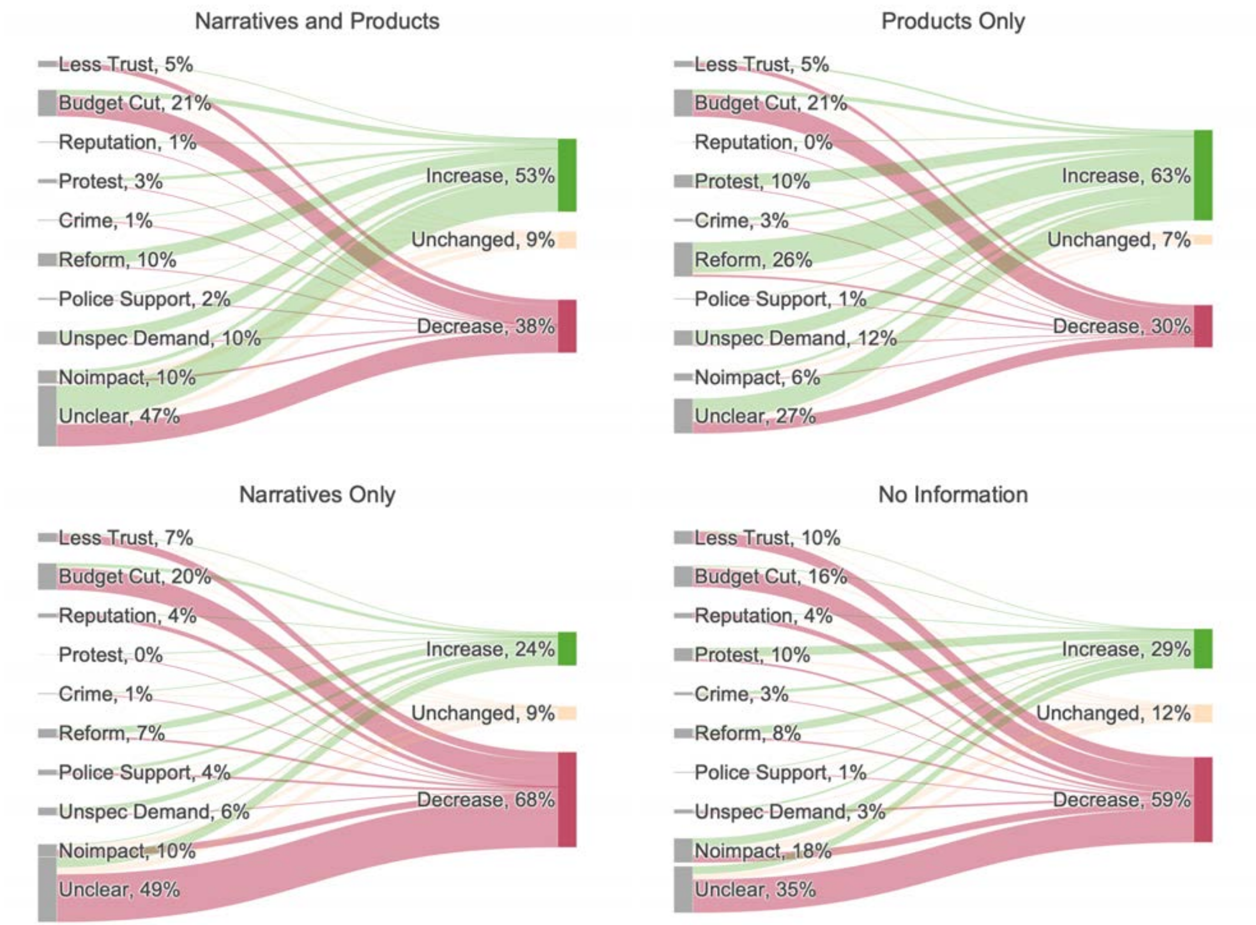


Figure 5: Reasoning, Information, and Forecasts of Nonexperts

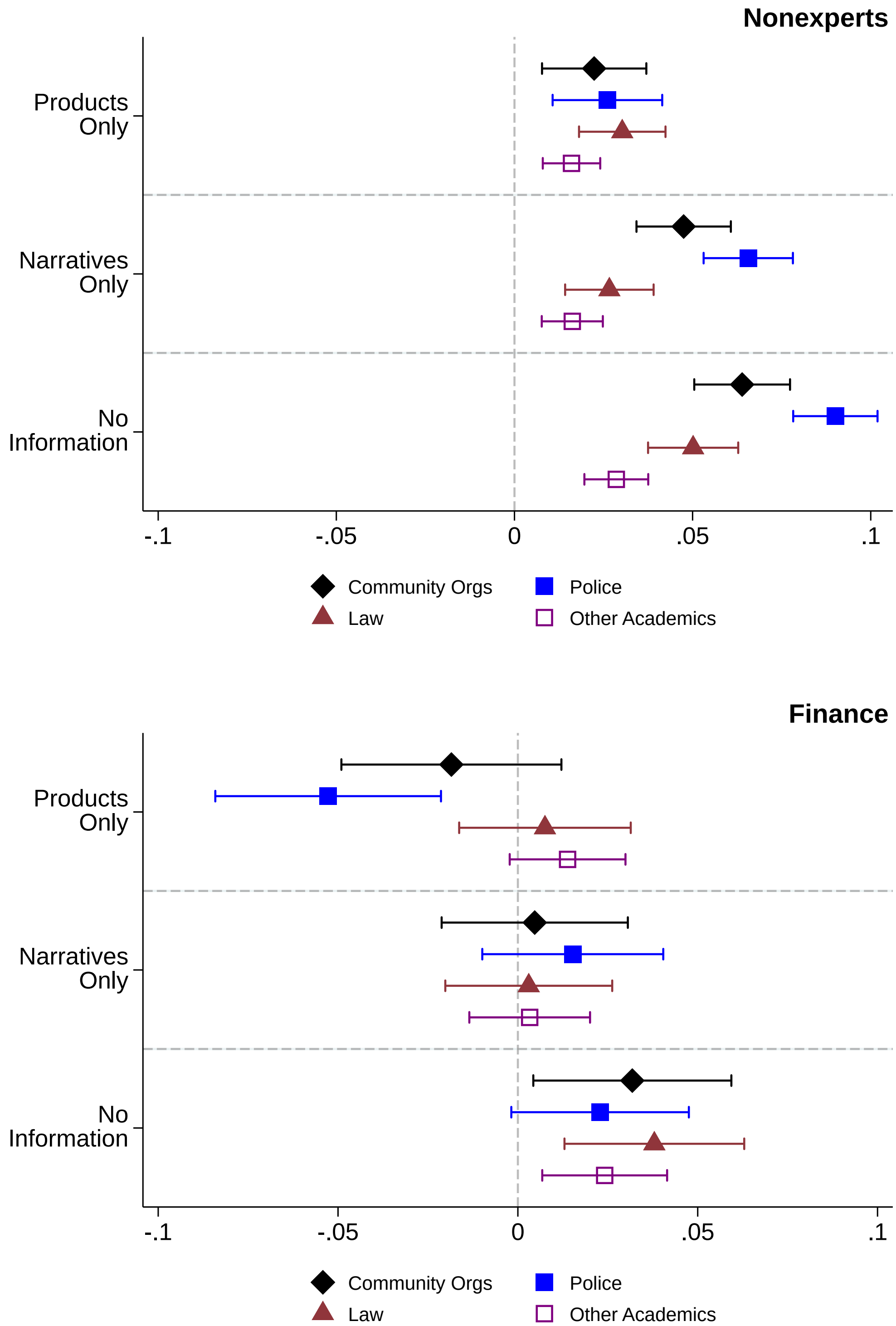
Notes: This figure presents the relationship between information (exposure to product and narrative information related to policing), respondents' reasoning, and forecasts for the nonexpert sample. We report the results by treatment arm. The prediction corresponds to a forecast of the price of a portfolio of firms with ties to policing 21 days after the killing of George Floyd. The left panel reports the shares of the different reasons invoked by respondents to explain their forecasts and the right panel shows the share of respondents who predict an increase, no change, and a decrease in stock prices.

Figure 6: Reasoning, Information, and Forecasts for Finance Professionals



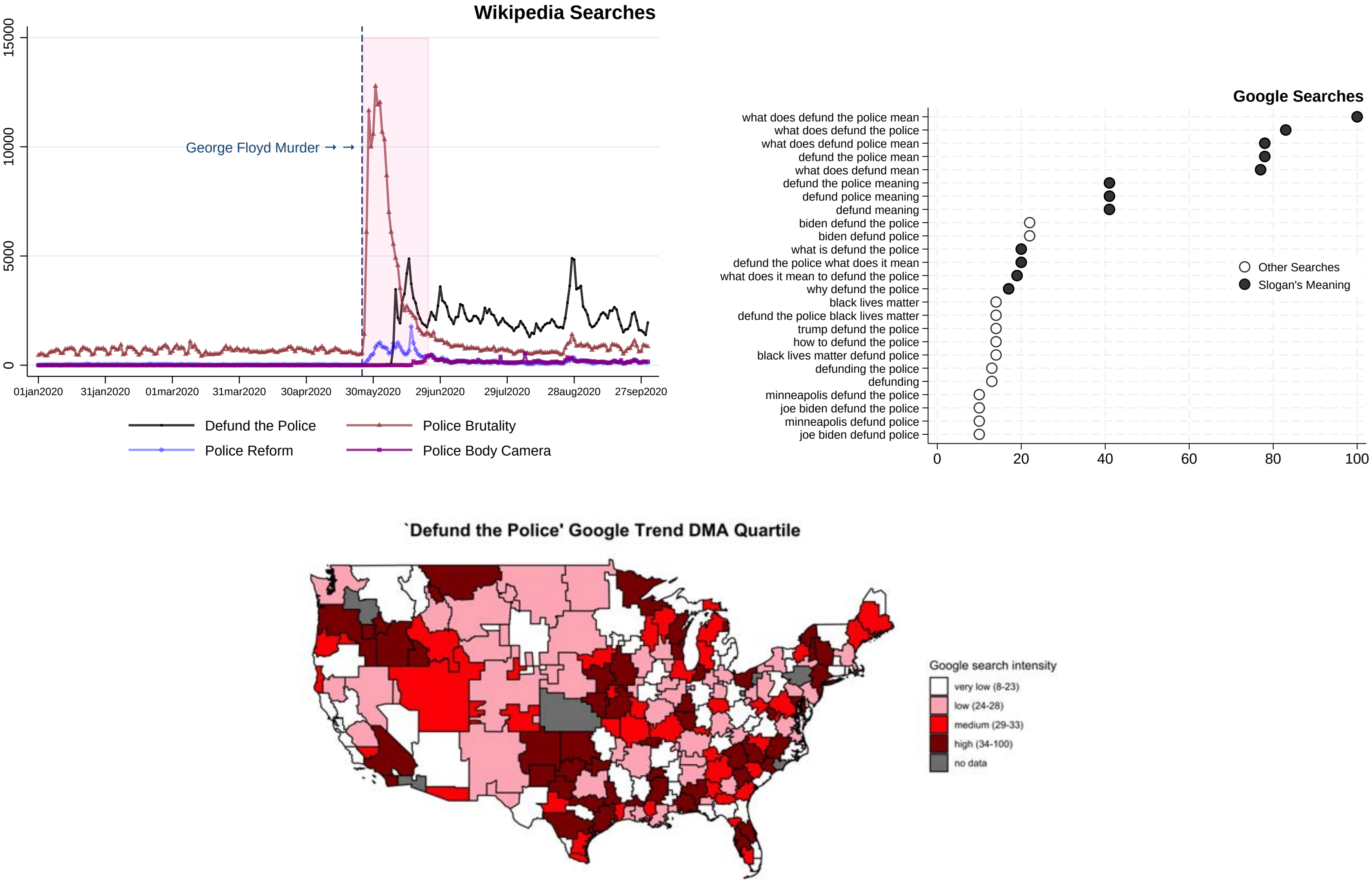
Notes: This figure presents the relationship between information (exposure to product and narrative information related to policing), respondents' reasoning, and the forecasts of the sample of finance professionals. We report the results by treatment arm. The prediction corresponds to a forecast of the price of a portfolio of firms with ties to policing 21 days after the killing of George Floyd. The left panel reports the shares of the different reasons invoked by respondents to explain their forecasts, and the right panel shows the share of respondents who predict an increase, no change and a decrease in stock prices.

Figure 7: Impact of Information Treatments on Reasoning Dissimilarity



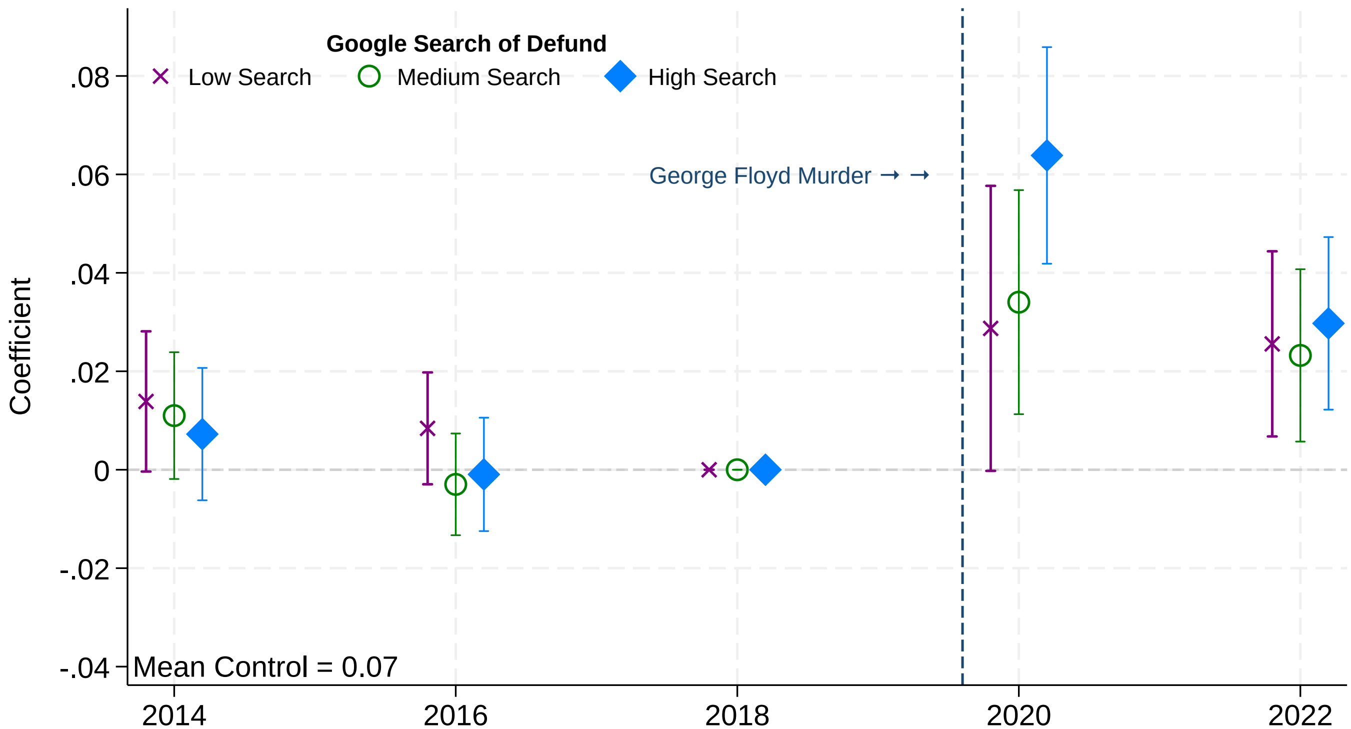
Notes: This figure reports the regression results on the impact of the information treatment (exposure to product and narrative information related to policing) on reasoning dissimilarity between the experimental sample (nonexperts and finance professionals) and community organizers, police experts, law experts, and other academics. The dependent variable is a Jaccard dissimilarity index, i.e., taking values between zero and one, where a higher value corresponds to greater dissimilarity between the two groups. The top and bottom panels present the results for the nonexpert and finance samples, respectively. We provide the estimates and their 95% confidence intervals using bootstrap standard errors.

Figure 8: Salience of "Defund the Police"



Notes: The Wikipedia searches chart uses Wikipedia's pageviews tool to track the total number of page visits for various groups of pages over time. For example, for the "defund the police" series, we use the page "Defund the police". The Google searches chart uses Google Trend data to report an index of Google search frequency for various search terms in the United States from May 1 to August 31, 2020. The "defund the police" map plots the intensity of Google searches for "defund the police" across DMAs in the United States. Google Trend data are also recorded at the designated market area (DMA) level. We use the Google Trend data to place DMAs into quartiles by Google Trend index. The range of the Google Trend index within the quartiles is reported in the figure.

Figure 9: George Floyd's Murder and Public Support for Reducing Police Funding



Notes: This figure presents the impact of George Floyd"s murder on support for reducing police funding, categorized by quartiles of Google search activity for "defund the police". We report the 95% confidence intervals, with standard errors clustered at the designated market area (DMA) level. Additionally, we provide the mean of the dependent variable for the omitted category, corresponding to the lowest quartile of Google searches.

Table 1: Summary Statistics

	All Respondents	Community Organizers	Nonexperts	Police	Finance	Law	Other Academics
Female	0.37	0.71	0.53	0.19	0.20	0.28	0.35
Born in the U.S.A.	0.78	0.87	0.72	0.92	0.65	0.92	0.89
White	0.72	0.56	0.61	0.69	0.77	0.88	0.72
Age: 18 to 34	0.23	0.49	0.50	0.04	0.10	0.01	0.13
Age: 55+ or missing	0.57	0.47	0.36	0.58	0.64	0.78	0.59
Check Investment Weekly/Daily	0.24	0.09	0.22	0.12	0.35	0.27	0.19
Response Time:							
0-6 min	0.14	0.09	0.30	0.04	0.08	0.05	0.11
7-13 min	0.52	0.53	0.50	0.58	0.51	0.50	0.56
14+ min	0.35	0.38	0.19	0.38	0.41	0.45	0.33
Observations	511	45	139	26	143	104	54

Notes: The table presents means of the covariates for respondents by category of expertise.

Table 2: Summary Statistics by Treatment Arm

	(1) All	(2) Narratives and Products	(3) Products Only	(4) Narratives Only	(5) No Information	(6) p-value
Panel A: Nonexperts						
Female	0.44	0.47	0.46	0.45	0.38	0.005
Born in the US	0.92	0.91	0.92	0.94	0.89	0.036
White	0.72	0.69	0.75	0.72	0.73	0.135
Age 18 to 34	0.40	0.39	0.40	0.41	0.39	0.803
Age 55+ or missing	0.45	0.46	0.45	0.44	0.45	0.926
Check Investment Weekly	0.34	0.33	0.37	0.37	0.32	0.162
0-6 min	0.44	0.42	0.46	0.41	0.47	0.164
7-13 min	0.43	0.44	0.43	0.45	0.39	0.224
14-20 min	0.13	0.14	0.11	0.14	0.14	0.446
Observations	2346	591	579	591	585	2346
Panel B: Finance						
Female	0.20	0.22	0.23	0.17	0.19	0.597
Born in the US	0.93	0.90	0.93	0.93	0.94	0.665
White	0.81	0.79	0.82	0.83	0.80	0.798
Age 18 to 34	0.06	0.04	0.03	0.08	0.08	0.257
Age 55+ or missing	0.70	0.74	0.77	0.67	0.64	0.090
Check Investment Weekly	0.43	0.42	0.44	0.46	0.42	0.924
0-6 min	0.06	0.03	0.09	0.05	0.07	0.275
7-13 min	0.46	0.44	0.56	0.41	0.45	0.091
14-20 min	0.47	0.53	0.34	0.54	0.49	0.007
Observations	467	117	117	114	119	467

Notes: The table presents the mean of the covariates from the online experiment for nonexperts (Panel A) and finance professionals (Panel B). Column (1) provides the mean level of each variable for the full sample. Columns (2) to (5) report the mean level of each variable by treatment arm. Column (6) reports the p-value from a test of the hypothesis of equal means across the experimental conditions.

Table 3: Impact of Information Treatments on Forecasts

	(1) Predict an Increase	(2) Predict an Increase	(3) Neg. Abs Error	(4) Neg. Abs Error
Products Only (P)	-0.0211	0.109*	-2.491**	3.376*
	(0.0291)	(0.0656)	(1.179)	(2.017)
Narratives Only (N)	-0.311***	-0.301***	-10.49***	-6.590***
	(0.0261)	(0.0616)	(1.115)	(2.019)
No Information (O)	-0.344***	-0.241***	-12.76***	-3.804**
	(0.0257)	(0.0630)	(1.140)	(1.888)
Sample	Nonexperts	Finance	Nonexperts	Finance
Controls	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	0.50	0.53	-23.48	-19.58
Observations	2346	467	2346	467

Notes: This table presents the impact of exposure to product and narrative information related to policing on the forecast accuracy of nonexperts (odd columns) and finance professionals (even columns). The dependent variables are measures of accuracy given by a binary variable that equals one if the respondent predicts an increase in the price of a portfolio of policing-connected firms or individual stocks and zero otherwise (columns (1) and (2)) and negative absolute error (columns (3) and (4)). We report robust standard errors in parentheses. In addition, we report the mean of the dependent variable of the omitted category, i.e., individuals receiving both product and narrative information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 4: Impact of Information Treatments on Likelihood of Predicting a Portfolio Price Increase by Type of Forecast

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Nonexperts								
Products Only (P)	-0.0211	-0.0381	-0.0215	0.0383	-0.0242	0.0170	-0.00572	-0.00828
	(0.0291)	(0.0272)	(0.0278)	(0.0293)	(0.0287)	(0.0290)	(0.0215)	(0.0212)
Narratives Only (N)	-0.311***	0.00919	0.0278	-0.0102	-0.0118	-0.0460	-0.00620	-0.0570***
	(0.0261)	(0.0264)	(0.0270)	(0.0290)	(0.0284)	(0.0290)	(0.0204)	(0.0194)
No Information (O)	-0.344***	-0.0600**	-0.0375	-0.0343	-0.0378	-0.0361	-0.0411*	-0.0915***
	(0.0257)	(0.0274)	(0.0279)	(0.0291)	(0.0287)	(0.0292)	(0.0214)	(0.0202)
Forecast	Portfolio	Axon	Flir	Motorola	Shotspotter	Virtra	Stocks Only	All
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	0.50	0.70	0.67	0.46	0.62	0.57	0.60	0.59
Observations	2346	2346	2346	2346	2346	2346	11730	14076
Panel B: Finance								
Products Only (P)	0.109*	0.157***	0.167***	0.163**	0.184***	0.0715	0.148***	0.142***
	(0.0656)	(0.0555)	(0.0577)	(0.0659)	(0.0602)	(0.0635)	(0.0443)	(0.0442)
Narratives Only (N)	-0.301***	0.0468	0.0786	-0.00722	0.0138	-0.0830	0.00981	-0.0420
	(0.0616)	(0.0598)	(0.0618)	(0.0655)	(0.0643)	(0.0667)	(0.0457)	(0.0440)
No Information (O)	-0.241***	-0.00493	0.0982	0.0445	0.0643	0.0210	0.0446	-0.00302
	(0.0630)	(0.0615)	(0.0604)	(0.0646)	(0.0633)	(0.0644)	(0.0466)	(0.0449)
Forecast	Portfolio	Axon	Flir	Motorola	Shotspotter	Virtra	Stocks Only	All
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	0.53	0.68	0.65	0.42	0.61	0.61	0.59	0.58
Observations	467	467	467	467	467	467	2335	2802

Notes: This table presents the impact of exposure to product and narrative information related to policing on the forecast accuracy of nonexperts (Panel A) and finance professionals (Panel B). Each respondent provided forecasts of the stock price of firms with ties to policing at 21 days after the killing of George Floyd. The firms were anonymized, but respondents were given keywords associated with the firms' products and services (e.g., body-worn cameras, dispatch systems, weapons, less-than-lethal weapons). For detailed information about the keywords associated with the firms, see Section A.1. The dependent variables are measures of accuracy given by a binary variable that equals one if the respondent predicts an increase in the price of the portfolio or individual stocks and zero otherwise. We report robust standard errors in parentheses. In addition, we report the mean of the dependent variable of the omitted category, i.e., individuals receiving both product and narrative information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 5: Impact of Information Treatments on Willingness to Change the Forecast

	(1) Any Redo	(2) Any Redo	(3) Predict an Increase	(4) Predict an Increase	(5) Neg. Abs Error	(6) Neg. Abs Error
Products Only (P)	-0.00959	0.0521	-0.00748	0.127*	-1.568	3.473*
	(0.0210)	(0.0445)	(0.0289)	(0.0648)	(1.165)	(2.032)
Narratives Only (N)	0.0664***	0.128**	-0.227***	-0.242***	-6.650***	-4.291**
	(0.0228)	(0.0501)	(0.0279)	(0.0638)	(1.137)	(2.062)
No Information (O)	0.113***	0.0885*	-0.247***	-0.158**	-8.526***	-2.714
	(0.0235)	(0.0464)	(0.0277)	(0.0650)	(1.160)	(1.977)
Sample	Nonexperts	Finance	Nonexperts	Finance	Nonexperts	Finance
Portfolio Forecast	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	0.17	0.12	0.54	0.55	-22.81	-19.09
Observations	2346	467	2346	467	2346	467

Notes: This table presents the impact of exposure to product and narrative information related to policing on the stock forecasts of nonexperts (odd columns) and finance professionals (even columns). Each respondent provided forecasts of the price of a portfolio of firms with ties to policing at 21 days after the killing of George Floyd. The dependent variables in columns (1) and (2) equal one if the respondent is willing to submit a new forecast and zero otherwise. The dependent variables are measures of accuracy given by negative absolute error and a binary variable that equals one if the respondent predicts an increase in the price of the portfolio or individual stocks and zero otherwise. Columns (3) to (6) are based on the final submitted forecast. The dependent variables for columns (3) to (6) are measures of accuracy given by the negative of the absolute forecast error and a binary variable that equals one if the respondent predicts an increase in the price of the portfolio or individual stocks and zero otherwise. We report robust standard errors in parentheses. In addition, we report the mean of the dependent variable of the omitted category, i.e., individuals receiving both product and narrative information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 6: Impact of Information Treatments on Willingness to Support Policies

	(1) Any Donation	(2) Donation Amount	(3) Police Wellness	(4) Police Reform	(5) Reduce Scope Police	(6) No Support
Products Only (P)	-0.0234	-0.0346	0.00574	-0.0142	-0.0149	0.0234
	(0.0290)	(0.175)	(0.0260)	(0.0193)	(0.0206)	(0.0290)
Narratives Only (N)	0.0000744	-0.00813	0.00501	-0.000642	-0.00429	-0.0000744
	(0.0287)	(0.173)	(0.0258)	(0.0196)	(0.0207)	(0.0287)
No Information (O)	0.00103	-0.0826	-0.0199	0.0177	0.00324	-0.00103
	(0.0288)	(0.170)	(0.0256)	(0.0204)	(0.0210)	(0.0288)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	0.56	2.47	0.27	0.14	0.15	0.44
Observations	2346	2346	2346	2346	2346	2346

Notes: This table presents the impact of exposure to product and narrative information related to policing on donations and support for different policies among nonexperts. We report robust standard errors in parentheses. We report the mean of the dependent variable of the omitted category, i.e., individuals receiving both product and narrative information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 7: Categories of Reasoning behind Price Forecasts

Category	**Description**	**Example**
Less Trust	Responses related to an emotional response leading to loss of trust or a desire to hold the police accountable. These response may be vague or not describe a precise mechanism for how stocks actually fall	"Faith in the police would have been negatively impacted after this event. As such, the companies would have likely decreased in share price by a decently sizable amount."
Budget Cut	Responses related to protests, riots, or general unrest. Responses should specifically reference the resources required to deal with protests.	"There might be a cutback to city budgets in response to the protest. This would cause police departments to purchase less products and services being offered by these companies."
Reputation	Responses related to ethical issues, divestment, environmental and reputational concerns. Boycotts of companies should also be included. Companies' distancing themselves from the police should also be included.	"The companies that were associated with police departments would be socially chastised. In this case, I predict that the stock options would decrease in value."
Protest	Responses related to protests, riots, or general unrest. Responses should specifically reference the resources required to deal with protests.	"There are a lot of protests after the incident, which will encourage the police to purchase more anti riot equipments."
Crime	Response related to how crime will be impacted by the events or impacts on crime not directly related to protests or unrests (e.g., violent crime, property crime, need for more surveillance). This could also include public fears of more crime.	"I imagine that the value would increase, because uprisings and civil unrest seem to feed into narratives about crime and lawlessness. A state response to that, often, is to funnel more resources toward policing and military. Since the companies in the portfolio produce material goods for policing, I predicted an increase."
Reform	Responses related to calls for investment in police reform with a demand for police accountability tools: training, body-worn cameras, etc.	"Pressure on police departments to do more training, have more body-worn cameras, purchase more surveillance equipment would tend to cause the stocks of the companies providing these products and services to increase."
Police Support	Responses discussing how support for police actually increases after the killing of George Floyd. This includes discussion of how pro-police groups (e.g., Blue Lives Matter or All Lives Matter) gained traction as a backlash to Black Lives Matter (BLM).	"I would hope it would go down, but I suspect it would have gone up because a large section of the population felt the police were justified in the murder. The police were getting an immense amount of support by the 'Blue Lives Matter' folks."
Unspecified Demand	Responses suggesting that demand for the products in the portolfio will change (either up or down). However, the types of products demanded are not specified.	"The product are more in demand. Because of that I think the stocks will go up."
No Impact	Responses that suggest the event did not have any impact on stock price movement.	"The police were not defunded. The companies contracted to police departments held their ground and their worth remained the same."
Unclear	Responses that cannot be classified. These could also be clear narratives that do not fit into the categories.	"I think that the stocks will go up."

Notes: This table provides details of the different categories of reasons mentioned by respondents to explain their forecasts with descriptions and examples related to our coding scheme.

Table 8: Impact of Information Treatments on Reasoning Cited by Nonexperts

	(1) Less Trust	(2) Budget Cut	(3) Reform	(4) Unclear	(5) Unspecified Demand	(6) Reputation	(7) No Impact	(8) Protest	(9) Crime	(10) Police Support
Products Only (P)	0.0620***	-0.0878***	-0.0341	-0.0500*	-0.0311*	0.0332**	0.0156	0.0959***	0.00616	-0.0151
	(0.0211)	(0.0207)	(0.0233)	(0.0255)	(0.0164)	(0.0151)	(0.0126)	(0.0181)	(0.00969)	(0.00986)
Narratives Only (N)	0.107***	0.0164	-0.161***	0.0367	-0.0795***	0.0653***	0.0412***	-0.0290**	-0.0183**	0.00723
	(0.0221)	(0.0233)	(0.0194)	(0.0267)	(0.0139)	(0.0163)	(0.0139)	(0.0122)	(0.00727)	(0.0116)
No Information (O)	0.210***	-0.0734***	-0.202***	0.0319	-0.0898***	0.121***	0.0279**	0.00580	-0.0108	-0.00640
	(0.0239)	(0.0211)	(0.0176)	(0.0268)	(0.0134)	(0.0184)	(0.0134)	(0.0143)	(0.00815)	(0.0103)
Sample	Nonexperts	Nonexperts	Nonexperts	Nonexperts	Nonexperts	Nonexperts	Nonexperts	Nonexperts	Nonexperts	Nonexperts
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	0.13	0.19	0.22	0.28	0.10	0.06	0.04	0.06	0.03	0.04
Observations	2346	2346	2346	2346	2346	2346	2346	2346	2346	2346

Notes: This table presents the impact of exposure to product and narrative information related to policing on the reasons mentioned by nonexperts for their forecasts. The dependent variable equals one if the respondent provided a reason associated with the respective category and zero otherwise. Table 7 provides details of the categories with descriptions and examples related to our coding scheme. We report robust standard errors in parentheses. In addition, we report the mean of the dependent variable of the omitted category, i.e., individuals receiving both product and narrative information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 9: Impact of Information Treatments on Reasoning Cited by Finance Professionals

	(1) Less Trust	(2) Budget Cut	(3) Reform	(4) Unclear	(5) Unspecified Demand	(6) Reputation	(7) No Impact	(8) Protest	(9) Crime	(10) Police Support
Products Only (P)	0.00192	0.0109	0.172***	-0.185***	0.0172	-0.0137	-0.0602	0.0700**	0.0186	-0.00853
	(0.0322)	(0.0543)	(0.0499)	(0.0626)	(0.0418)	(0.0107)	(0.0380)	(0.0328)	(0.0164)	(0.0159)
Narratives Only (N)	0.0243	-0.00675	-0.0279	0.0178	-0.0386	0.0296	-0.00899	-0.0391**	-0.00206	0.0278
	(0.0329)	(0.0538)	(0.0369)	(0.0666)	(0.0359)	(0.0202)	(0.0390)	(0.0172)	(0.0127)	(0.0225)
No Information (O)	0.0553	-0.0462	-0.0231	-0.121*	-0.0631*	0.0359*	0.0757*	0.0600*	0.0145	-0.00747
	(0.0359)	(0.0511)	(0.0369)	(0.0644)	(0.0325)	(0.0208)	(0.0449)	(0.0314)	(0.0173)	(0.0149)
Sample	Finance	Finance	Finance	Finance	Finance	Finance	Finance	Finance	Finance	Finance
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	0.05	0.21	0.10	0.47	0.10	0.01	0.10	0.03	0.01	0.02
Observations	467	467	467	467	467	467	467	467	467	467

Notes: This table presents the impact of exposure to product and narrative information related to policing on finance professionals' reasoning. The dependent variable equals one if the respondent provided a reason associated with the category and zero otherwise. Table 7 provides details of the categories with descriptions and examples related to our coding scheme. We report robust standard errors in parentheses. In addition, we report the mean of the dependent variable of the omitted category, i.e., individuals receiving both product and narrative information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 10: Impact of Information Treatments on Reasoning Dissimilarity

	(1) Nonexperts vs Comm. Orgs.	(2) Finance vs Comm. Orgs.	(3) Nonexperts vs Police	(4) Finance vs Police	(5) Nonexperts vs Law	(6) Finance vs Law	(7) Nonexperts vs Oth. Academics	(8) Finance vs Oth. Academics
Products Only (P)	0.0224***	-0.0185	0.0261***	-0.0528***	0.0303***	0.00753	0.0160***	0.0138*
	(0.00747)	(0.0155)	(0.00785)	(0.0163)	(0.00619)	(0.0121)	(0.00412)	(0.00790)
Narratives Only (N)	0.0475***	0.00469	0.0656***	0.0153	0.0266***	0.00303	0.0162***	0.00328
	(0.00676)	(0.0139)	(0.00639)	(0.0129)	(0.00634)	(0.0124)	(0.00437)	(0.00886)
No Information (O)	0.0639***	0.0318**	0.0901***	0.0229*	0.0502***	0.0379***	0.0286***	0.0241***
	(0.00686)	(0.0142)	(0.00604)	(0.0128)	(0.00645)	(0.0128)	(0.00457)	(0.00886)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	0.83	0.83	0.85	0.87	0.83	0.80	0.86	0.83
Observations	2346	467	2346	467	2346	467	2346	467

Notes: This table presents the impact of exposure to product and narrative information related to policing on reasoning dissimilarity between the experimental sample (nonexperts and finance professionals) and community organizers, police specialists, law experts, and academics. The dependent variable is a Jaccard dissimilarity index, i.e., taking values between zero and one, where higher values correspond to a greater dissimilarity between the two groups. We report bootstrap standard errors in parentheses. In addition, we report the mean of the dependent variable of the omitted category, i.e., individuals receiving both product and narrative information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 11: Summary Statistics of Cooperative Election Survey Respondents

	(1) All	(2) No Search	(3) Low Search	(4) Medium Search	(5) High Search
Male	0.45	0.44	0.45	0.46	0.46
Age	51.88	51.65	51.39	52.11	52.07
White	0.76	0.69	0.73	0.77	0.80
Black	0.09	0.13	0.11	0.09	0.08
Hispanic	0.07	0.10	0.09	0.07	0.05
Asian	0.03	0.03	0.03	0.03	0.03
Native American	0.01	0.01	0.01	0.01	0.01
Mixed	0.02	0.02	0.02	0.02	0.02
Other Race	0.02	0.02	0.01	0.01	0.02
Middle Eastern	0.00	0.00	0.00	0.00	0.00
No HS	0.02	0.03	0.02	0.02	0.02
High School Graduate	0.24	0.25	0.24	0.24	0.24
Some College	0.22	0.24	0.23	0.21	0.22
2-Year	0.11	0.12	0.11	0.11	0.11
4-Year	0.26	0.23	0.25	0.26	0.26
Postgrad	0.15	0.13	0.14	0.16	0.16
Full-Time	0.40	0.38	0.40	0.40	0.41
Part-Time	0.10	0.09	0.10	0.10	0.10
Temporarily Laid Off	0.01	0.01	0.01	0.01	0.01
Unemployed	0.05	0.06	0.05	0.05	0.05
Retired	0.26	0.26	0.24	0.26	0.26
Permanently Disabled	0.06	0.07	0.07	0.06	0.06
Homemaker	0.07	0.08	0.07	0.06	0.06
Student	0.03	0.03	0.03	0.03	0.03
Other Employment	0.02	0.02	0.02	0.02	0.02
Married	0.54	0.55	0.54	0.54	0.54
Separated	0.01	0.02	0.02	0.01	0.01
Divorced	0.11	0.12	0.12	0.11	0.11
Widowed	0.06	0.06	0.06	0.06	0.05
Single/Never Married	0.23	0.21	0.23	0.23	0.24
Domestic Partnership	0.05	0.05	0.05	0.05	0.05
Family Income – Less than 10k	0.04	0.04	0.04	0.03	0.03
Family Income – 10k–20k	0.07	0.08	0.07	0.06	0.06
Family Income – 20k–30k	0.09	0.11	0.10	0.09	0.08
Family Income – 30k–40k	0.10	0.11	0.11	0.10	0.10
Family Income – 40k–50k	0.09	0.09	0.09	0.08	0.09
Family Income – 50k–60k	0.09	0.09	0.09	0.09	0.09
Family Income – 60k–70k	0.07	0.07	0.07	0.07	0.07
Family Income – 70k–80k	0.08	0.07	0.08	0.07	0.08
Family Income – 80k–100k	0.09	0.08	0.08	0.09	0.09
Family Income – 100k–120k	0.07	0.06	0.06	0.07	0.07
Family Income – 120k–150k	0.06	0.05	0.06	0.06	0.07
Family Income – 150k+	0.07	0.06	0.07	0.08	0.08
Family Income – Prefer not to say	0.09	0.09	0.09	0.10	0.09
Observations	237035	25045	56067	77926	77997

Notes: The table provides the mean values of the covariates for respondents participating in the Cooperative Election Survey across the years 2014, 2016, 2018, 2020, and 2022. Column (1) displays the aggregate results for the entire sample. Columns (2) through (5) break down these mean values according to different levels of Google search activity related to the term "defund the police," categorized as no search, low search, medium search, and high search.

Table 12: Correlation between "Defund the Police" Search Activity and Police Reforms

	(1) Police Makes Feel Safe	(2) More Police Less Others	(3) Less Police More Others	(4) Ban Chokeholds	(5) End Militarization	(6) Body-Worn Camera	(7) Misconduct Registry	(8) Lawsuit
Low Search	-0.0082	-0.0122	0.0227**	0.0240***	0.0252***	0.0075*	0.0100*	0.0112*
	(0.0062)	(0.0091)	(0.0098)	(0.0083)	(0.0092)	(0.0039)	(0.0060)	(0.0067)
Medium Search	-0.0107*	-0.0270**	0.0335***	0.0459***	0.0435***	0.0015	0.0161**	0.0135**
	(0.0064)	(0.0131)	(0.0079)	(0.0080)	(0.0099)	(0.0042)	(0.0067)	(0.0061)
High Search	-0.0201***	-0.0445***	0.0535***	0.0610***	0.0671***	0.0116***	0.0237***	0.0280***
	(0.0071)	(0.0115)	(0.0098)	(0.0082)	(0.0107)	(0.0036)	(0.0067)	(0.0073)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	0.80	0.49	0.36	0.73	0.46	0.93	0.81	0.76
Observations	96,055	96,055	96,055	96,055	96,055	96,055	96,055	96,055

Notes: This table presents the correlation between quartiles of Google search activity for "defund the police" and support for policies and attitudes toward the police in 2020 and 2022. All specifications control for demographics, marital status, education, income and employment status and include year fixed effects. We report standard errors clustered at the DMA level in parentheses. Additionally, we provide the mean of the dependent variable for the omitted category, corresponding to the bottom quartile of Google search activity, i.e., no search. **Police Makes Feel Safe:** equals one if respondents indicate that the police make them feel "mostly safe" or "somewhat safe" and zero otherwise. Outcomes in columns (2) to (8) equal one if the respondent supports the policy proposals described below and zero otherwise. **Body-Worn Camera:** *"Require police specialists to wear body cameras that record all of their activities while on duty"*. **More Police, Less Others:** *"Increase the number of police on the street by 10%, even if it means fewer funds for other public services"*.**Less Police, More Others:** *"Decrease the number of police on the street by 10%, and increase funding for other public services"*. **Ban Chokeholds:** *"Ban the use of chokeholds by police"*. **Misconduct Registry:** *"Create a national registry of police who have been investigated or disciplined for misconduct"*. **End Militarization:** *"End the Department of Defense program that sends surplus military weapons and equipment to police departments"*. **Lawsuit:** *"Allow individuals or their families to sue a police officer for damages if the officer is found to have 'recklessly disregarded' the individual's rights"*. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Contents

Supplementary Materials

A Data

A.1 Company Information

For each company, we counted the frequency of each keyword associated with the company in *Police Chief Magazine* since 2010. For the surveys, we selected the top 5 keywords for each company to show participants. We also provided the business description available in CRSP/Compustat.

Company A: Axon Enterprise, Inc. *"develops, manufactures, and sells conducted energy weapons (CEWs) under the Taser brand in the United States and internationally. It operates through two segments, Taser and Software, and Sensors."* (CRSP/Compustat)

- **Keywords:** audiovisual equipment; cameras, body-worn; weapons, firearms and ammunition; weapons, less lethal; recording systems

Company B: Teledyne FLIR, LLC designs *"develops, markets, and distributes thermal imaging systems, visible-light imaging systems, locater systems, measurement and diagnostic systems, and threat-detection solutions worldwide."* (CRSP/Compustat)

- **Keywords:** surveillance systems; night vision systems; thermal imaging systems; cameras; CCTV, security

Company C: Motorola Solutions, Inc. *"provides mission-critical communications and analytics in the United States, the United Kingdom, Canada, and internationally. The company operates in two segments, Products and Systems Integration and Services and Software."* (CRSP/Compustat)

- **Keywords:** dispatch systems, E9-1-1, CAD (computer-aided police dispatch systems); surveillance systems; detention, jail equipment; identification (personnel identification and photo identification); personnel (human resources)

Company D: ShotSpotter, Inc. "provides precision policing and security solutions for law enforcement and security personnel in the United States, South Africa, and the Bahamas."(CRSP/Compustat)

- **Keywords:** surveillance systems; community policing; gunshot location; security devices, systems

Company E: VirTra, Inc. *"provides force training simulators, firearms training simulators, and driving simulators for law enforcement, military, educational, and commercial markets worldwide."* (CRSP/Compustat)

- **Keywords:** equipment, training; firearms training; tactical training; shooting ranges, equipment; simulation-based training (for example, simulating police scenarios in a virtual environment).

A.2 Sample Attrition by Email Solicitation

Sample attrition statistics are summarized in Table A.1. "Other academic" has a substantially higher response rate than other expert groups, with 4.9% of those in the "Other academic" group completing the survey, conditional on being sent an email. This rate varies from 0.4% to 0.7% in the other expert groups. Conditional on opening the survey link, between 38.5% and 49.1% of experts completed the survey, with "Law" experts having the highest completion rate and those in the "Finance experiment" having the lowest completion rate. Most participants who opened the survey link consented to take part in the survey. The majority of the attrition from the start to the end of the survey is due to participants leaving the survey.

A.3 Quality of Hand-Coded Data

We used a number of strategies to assess the quality of our classification procedure. First, we calculated how often all five (and four out of the five) independent reviewers assigned the same categorization to a response. Figure A.7 presents the proportion of responses where 5 out of the 5 coders agreed on the categorization for a particular narrative category across the expert survey, the Prolific experiment, and the Qualtrics finance survey. Figure A.6 repeats this analysis for the proportion of responses where 4 out of the 5 coders agreed. According to Figure A.7, if one coder assigned a response to a particular category, depending on the narrative and sample, the likelihood that all the other coders adopted a similar classification is between 0.38 and 0.95. Given a random response and narrative category, the chance of all five coders agreeing is 0.82. According to Figure A.6, given a participant's response and a narrative, the likelihood that 4 out of the 5 coders agreed falls between 0.74 and 0.98, depending on the category and sample. Given a random response and narrative category, the chance of four out of the five coders agreeing is 0.93.

A substantial portion of the disagreement corresponds to the use of the *unclear* category. This is expected, as we requested that coders try to infer the narrative if it was unclear. There is also relatively high disagreement in the assignment of the *unspecified demand* category. The majority of disagreements are attributable to coder disagreement over whether a response was specific enough to be placed into the *crime* or *reform* category.

B Supplemental Analysis

B.1 Additional Analysis for the Experimental Samples

B.1.1 Descriptives

Forecast Distribution Figure 3 presents the distribution of portfolio forecasts for nonexperts and finance professionals across the different treatment arms. Overall, finance professionals exhibit lower variance in their forecasts and higher means than their nonexpert counterparts. This indicates that there is greater consensus among finance experts than among nonexperts. Additionally, the range of forecasts is wider for nonexperts. However, both groups tend to predict average or median portfolio prices that deviate significantly from the actual price.

Furthermore, the figure highlights that information affects the two groups differently. First, exposure to product information shifts the forecast of finance professionals to the right, meaning that they predict an increase in the portfolio value, whereas the absence of this information shifts their forecast to the left. Moreover, respondents treated with full information and those treated with only product information display similar distributions, with the distinction that the distribution of those exposed only to product information peaks at a higher density. In contrast, among nonexperts, exposure to product information leads to a bimodal distribution of forecasts, where respondents predict either an increase or a decrease in the portfolio price.

Distribution of the Negative Absolute Error of the Main Forecast In Figure A.3, we present the distribution of negative absolute errors in respondents' main forecasts across the different treatment arms. Consistent with the observations in Figure A.2, nonexperts exhibit longer tails in their accuracy measure than finance professionals. Furthermore, both nonexperts and finance professionals who receive information about products demonstrate improved forecasts compared to their counterparts who are not exposed to this information.

This finding is supported by the p-value obtained from a Kolmogorov–Smirnov test, which rejects the null hypothesis of equal distribution between respondents treated with full information and those not exposed to product information ($p < 0.01$). In other words, the evidence suggests that exposure to product information positively impacts the forecast accuracy of both nonexperts and finance professionals.

Additionally, we find suggestive evidence indicating that finance professionals with product information have better forecasts only than their peers treated with full information, with $p < 0.1$. This finding implies that exposure only to product information can potentially enhance the accuracy of forecasts among finance professionals, while exposure to narratives related to the implications of police violence might reduce finance professionals' forecast accuracy.

Distribution of the Negative Absolute Errors of All Forecasts Figure A.4 illustrates the distribution of negative absolute errors of respondents' forecasts across the different treatment arms. We investigate whether combining exposure to narrative information with exposure to portfolio product information improves forecast accuracy.

Among nonexperts, we observe that respondents exposed to full information tend to have superior forecasts compared to those of their counterparts treated with less information. This finding is supported by the p-value of the Kolmogorov–Smirnov test, which rejects the null hypothesis of equal distribution between the reference group and other treatment arms. Additionally, providing information about products leads to improved accuracy relative to that of respondents exposed to narratives or to no information. On the other hand, we find that the accuracy distributions of finance professionals provided with less information do not differ from those of their peers treated with full information.

Our results highlight the distinct ways in which financial professionals and nonexperts update their beliefs regarding police violence. Among finance professionals, exposure to information about products associated with the policing industry helps to narrow the accuracy gap between respondents with varying exposure to narrative and product information. In contrast, among nonexperts, this gap persists even when more product information is provided.

B.1.2 Regression Analysis

Distribution of Beliefs Table A.5 provides an analysis of how the different information treatments affect the distributions of portfolio price forecasts among nonexperts (Panel A) and finance professionals (Panel B) relative to the forecast distribution of their counterparts receiving full information. More precisely, we follow Manski (2004); Hanspal et al. (2021) by collecting respondents' probabilistic expectations of their forecast accuracy. The dependent variables in this analysis are dummy variables that categorize the probability of a stock valuation's falling into one of five groups: substantial decrease (< 81), large decrease ($81 - 97$), little change ($98 - 102$), large increase ($103 - 120$), and substantial increase (> 120), with 100 as the baseline. These findings align with the results presented in Table 3.

Among nonexperts, those exposed only to product information do not exhibit predictions differing from those of their peers treated with full information. However, nonexperts are significantly more likely to predict a substantial or significant decrease in the portfolio price than the reference group treated with full information. The largest impact is observed in the < 81 category, where nonexperts not exposed to any information have a 16.8 pp ($SE = 0.0182$) higher likelihood of predicting a decline and nonexperts exposed only to narrative information have a 13.1 pp ($SE = 0.0174$) higher likelihood of predicting a decline. Furthermore, the absence of product information makes nonexperts less likely to predict a substantial or significant increase in the portfolio value than their peers treated with product information.

In contrast to nonexperts, finance professionals tend to assign higher probabilities to values between 81 and 120, indicating lower expectations of dramatic changes. However, we find that lack of exposure to product information leads to a higher belief in a portfolio decrease among finance professionals. Similarly to the nonexpert group, finance professionals provided with only product information predict minimal changes in stock valuations, with most of these results not being statistically significant. However, in the finance group, those given only product information predict a 7.50 pp higher probability of a large increase in the stock valuation than the reference group ($p < 0.05$).

Quantile Regressions Figure A.5 examines whether the effect of the information treatment on the forecast varies differently across quantiles with respect to the mean of the dependent variable when we use ordinary least squares (OLS). Consistent with the OLS results, we find no significant differences across quantiles between respondents treated with full information and those exposed only to product information. However, there is some evidence suggesting that finance professionals exposed only to product information have a slightly higher forecast than the reference group at the 30th to 50th quantiles, although the 95% confidence interval includes zero. On the other hand, respondents not exposed to product information predict a larger decrease in stock prices, and this effect is more pronounced in absolute value from the 10th to 90th percentiles. Nonexperts, on the other hand, predict a larger decline in values above the median. Overall, the removal of product information leads respondents to predict a greater decline in portfolio value at the higher quantiles than at the lower quantiles of the conditional distribution of forecasts.

B.1.3 Decomposing the Variation in Beliefs

Variation across Individuals and Predictions We adopt the approach of Giglio et al. (2021a) and leverage the six predictions provided by survey participants in the experimental samples to examine the factors influencing their beliefs. Specifically, we aim to determine whether belief variation arises from differences across individual forecasts, persistent heterogeneity in beliefs (captured by fixed effects), or a combination of both. To shed light on the need for this decomposition, we present Figure A.10, which displays the distribution of beliefs categorized by type of forecast for both nonexperts and finance professionals. The box plots depict the mean and 10th, 25th, 50th, 75th, and 90th percentiles of the belief distribution.

Among both nonexperts and finance professionals, we observe considerable variation in beliefs across the different forecasts. For instance, the interquartile ranges range from 24 pp to 33 pp for the nonexperts group and from 10 pp to 25 pp for the finance sample. Moreover, this figure confirms that finance professionals exhibit a narrower distribution of beliefs than nonexperts. Furthermore, the disparities between the true prices and various statistical measures indicate an additional level of heterogeneity in individuals' ability to accurately forecast the impact of George Floyd's murder on the policing industry. This finding underscores the importance of considering additional drivers of beliefs beyond the information contained in the forecasts.

Individual and Prediction Fixed Effects To provide deeper insights into the intriguing patterns identified above, we conduct a variance decomposition analysis. By disentangling the sources of belief variation, we aim to uncover the underlying mechanisms responsible for the observed patterns. This decomposition exercise provides insights into the dynamics of forecast predictions and the factors influencing belief formation among nonexperts and finance professionals. To explore the determinants of respondents' beliefs, we estimate the following equation for individual i and forecast k:

$$Forecast_{ik} = \alpha_i + \gamma_k + \epsilon_{ik} \tag{4}$$

where α_i and γ_k capture individual and prediction fixed effects. We also estimate similar models where we include individual fixed effects only and product fixed effects only.

Table A.7 presents the R^2 associated with equation 4. For the nonexperts and finance professionals, the prediction fixed effects explain only 5.2% and 4.6% of the total panel variation. On the other hand, the individual fixed effects explain 55.5% and 53.8% of the total variation. Estimating equation 4 yields an R^2 of 60.7% and 58.3% of the total variation for nonexperts and finance professionals. These findings indicate that the persistent heterogeneity in beliefs is the main driver of an individual's forecast.

Beliefs and Respondents' Characteristics Having found that the individual fixed effects have significant power in explaining respondents' forecasts, we explore the correlation between observable characteristics and the fixed effects by running the following regression:

$$\alpha_i = \beta_0 + \beta_1 X_i + u_i \tag{5}$$

where α_i are the individual fixed effects estimated from equation 4 and X_i are respondent characteristics (demographics, treatment arm dummy, etc.) and investment preferences (ethics, regulation, and priorities). Table A.8 presents the results for the nonexpert and finance experimental samples. Including all the covariates yields R^2 values of 2.4% and 10.6% for the nonexperts and finance samples, respectively. Overall, compared to the individual fixed effects, the observed characteristics have only little explanatory power.

However, some characteristics impact the individual fixed effects statistically significantly. For example, nonexperts assigned to the $NoInformation$ or $Narratives$ treatment arms are substantially less likely to predict higher stock returns. In contrast, finance professionals in the *Products* treatment arm are more likely to be optimistic about the policing industry. Moreover, finance professionals whose top priorities when investing are environmental sustainability or fair treatment of employees or who believe that buying police stocks is unethical forecast higher returns for the policing industry resulting from the murder of George Floyd. The inclusion of investment and regulation preferences and ethical views increases the R^2 by more than 7 pp for finance professionals but only by less than 1 pp for nonexperts.

B.2 Analyzing Reasoning

B.2.1 Correlations in Reasoning

Figure A.8 illustrates the correlation between the citation of different reasons among nonexperts and finance professionals. Darker green tiles represent stronger positive correlations, while darker pink tiles indicate stronger negative correlations. The majority of the correlations are negative, suggesting that citing one reason makes it less likely that the respondent cites another reason. Reasons coded in the *unclear* category have the strongest negative correlations for both groups since green indicates reasoning instead of observed pattern.

Interestingly, one tile stands out in that it shows a positive correlation for both nonexperts and finance professionals: namely, the tile showing the correlation between *reputation* and *less trust*. The correlation coefficients are $corr = 0.12$ for nonexperts and $corr = 0.08$ for finance professionals. This finding could be attributed to the fact that reputation is a crucial factor in determining trust in any institution, leading to a positive association between the reputation of firms or police and lower levels of trust in them.

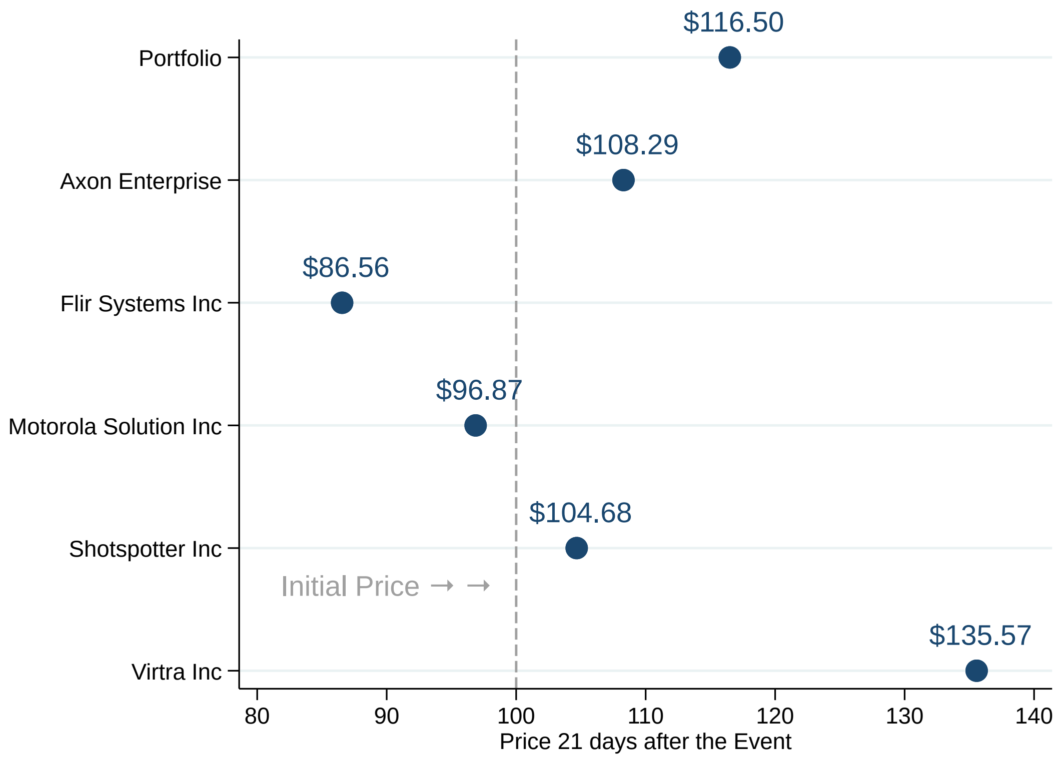
In contrast, the other correlations differ between nonexperts and finance professionals. For example, while finance professionals show a positive correlation ($corr = 0.15$) in their propensities to cite police support and lower levels of trust, nonexperts exhibit a negative and weaker association ($corr = -0.02$) between their propensities to mention these two reasons. Similarly, nonexperts show a positive correlation ($corr = 0.13$) in their mentions of *crime* and *protests*, whereas finance professionals display a negative correlation ($corr = -0.03$) in their mentions of these reasons. These discrepancies suggest that the relationship between citing certain reasons and citing trust varies between nonexperts and finance professionals, highlighting the different perspectives and interpretations within these groups.

B.2.2 Experts' Reasoning

Figure A.9 provides valuable insights into the predictions and reasoning of different groups. A notable pattern emerges, with the majority of the expert groups predicting an increase in the portfolio price and nonexperts being the only group in which a majority does not predict an increase. Among all groups, police reform stands out as the most commonly cited forecast explanation among those forecasting an increase in the portfolio price. Both police experts and community organizers, who are more likely to anticipate a price increase, consistently attribute this prediction to reform (46% and 40%, respectively), regardless of their overall forecast. In contrast, only 27% of finance professionals, 26% of nonexperts, 33% of law experts, and 20% of other academics cite police reform as a reason for their forecasts. However, it is noteworthy that among those citing reform as a reason, a strong majority across all groups predicts an increase in the portfolio price. On the other hand, within each group, those who forecast an increase most frequently mention the potential for budget cuts or provide unclear reasoning as the rationale for their forecasts.

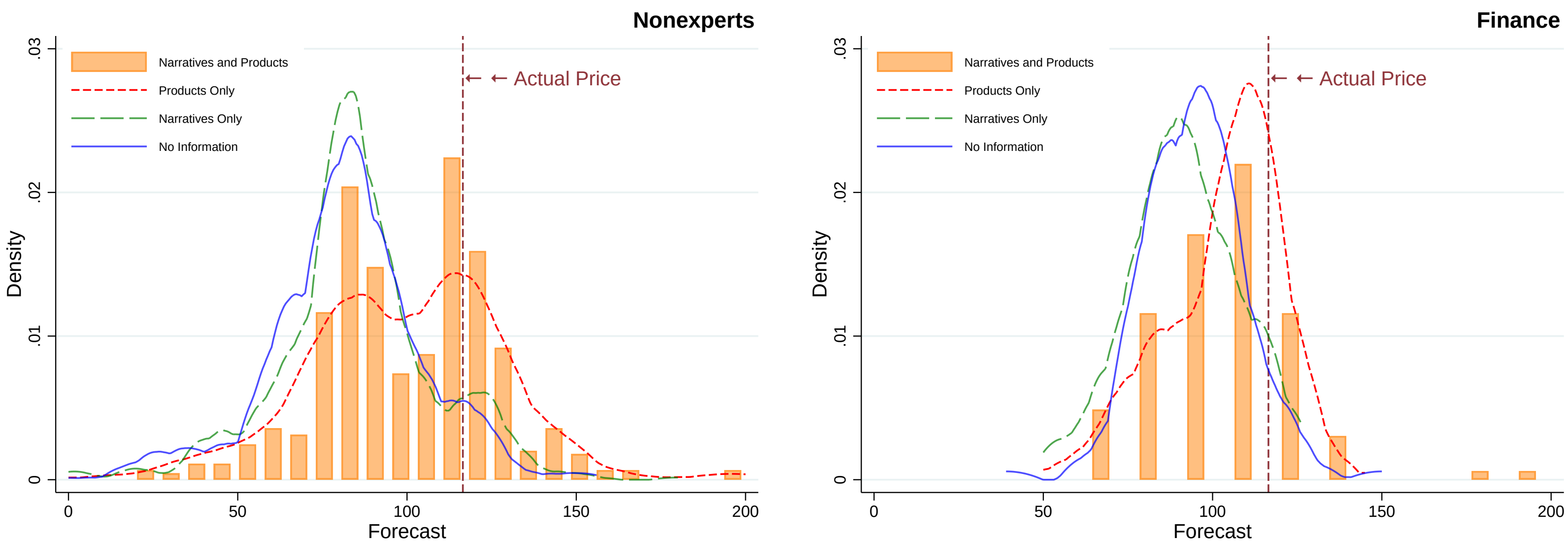
Additional Figures and Tables

Figure A.1: Impact of George Floyd's Murder on Stock Performance



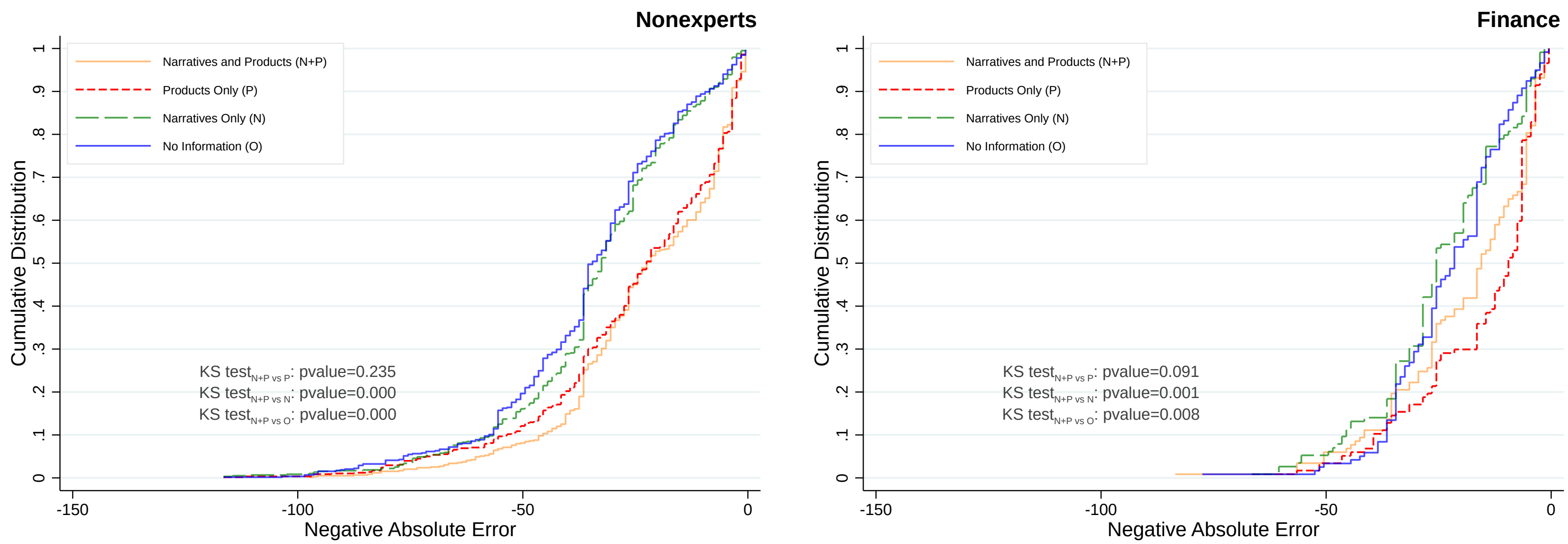
Notes: This figure presents the impact of George Floyd's murder on the cumulative abnormal returns (CARs) of firms contracting intensively with police departments. We compute the estimates by comparing connected firms and their synthetic difference-in-differences (SDID) counterfactuals. We report the actual price of the stocks or portfolio 21 days after the event. The vertical dashed line represents the initial price of the stock or portfolio, $100. The SDID estimates are computed on the basis of the sum of all abnormal returns since 63 trading days (i.e., a quarter) before the event. Abnormal returns are calculated on the basis of the Carhart four-factor model with an estimation window of 252 trading days ending 30 days before the day of interest.

Figure A.2: Distribution of Forecasts by Information Treatment



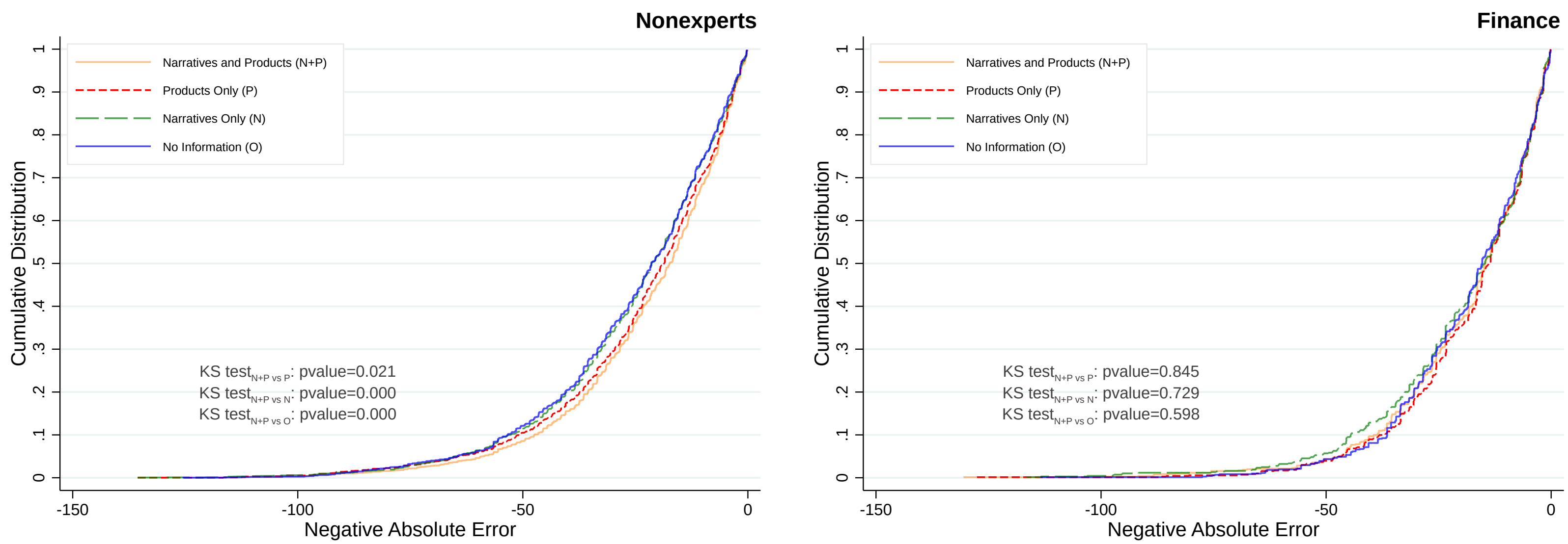
Notes: This figure presents the distribution of the portfolio forecasts by treatment arm of nonexperts and finance professionals. Each respondent provided a forecast of the price of a portfolio of firms with ties to policing at 21 days after the killing of George Floyd. The vertical line represents the actual price of the portfolio. We report the 95% confidence intervals.

Figure A.3: CDFs of Negative Absolute Error by Treatment Arm



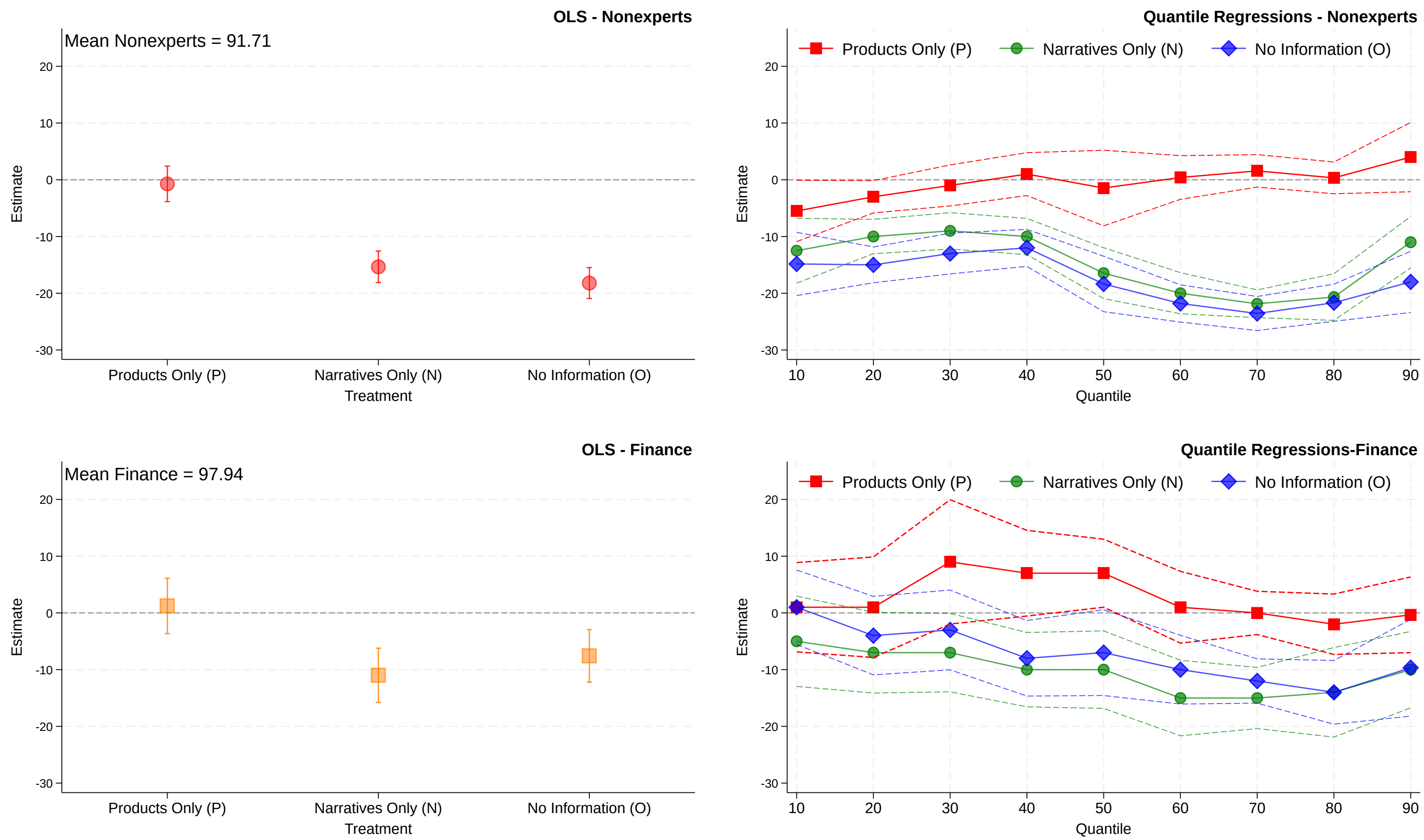
Notes: These figures present the cumulative distribution functions (CDFs) of the negative absolute error (accuracy) by treatment arm for nonexperts and finance professionals. Respondents provided a forecast of the price of a portfolio of firms with ties to policing 21 days after the killing of George Floyd. We also report the *p*-value of a Kolmogorov–Smirnov (KS) test of the hypothesis of equal distributions for pairs among the narratives-and-products (N+P), narratives-only (N), products-only (P), and no-information (O) treatments.

Figure A.4: CDFs of Negative Absolute Error for All Forecasts by Treatment Arm



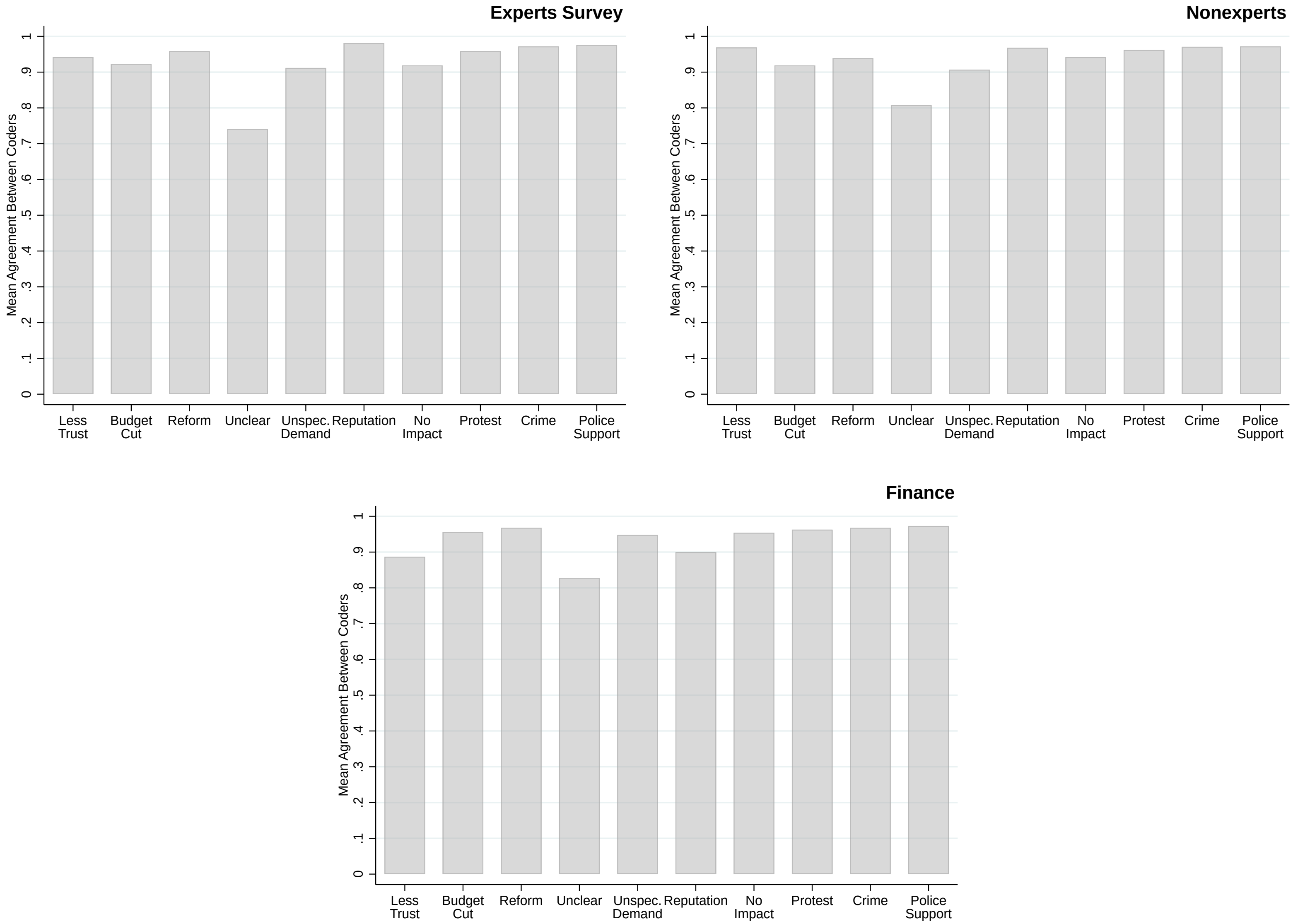
Notes: These figures present the cumulative distribution functions (CDFs) of the negative absolute error (accuracy) by treatment arm for nonexperts and finance professionals. Each respondent provided forecasts of the stock price of firms with ties to policing at 21 days after the killing of George Floyd. The firms were anonymized, but respondents were given keywords associated with the firms' products and services (e.g., body-worn cameras, dispatch systems, weapons, less-than-lethal weapons). For detailed information about the keywords associated with the firms, see Section A.1. We also report the *p*-value of a Kolmogorov–Smirnov (KS) test of equality for pairs of distributions among the narratives-and-products (N+P), narratives-only (N), products-only (P), and no-information (O) treatments.

Figure A.5: Impact of Information Treatments Estimated from OLS and Quantile Regressions



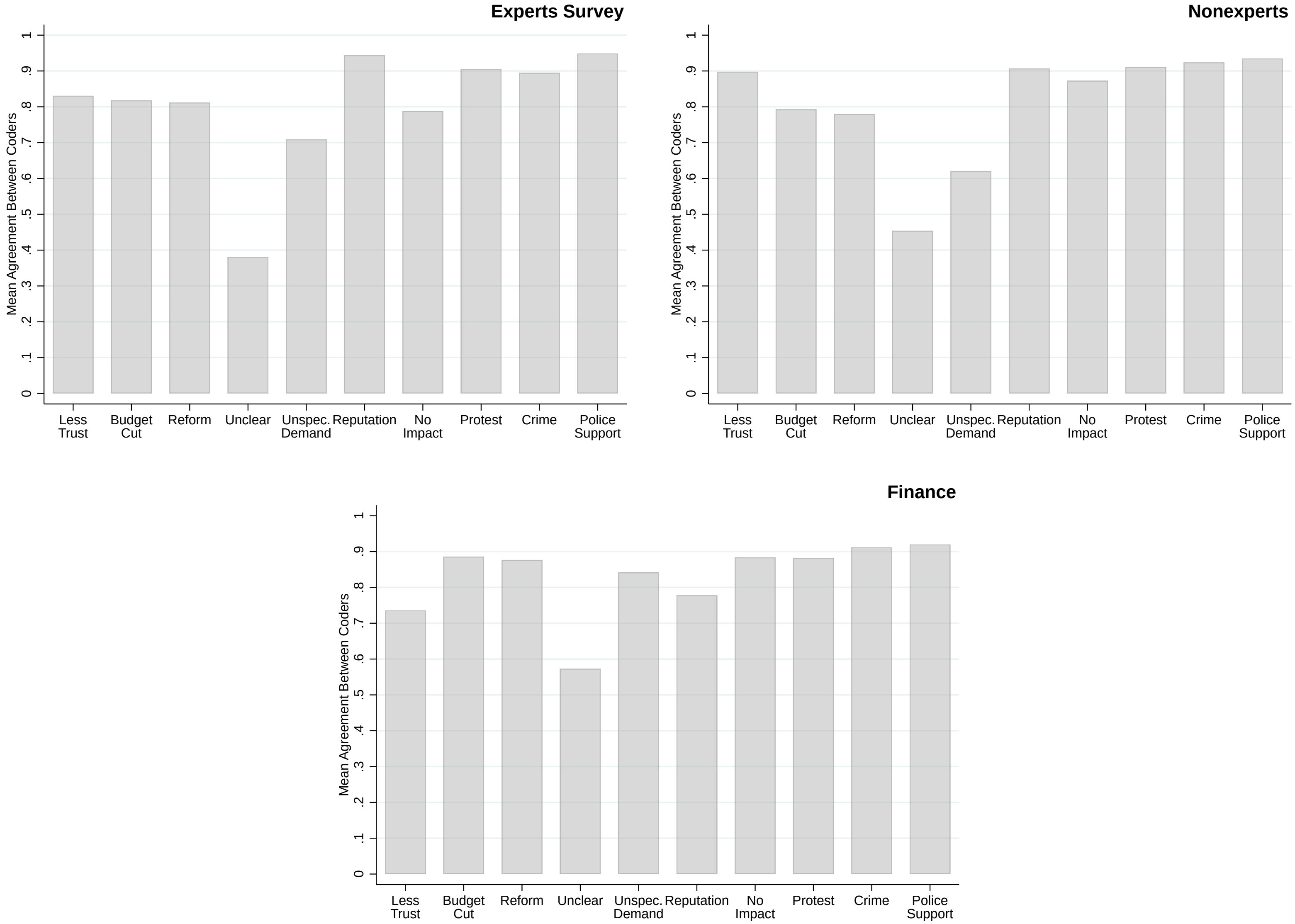
Notes: This figure reports the result of ordinary least squares (OLS) and quantile regressions estimating the impact of the information treatment (exposure to product and narrative information related to police) on the portfolio forecasts of nonexperts and finance professionals. The omitted category is individuals receiving both product and narrative information. In addition, we report the mean of the dependent variable of the omitted category. We provide the estimates and their 95% confidence intervals using bootstrap standard errors with 100 replications.

Figure A.6: Categorization Agreement across Four of the Five Coders



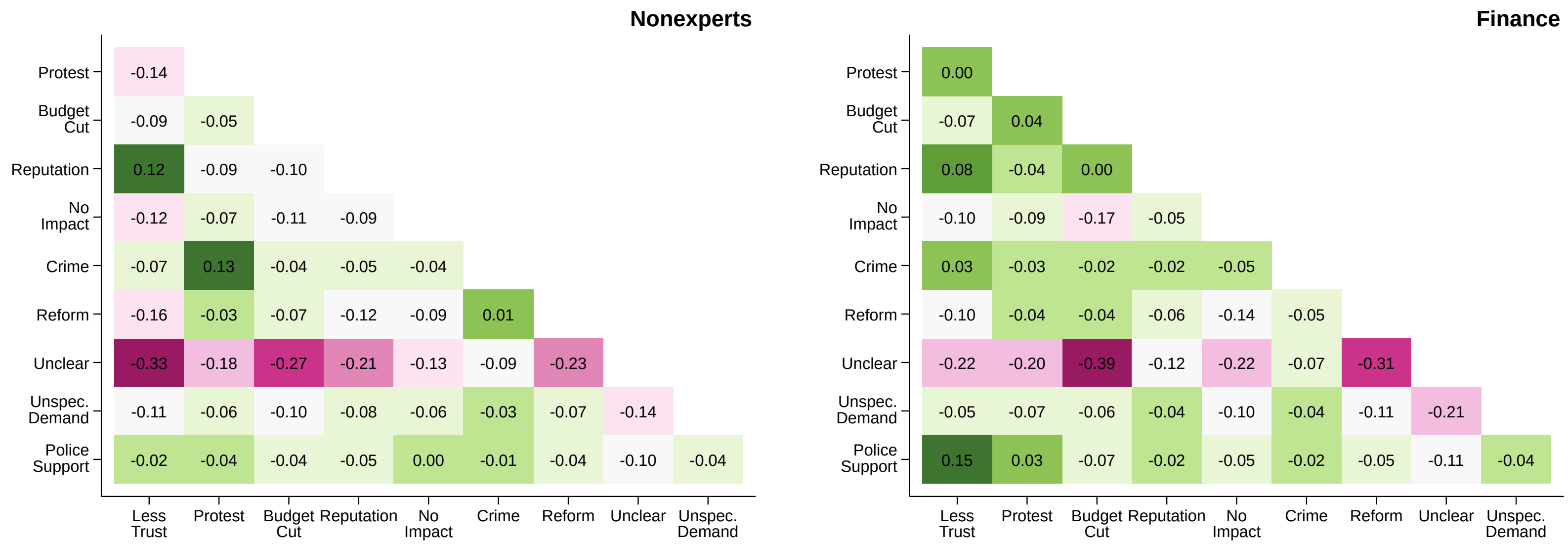
Notes: The figure reports the agreement by coders across categories for the expert survey, nonexpert experiment and the finace experiment. Given a sample (e.g., expert survey) and a category (e.g., *less trust*), the bar height represents the proportion of responses where at least 4 out of 5 coders agree on the coding.

Figure A.7: Categorization Agreement across All Coders



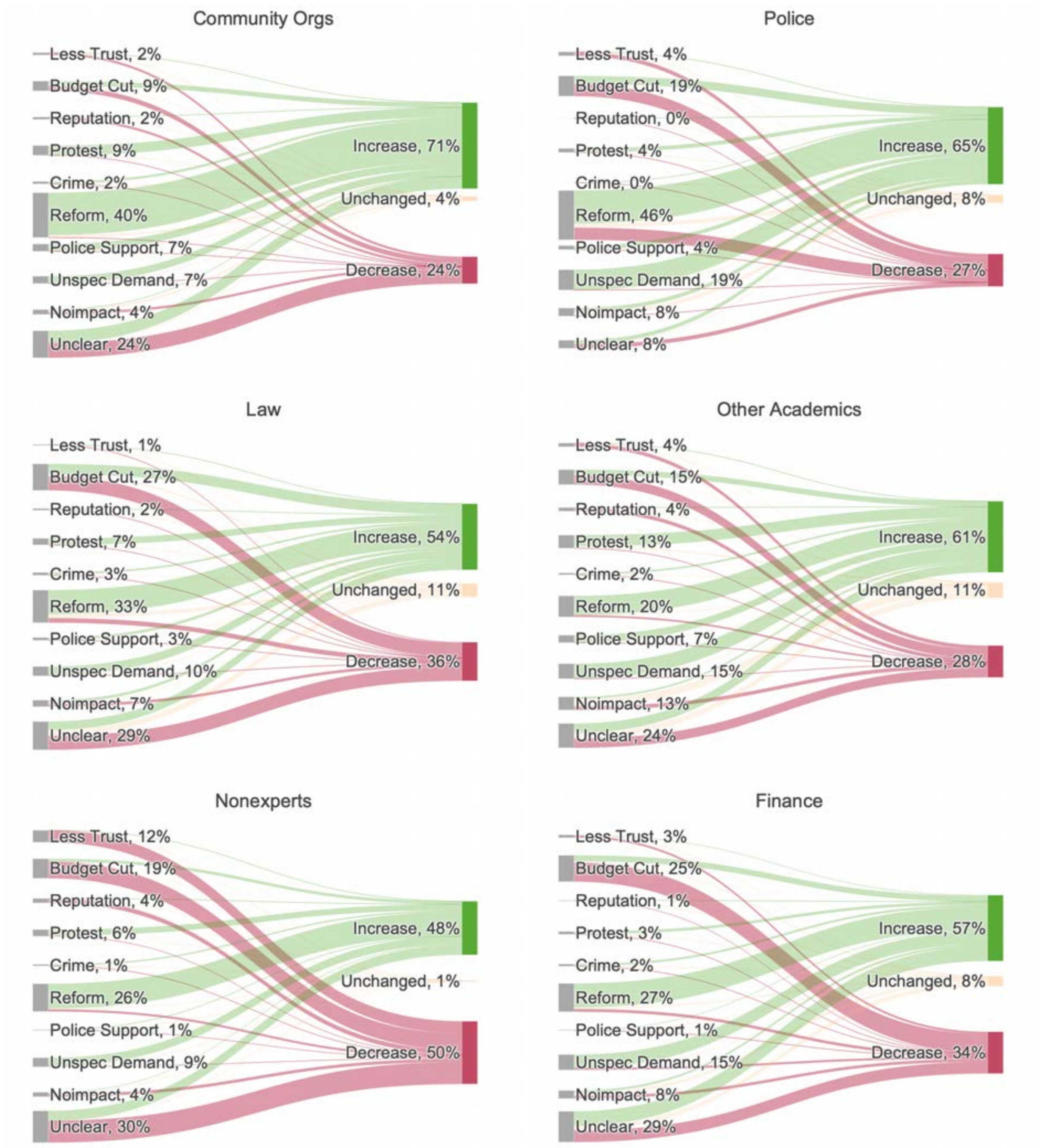
Notes: The figure reports the agreement by coders across categories for the expert survey, nonexpert experiment and the finace experiment. Given a sample (e.g., expert survey) and a category (e.g., *less trust*), the bar height represents the proportion of responses where exactly 5 out of 5 coders agree on the coding.

Figure A.8: Correlations of Reasoning between Nonexperts and Finance Professionals



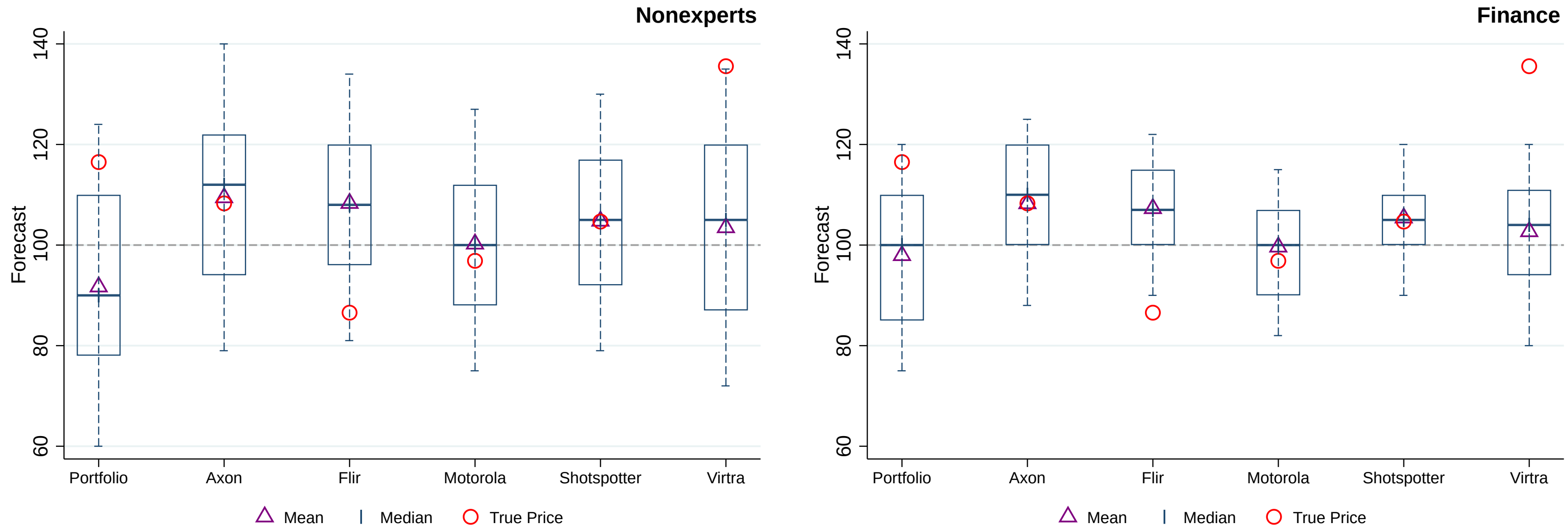
Notes: This figure presents the correlations in the reasoning of nonexperts and finance professionals. Table 7 provides details of the categories with descriptions and examples related to our coding scheme.

Figure A.9: Reasoning and Forecasts by Category of Expertise



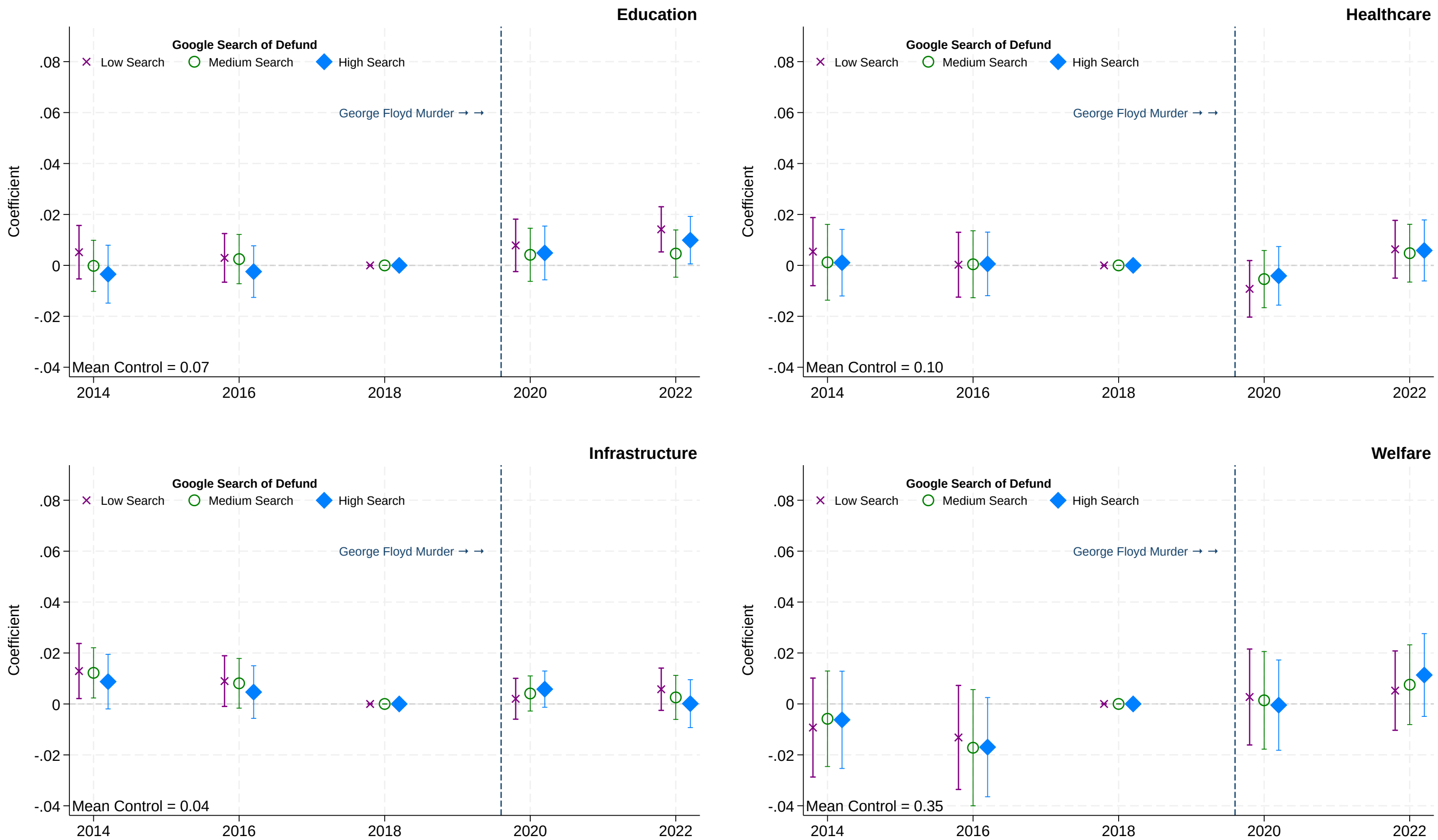
Notes: This figure presents the relationship between respondents' reasoning and forecast by category of expertise. The prediction corresponds to a forecast of the price of a portfolio of firms with ties to policing at 21 days after the killing of George Floyd. The left panel reports the shares of different reasons invoked by respondents to explain their forecasts, and the right panel shows the share of respondents who predict an increase, no change and a decrease in stock prices.

Figure A.10: Distribution of Beliefs by Type of Forecast



Notes: This figure presents the distribution of beliefs by type of forecast for nonexperts and finance professionals. The box plots show the distributions' means and 10th, 25th, 50th, 75th, and 90th percentiles. We also report the true value of the impact of George Floyd's murder on firms' stock prices derived with the synthetic difference-in-differences (SDID) method (see Figure A.1 for more details). Each respondent provided forecasts of the stock prices of firms with ties to policing at 21 days after the killing of George Floyd. The firms were anonymized, but respondents were given keywords associated with these firms' products and services (e.g., body-worn cameras, dispatch systems, weapons, less-than-lethal weapons). For detailed information about the keywords associated with the firms, see Section A.1.

Figure A.11: George Floyd's Murder and Public Support for Reducing Funding in Various Areas



Notes: This figure presents the impact of George Floyd"s murder on public support for reducing funding in various areas, categorized by quartiles of Google search activity for "defund the police." We report the 95% confidence intervals, with standard errors clustered at the designated market area (DMA) level. Additionally, we provide the mean of the dependent variable for the omitted category, corresponding to the bottom quartile of Google search activity, i.e., no search.

Table A.1: Survey Completion Rates

	sample	N solicited	N opened	N consented	N completed	% opened	% complete	% completed given opened
1	Finance	53252	398	356	180	0.7	0.3	45.2
2	Law	50632	222	202	109	0.4	0.2	49.1
3	Police	23810	117	101	46	0.5	0.2	39.3
4	Other academic	2356	115	106	55	4.9	2.3	47.8
5	Finance experiment	204494	1212	1101	467	0.6	0.2	38.5

Notes: This table reports the survey completion rates from the email solicitations for various expert groups. *N solicited* corresponds to the total number of emails sent. *N opened* corresponds to the number of email recipients who clicked on the link to take part in the survey. *N consented* corresponds to the number of participants who consented to take part in the survey, and *N completed* corresponds to the total number of participants who finished the survey and passed both a comprehension check and an attention check. *% opened* is equal to 100(*N opened/N solicited*). *% complete* is equal to 100(*N completed/N solicited*). *% completed given opened* is equal to 100(*N completed/N opened*).

Table A.2: Heterogeneity Analysis: Likelihood of Predicting a Price Increase, Nonexperts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Female	Male	White	Nonwhite	Age: 18-34	Other Age	Check Invt. Weekly	Does not Check Invt. Weekly	Liberal	Conservative
Products Only (P)	-0.0256	-0.0137	-0.0380	0.0125	-0.0400	-0.00887	-0.0709	0.00387	-0.0632	0.0295
	(0.0429)	(0.0397)	(0.0344)	(0.0548)	(0.0461)	(0.0376)	(0.0494)	(0.0362)	(0.0396)	(0.0429)
Narratives Only (N)	-0.354***	-0.273***	-0.325***	-0.283***	-0.291***	-0.326***	-0.323***	-0.307***	-0.310***	-0.316***
	(0.0375)	(0.0362)	(0.0319)	(0.0453)	(0.0401)	(0.0344)	(0.0446)	(0.0323)	(0.0354)	(0.0387)
No Information (O)	-0.365***	-0.325***	-0.370***	-0.284***	-0.299***	-0.372***	-0.366***	-0.331***	-0.315***	-0.376***
	(0.0386)	(0.0343)	(0.0308)	(0.0464)	(0.0405)	(0.0332)	(0.0447)	(0.0314)	(0.0355)	(0.0369)
Sample	Nonexperts	Nonexperts	Nonexperts	Nonexperts	Nonexperts	Nonexperts	Nonexperts	Nonexperts	Nonexperts	Nonexperts
Portfolio Forecast	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	0.51	0.49	0.53	0.43	0.44	0.54	0.51	0.50	0.49	0.51
Observations	1028	1318	1689	657	935	1411	807	1539	1248	1098

Notes: This table reports the heterogeneity in the treatment effects for the nonexperts sample. The dependent variables are measures of accuracy given by a binary variable that equals one if the respondent predicts an increase in the price of the portfolio or individual stocks and zero otherwise. Each column shows the results for a different subsample across five characteristics (gender, race, age, investment patterns, and political leaning). We report robust standard errors in parentheses. In addition, we report the mean of the dependent variable of the omitted category, i.e., individuals receiving both product and narrative information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.3: Heterogeneity Analysis: Likelihood of Predicting a Price Increase, Finance Professionals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Female	Male	White	Nonwhite	Age: 18-34	Other Age	Check Invt. Weekly	Does not Check Invt. Weekly
Products Only (P)	-0.0873	0.183**	0.0749	0.227	0.409	0.105	0.207**	0.0364
	(0.150)	(0.0737)	(0.0732)	(0.150)	(0.493)	(0.0668)	(0.0983)	(0.0880)
Narratives Only (N)	-0.588***	-0.220***	-0.320***	-0.233*	-0.0462	-0.310***	-0.162*	-0.402***
	(0.121)	(0.0705)	(0.0687)	(0.131)	(0.341)	(0.0631)	(0.0978)	(0.0790)
No Information (O)	-0.449***	-0.181**	-0.297***	-0.0654	0.0113	-0.252***	-0.103	-0.347***
	(0.136)	(0.0708)	(0.0694)	(0.149)	(0.353)	(0.0648)	(0.100)	(0.0803)
Sample	Finance	Finance	Finance	Finance	Finance	Finance	Finance	Finance
Portfolio Forecast	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	0.65	0.49	0.57	0.40	0.40	0.54	0.47	0.57
Observations	95	372	378	89	28	439	203	264

Notes: This table reports heterogeneity in the treatment effects for the finance professionals sample. The dependent variables are measures of accuracy given by a binary variable that equals one if the respondent predicts an increase in the price of the portfolio or individual stocks and zero otherwise. Each column shows the results for a different subsample across four characteristics (gender, race, age, and investment patterns). We report robust standard errors in parentheses. In addition, we report the mean of the dependent variable of the omitted category, i.e., individuals receiving both product and narrative information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.4: Heterogeneity Analysis by Preferences: Likelihood of Predicting a Price Increase

	(1) Police Investing Unethical	(2) Police Investing Not Unethical	(3) More Regulation	(4) Less Regulation	(5) Police Investing Unethical	(6) Police Investing Not Unethical	(7) More Regulation	(8) Less Regulation
Products Only (P)	0.0291	-0.0347	0.0319	-0.0847**	0.0470	0.117*	0.0443	0.157*
	(0.0578)	(0.0335)	(0.0401)	(0.0420)	(0.319)	(0.0674)	(0.0973)	(0.0914)
Narratives Only (N)	-0.179***	-0.356***	-0.279***	-0.348***	-0.384	-0.285***	-0.333***	-0.275***
	(0.0522)	(0.0299)	(0.0364)	(0.0373)	(0.289)	(0.0637)	(0.0964)	(0.0845)
No Information (O)	-0.198***	-0.385***	-0.297***	-0.397***	0.0722	-0.255***	-0.235**	-0.268***
	(0.0569)	(0.0287)	(0.0360)	(0.0361)	(0.244)	(0.0637)	(0.0934)	(0.0858)
Sample	Nonexperts	Nonexperts	Nonexperts	Nonexperts	Finance	Finance	Finance	Finance
Portfolio Forecast	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	0.42	0.53	0.47	0.53	0.60	0.53	0.58	0.48
Observations	591	1755	1256	1090	28	439	222	245

Notes: This table reports heterogeneity in the treatment effects for the finance professionals sample. The dependent variables are measures of accuracy given by a binary variable that equals one if the respondent predicts an increase in the price of the portfolio or individual stocks and zero otherwise. Each column shows the results for a different subsample across respondents' views of the policing industry as an unethical destination for investment and preferences related to regulation. We report robust standard errors in parentheses. In addition, we report the mean of the dependent variable of the omitted category, i.e., individuals receiving both product and narrative information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.5: Impact of Information Treatments on the Forecast Distribution

	(1) $<$81	(2) 81-97	(3) 98-102	(4) 103-120	(5) $>$120
Panel A: Nonexperts					
Products Only (P)	0.0140	-0.00628	-0.000820	-0.00925	0.00232
	(0.0171)	(0.0131)	(0.0106)	(0.0139)	(0.0121)
Narratives Only (N)	0.131***	0.0819***	-0.0272***	-0.114***	-0.0714***
	(0.0174)	(0.0138)	(0.00986)	(0.0122)	(0.0108)
No Information (O)	0.168***	0.0583***	-0.0237**	-0.128***	-0.0740***
	(0.0182)	(0.0138)	(0.0105)	(0.0120)	(0.0104)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	0.23	0.23	0.18	0.22	0.14
Observations	2346	2346	2346	2346	2346

	(1) $<$81	(2) 81-97	(3) 98-102	(4) 103-120	(5) $>$120
Panel B: Finance					
Products Only (P)	-0.0157	-0.0413	-0.0256	0.0750**	0.00760
	(0.0339)	(0.0316)	(0.0311)	(0.0360)	(0.0218)
Narratives Only (N)	0.0669*	0.114***	-0.0164	-0.119***	-0.0455**
	(0.0354)	(0.0336)	(0.0318)	(0.0299)	(0.0210)
No Information (O)	0.0255	0.0924***	0.0323	-0.0996***	-0.0506***
	(0.0329)	(0.0334)	(0.0337)	(0.0311)	(0.0189)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	0.16	0.23	0.24	0.26	0.10
Observations	467	467	467	467	467

Notes: This table presents the impact of exposure to product and narrative information related to policing on the forecast distribution for nonexperts (Panel A) and finance professionals (Panel B). The dependent variables are the percent chance that the forecast falls within the category $k = \{< 81; ...; > 120\}$. We report robust standard errors in parentheses. In addition, we report the mean of the dependent variable of the omitted category, i.e., individuals receiving both product and narrative information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.6: Impact of Information Treatments on the Negative Absolute Forecast Error by Type of Forecast

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Nonexperts								
Products Only (P)	-2.491**	-2.667***	-1.113	-2.365**	-1.252	0.157	-1.448**	-1.622**
	(1.179)	(0.990)	(1.064)	(0.984)	(0.946)	(1.298)	(0.725)	(0.717)
Narratives Only (N)	-10.49***	-0.935	-1.925*	-0.988	-1.918*	-2.368*	-1.627**	-3.103***
	(1.115)	(0.967)	(1.017)	(0.937)	(0.998)	(1.274)	(0.729)	(0.701)
No Information (O)	-12.76***	-2.763***	-1.582	-1.647*	-1.821*	-1.732	-1.909***	-3.718***
	(1.140)	(0.966)	(1.062)	(0.928)	(0.939)	(1.284)	(0.702)	(0.686)
Forecast	Portfolio	Axon	Flir	Motorola	Shotspotter	Virtra	Stocks Only	All
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	-23.48	-18.10	-25.07	-16.36	-15.84	-35.01	-22.07	-22.31
Observations	2346	2346	2346	2346	2346	2346	11730	14076

Panel B: Finance								
Products Only (P)	3.376*	1.978	-3.353**	0.0107	1.430	2.737	0.561	1.030
	(2.017)	(1.693)	(1.581)	(1.387)	(1.490)	(2.348)	(1.132)	(1.115)
Narratives Only (N)	-6.590***	1.177	-2.717	1.068	0.0227	-1.632	-0.416	-1.445
	(2.019)	(1.727)	(1.884)	(1.677)	(1.765)	(2.284)	(1.325)	(1.260)
No Information (O)	-3.804**	-0.619	-1.639	2.218*	2.023	1.716	0.740	-0.0176
	(1.888)	(1.768)	(1.771)	(1.325)	(1.492)	(2.114)	(1.121)	(1.081)
Forecast	Portfolio	Axon	Flir	Motorola	Shotspotter	Virtra	Stocks Only	All
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (N+P)	-19.58	-13.70	-20.76	-11.88	-10.81	-34.87	-18.41	-18.60
Observations	467	467	467	467	467	467	2335	2802

Notes: This table presents the impact of exposure to product and narrative information related to policing on the forecast accuracy of nonexperts (Panel A) and finance professionals (Panel B). Each respondent provided forecasts of the stock price of firms with ties to policing at 21 days after the killing of George Floyd. The firms were anonymized, but respondents were given keywords associated with the firms' products and services (e.g., body-worn cameras, dispatch systems, weapons, less-than-lethal weapons). For detailed information about the keywords associated with the firms, see Section A.1. The dependent variable is a measure of accuracy given by the negative of the absolute forecast error. We report robust standard errors in parentheses. In addition, we report the mean of the dependent variable of the omitted category, i.e., individuals receiving both product and narrative information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.7: Role of Individual and Forecast Fixed Effects

	(1) Forecast Nonexperts	(2) Forecast Nonexperts	(3) Forecast Nonexperts	(4) Forecast Finance	(5) Forecast Finance	(6) Forecast Finance
R-Squared	0.0519	0.555	0.607	0.0456	0.538	0.583
Prediction FE	Yes	No	Yes	Yes	No	Yes
Indiv. FE	No	Yes	Yes	No	Yes	Yes
Observations	14076	14076	14076	2802	2802	2802

Notes: This table reports the R^2 corresponding to equation 4 for the nonexperts and finance professionals experimental samples. Each respondent provided forecasts of the stock price of firms with ties to policing at 21 days after the killing of George Floyd. Each respondent provided six predictions.

Table A.8: Heterogeneity in Beliefs and Respondent Characteristics

	(1) Forecast Nonexperts	(2) Forecast Nonexperts	(3) Forecast Nonexperts	(4) Forecast Finance	(5) Forecast Finance	(6) Forecast Finance
Products Only	0.289	0.373	0.280	3.553**	3.651**	3.400*
	(1.177)	(1.176)	(1.178)	(1.788)	(1.710)	(1.817)
Narratives Only	-3.031***	-2.996***	-2.958***	0.915	1.255	1.372
	(1.088)	(1.088)	(1.091)	(1.891)	(1.851)	(1.947)
No Information	-3.711***	-3.470***	-3.618***	1.045	1.312	1.797
	(1.092)	(1.086)	(1.086)	(1.775)	(1.744)	(1.795)
Female		2.278***	2.036**		4.468**	3.045
		(0.849)	(0.869)		(2.084)	(2.008)
Born in the U.S.A.		0.385	0.569		-3.167	-4.367
		(1.299)	(1.323)		(2.844)	(2.740)
White		-0.168	0.0843		0.349	0.885
		(0.987)	(0.996)		(2.083)	(1.913)
Age: 18 to 34		-1.936	-2.132*		-2.402	-2.555
		(1.252)	(1.289)		(2.996)	(3.086)
Age: 55+ or missing		-1.080	-1.190		-1.200	-1.181
		(1.239)	(1.257)		(1.498)	(1.426)
Check Investment Weekly/Daily		0.190	0.328		0.286	0.809
		(0.843)	(0.857)		(1.249)	(1.250)
7-13 min		1.011	1.096		1.144	1.486
		(0.848)	(0.850)		(4.112)	(3.798)
14+ min		1.878	1.702		0.978	1.457
		(1.353)	(1.364)		(4.102)	(3.725)
Top Preference: Social Justice			1.618			10.33
			(1.542)			(6.367)
Top Preference: Environmental Sustainability			1.841			4.491*
			(1.269)			(2.331)
Top Preference: Fair Treatment of Employees			0.524			4.041**
			(1.133)			(1.788)
Top Preference: Family Values			3.793*			4.474
			(2.197)			(2.859)
Unethical Investment: Green Energy			-1.521			2.367
			(2.080)			(1.800)
Unethical Investment: Military			-0.865			-0.684
			(1.078)			(2.489)
Unethical Investment: Tobacco			-1.077			-0.486
			(0.925)			(1.562)
Unethical Investment: Police			-0.0342			6.879**
			(1.156)			(2.955)
Unethical Investment: Gambling			1.258			-2.247
			(0.874)			(1.668)
Unethical Investment: Alcohol			-1.413			2.004
			(0.993)			(2.271)
Unethical Investment: Guns			-0.165			-0.218
			(0.930)			(1.556)
Unethical Investment: Fossil Fuels			-1.162			1.371
			(0.954)			(2.413)
Unethical Investment: Financial Companies			0.663			-3.219
			(1.136)			(2.345)
Unethical Investment: Prisons			0.508			-1.053
			(0.919)			(1.738)
Regulation Index			2.008**			1.873*
			(0.848)			(1.023)
R-Squared	0.00849	0.0149	0.0240	0.0102	0.0354	0.106
Observations	2346	2346	2345	467	467	467

Notes: This table presents the coefficients from regressing respondent fixed effects on respondent characteristics (demographics, treatment arm dummy, etc.) and investment preferences for the nonexperts and finance professionals experimental samples. Each respondent provided forecasts of the stock prices of firms with ties to policing at 21 days after the killing of George Floyd. Each respondent provided six predictions. We report robust standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.9: George Floyd's Murder and Public Support for Reducing Funding in Various Areas

	(1) Police	(2) Healthcare	(3) Welfare	(4) Education	(5) Infrastructure
Low Search X 2020	0.0287*	-0.00921	0.00272	0.00786	0.00204
	(0.0148)	(0.00567)	(0.00961)	(0.00525)	(0.00409)
Low Search X 2022	0.0256***	0.00633	0.00523	0.0142***	0.00578
	(0.00960)	(0.00578)	(0.00795)	(0.00452)	(0.00424)
Medium Search X 2020	0.0340***	-0.00538	0.00141	0.00416	0.00411
	(0.0116)	(0.00573)	(0.00978)	(0.00532)	(0.00352)
Medium Search X 2022	0.0232**	0.00479	0.00754	0.00464	0.00257
	(0.00893)	(0.00579)	(0.00799)	(0.00473)	(0.00441)
High X 2020	0.0639***	-0.00411	-0.000478	0.00489	0.00581
	(0.0112)	(0.00587)	(0.00905)	(0.00538)	(0.00363)
High X 2022	0.0297***	0.00586	0.0114	0.00990**	0.000125
	(0.00894)	(0.00611)	(0.00829)	(0.00475)	(0.00479)
Low Search X 2014	0.0139*	0.00540	-0.00928	0.00518	0.0129**
	(0.00727)	(0.00683)	(0.00991)	(0.00535)	(0.00551)
Low Search X 2016	0.00841	0.000265	-0.0132	0.00294	0.00898*
	(0.00580)	(0.00650)	(0.0104)	(0.00487)	(0.00508)
Medium Search X 2014	0.0110*	0.00121	-0.00583	-0.000183	0.0122**
	(0.00657)	(0.00759)	(0.00956)	(0.00512)	(0.00504)
Medium Search X 2016	-0.00297	0.000441	-0.0172	0.00248	0.00810
	(0.00527)	(0.00670)	(0.0116)	(0.00494)	(0.00498)
High X 2014	0.00724	0.00106	-0.00624	-0.00345	0.00876
	(0.00686)	(0.00666)	(0.00974)	(0.00580)	(0.00547)
High X 2016	-0.000946	0.000580	-0.0170*	-0.00245	0.00467
	(0.00588)	(0.00637)	(0.00994)	(0.00517)	(0.00527)
Year FE	Yes	Yes	Yes	Yes	Yes
DMA FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	0.07	0.10	0.35	0.07	0.04
Observations	236746	236746	236746	236746	236746

Notes: This table presents the impact of George Floyd's murder on support for reducing funding for various areas, categorized by quartiles of Google search activity for "defund the police". Standard errors are clustered at the designated market area (DMA) level. Additionally, we provide the mean of the dependent variable for the omitted category, corresponding to the bottom quartile of Google search activity, i.e., no search.

C Survey Information

Figure A.12: Baseline Survey

Consent and Intro

In this survey, we will ask you some questions relating to ethical investing and corporate social impact and we will use responses to improve our understanding of people's views towards these issues. This study is being run by researchers at Duke University. Further information is provided below.

The survey may include questions which some people may find controversial or triggering.

What is involved in the study? In this study, we ask you your views on corporates that interact with various social issues. The study does not require any background knowledge on financial markets. The study will be conducted on a computer, and your responses will be recorded using a keyboard/mouse. Your participation in this study will last for approximately 2-4 minutes. Your participation is voluntary, and you may choose to end the study at any time by closing the survey.

Why is this study being done? Our research examines people's views towards social movements and investing decisions.

What are the benefits to taking part in the study? This research study will not provide you with any direct benefit. However, the data you provide may help improve the scientific understanding of how people make decisions.

Is there compensation? After completing the study, you will be paid for your participation through Prolific. There will not be any partial payments. At the end of the survey you will be redirected to Prolific and receive a completion code that you must submit on Prolific to get paid. We may reject your submission if the instructions were not followed, or you provided information that is inconsistent with your Prolific prescreening responses.

Confidentiality? We will not ask your name at any point during the study, and your responses can never be identified and connected with you. Data (without your Prolific ID) collected in this study coupled with data collected about you by Prolific, may be shared with other researchers or used for future studies but in such a way that you cannot be identified.

Who to contact with questions? If you have questions about this research, you can email us at socialcapitalresearch@duke.edu. If you have any questions concerning your rights as a participant in this research study, please contact the Duke University Campus Institutional Review Board at campusirb@duke.edu. We request that in your contact you refer to protocol number 2022-0505.

Click here if you wish to participate

Click here if you do not wish to participate

proliflic_id

What is your Prolific ID?

Please note that this should auto-fill with your correct ID.

${e://Field/PROLIFIC_PID}

Attention_check

What proportion of days do you wake up before 8am in the morning? This is a data quality check. Regardless of your true answer, please move the slider to fifty four percent.

% of days

0 10 20 30 40 50 60 70 80 90 100

% days that you wake up before 8am in the morning

Are you sure?

What proportion of days do you wake up before 8am in the morning? This is a data quality check. Regardless of your true answer, please move the slider to fifty four percent.

% of days

0 10 20 30 40 50 60 70 80 90 100

% days that you wake up before 8am in the morning

newQ

Company X has a product that it believes may improve the world using data. However, opponents argue that there is no evidence that the product works. Company X has several contracts with various federal and local government agencies.

To what extent to you agree with the following statement:
Investing in Company X is unethical.

Strongly agree
Agree
Neither agree or disagree
Disagree
Strongly disagree

It is reasonable for local and federal governments to purchase technology that is well intended, even if there is not yet evidence it works (scientific evidence or audit).

Strongly agree
Agree
Neither agree or disagree
Disagree
Strongly disagree

Do you think Company X should be audited (for example by a regulator) before being able to sell its technology to local/federal governments?

Strongly agree
Agree
Neither agree or disagree
Disagree
Strongly disagree

2.5.1 Finance Questions pt1

In an investment decision, please rank the following factors in importance to you. (Drag and drop the options to adjust the ranking. The most important factor should be at rank 1, and the least important factor should be at rank 5.)

Social justice

Environmental sustainability

Getting the highest possible returns to my investments

Promoting traditional family values

Fair treatment of employees

How often do you check on your investments?

- I don't have any investments
- Once per year or less
- A few times a year
- Monthly
- Weekly
- Daily

2.5.1 Finance Questions pt2

To what extent do you agree with the following statement: "I would invest in an unethical stock if it brought me higher returns"

	Never	Rarely	Sometimes	Mostly	Almost always
	1	2	3	4	5
Agreement scale					

Which of the following industries do you consider to be unethical?

- Green energy
- Military
- Tobacco
- Gambling
- Alcohol
- Guns / Firearms / Weapons
- Police
- Fossil fuels
- Financial companies
- Prisons

covariates

What is your age group?

- 18 to 24
- 25 to 34
- 34 to 44
- 45 to 54
- 55 to 64
- 65+
- prefer not to say

What is your race/ethnicity?

- Asian
- Black or African American
- Hispanic or Latino
- Native Hawaiian or Pacific Islander
- Native American
- White
- Other

What is your highest level of education?

- Less than high school degree
- High school degree
- Some college but no degree
- Associate college degree (2-year)
- Bachelor degree (4-year)
- Advanced Degree (Master, PhD, JD, MD,...)

What is your sex

Male
Female
Other
Prefer not to say

As of today, are you?

	Very liberal	Liberal	Neither Liberal or Conservative	Conservative	Very Conservative
	1	2	3	4	5
Political stance					

Were you born in the United States of America?

Yes - I was born in the U.S.A.
No

Thank you

Thank you for taking part in our survey. Please click the button below to be redirected back to Prolific and register your submission.

Powered by Qualtrics

Figure A.16: Follow-up Survey

Duke UNIVERSITY

Consent and Intro

Welcome!

In this survey, we will ask you some questions relating to social movements and stock prices. We use responses to improve our understanding of people's views towards these issues. The study is being run by researchers at Duke University and key information is provided below.

The survey may include questions which some people may find controversial or triggering.

WHY IS THIS STUDY BEING DONE? Our research examines people's views towards social movements and investing decisions.

WHAT IS INVOLVED IN THE STUDY? In this study, we ask you to predict the stock price performance of certain companies. We will ask additional questions to help us understand your predictions. The study does not require any background knowledge on financial markets. The study will be conducted on a computer, and your responses will be recorded using a keyboard/mouse. Your participation in this study will last for approximately 6-7 minutes. Your participation is voluntary, and you may choose to end the study at any time by closing the survey.

CONFIDENTIALITY? **We will not ask your name at any point during the study, and your responses can never be identified and connected with you**. Data (without your Prolific ID) collected in this study coupled with data collected about you by Prolific, may be shared with other researchers or used for future studies but in such a way that you cannot be identified.

ARE THERE BENEFITS TO TAKING PART IN THE STUDY? This research study will not provide you with any direct benefit. However, the data you provide may help improve the scientific understanding of how people make decisions.

WHAT ABOUT COMPENSATION? **After completing the study, you will be paid for your participation through Prolific.** There will not be any partial payments. At the end of the survey you will be redirected to Prolific and receive a completion code that you must submit on Prolific to get paid. We may reject your submission if the instructions were not followed, or you provided information that is inconsistent with your Prolific prescreening responses.

WHOM TO CONTACT WITH QUESTIONS? If you have questions about this research, you may email us at bocar.ba@duke.edu. Additionally, if you have any questions concerning your rights as a participant in this research study, you may contact the Duke University Campus Institutional Review Board at campusirb@duke.edu. Please refer to protocol number 2022-0505 in your contact.

- ○ Click here if you wish to participate
- ○ Click here if you do not wish to participate

proliflic_id

What is your Prolific ID?

Please note that this should auto-fill with your correct ID.

${e://Field/PROLIFIC_PID}

Examples

Throughout this survey, we will ask you to predict how stock prices respond to certain events. We will ask you consider a series of 8 portfolios each worth $100. For each portfolio, we want you to predict how much that portfolio will be worth after an event.

Some participants will be randomly selected to receive an accuracy bonus payment. If you are selected, you will receive an accuracy bonus payment of up to $10, depending on the accuracy of your predictions. **The more accurate your predictions are, the higher your bonus payment. Therefore, you should answer questions as accurately as possible.**

Adding percentage changes to numbers

Throughout the tasks, it may be useful to know the following

- If $100 increases by X%, its value becomes $100 + $X
- If $100 decreases by X%, its value becomes $100 - $X

Example 1
If $100 increases by 11%, its value becomes $100 + $11 = $111.

Example 2
If $100 decreases by 6%, its value becomes $100 - $6 = $94.

Prediction 1

This question is to check your understanding of this task.

On December-21-2020, U.S. Senators announced a comprehensive set of clean energy measures to be voted on by Congress. The bipartisan bill was approved before the end of 2020. A key fact is that in the period from December-20-2020 to January-10-2021, the price of shares in the iShares Green Energy ETF increased by 28%.

Suppose you bought $100 of the iShares Green Energy ETF (an index of clean energy companies) on December-20-2020. Please predict what the portfolio is worth on January-10-2021.

$ amount

0 20 40 60 80 100 120 140 160 180 200

iShares Green Energy ETF 100

Are you sure? Recall that if $100 increases by 11%, its value becomes $100 + $11 = $111.

Prediction 1

This question is to check your understanding of this task.

On December-21-2020, U.S. Senators announced a comprehensive set of clean energy measures to be voted on by Congress. The bipartisan bill was approved before the end of 2020. A key fact is that in the period from December-20-2020 to January-10-2021, the price of shares in the iShares Green Energy ETF increased by 28%.

Suppose you bought $100 of the iShares Green Energy ETF (an index of clean energy companies) on December-20-2020. Please predict what the portfolio is worth on January-10-2021.

$ amount

0 20 40 60 80 100 120 140 160 180 200

iShares Green Energy ETF 100

pred2

Prediction 2

As COVID spread across the world in 2020, the World Health Organization (WHO) declared a pandemic on March 11th, 2020. Suppose you bought $100 of Expedia (a travel company) the day before this announcement. Please predict what your holding is worth 21 trading days later.

$ amount

0 20 40 60 80 100 120 140 160 180 200

Expedia 100

Baseline

On May 25th, police officers killed George Floyd, an event that led to massive protests across the country starting on May 26th.

Baseline + Narratives

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...).

pred3

Prediction 3

We constructed a portfolio that consists of twenty publicly traded companies that contract intensively with police departments.

Prediction 3

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.

Consider the ranges of prices listed below. What probability (percentage) do you place on your holding being in each range? The total must add up to 100.

$0 to $80	0
$81 to $97	0
$98 to $102	0
$103 to $120	0
greater than $121	0
Total	0

pred_4_to_10

Predictions 4 to 8

We would now like you to make predictions for companies that offer police departments different types of services. We will ask you to consider five different companies, each of whom sell goods or services to police departments. For each company, we list the most common goods or services provided.

Suppose you bought $100 of the stock of each of the companies below, the day before the killing of George Floyd. We would like you to predict the price of your holding of each the stocks, 21 trading days after the killing of George Floyd (May 25th, 2020).

Company A

- audio-visual equipment
- cameras, body-worn
- weapons, firearms and ammunition
- weapons, less lethal
- recording systems

$ amount

0 20 40 60 80 100 120 140 160 180 200

Company A

Company B

- surveillance systems
- night vision systems
- thermal imaging systems
- cameras
- cctv, security

$ amount

0 20 40 60 80 100 120 140 160 180 200

Company B

Company C

- dispatch systems, e911, cad (computer aided police dispatch systems)
- surveillance systems
- detention, jail equipment
- identification (personnel identification and photo identification)
- personnel (human resources)

$ amount

0 20 40 60 80 100 120 140 160 180 200

Company C

Company D

- surveillance systems
- community policing
- gunshot location
- security devices, systems

$ amount

0 20 40 60 80 100 120 140 160 180 200

Company D

Company E

- equipment, training

- firearms training
- tactical training
- shooting ranges, equipment
- simulation-based training (for example, simulating police scenarios in a virtual environment)

$ amount

0 20 40 60 80 100 120 140 160 180 200

Company E

recalibrate

Recall that for prediction 3, we asked you the following:

We constructed a portfolio that consists of twenty publicly traded companies that contract intensively with police departments. 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).

You responded that the portfolio is worth $${q://QID108/ChoiceNumericEntryValue/1}.

Would you like to change your prediction for question 3?

- YES - I would like to redo my prediction
- NO - I would NOT like to redo my prediction

Recalibration - Prediction 3 again

We constructed a portfolio that consists of twenty publicly traded companies that contract intensively with police departments.

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

Please explain why your prediction changed using 2 to 3 sentences.

Consider the ranges of prices listed below. What probability (percentage) do you place on your holding being in each range? The total must add up to 100.

0 to 80	0
81 to 97	0
98 to 102	0
103 to 120	0

greater than 121	0
Total	0

Donation

If you are randomly selected to receive an accuracy bonus payment, you will also be given a $10 charity bonus payment.

If selected, you can choose to divide up the $10 *charity bonus payment* between yourself and a non-profit organization. You will have the choice to select the non-profit organization later. What amount of your charity bonus payment would you like to donate? ($10 indicates you would like to donate all of your bonus payment). Any money you keep, is in addition to your participation payment, and your accuracy bonus payment.

$0 to the non-profit and $10 for you — $10 to the non-profit and $0 for you

0 1 2 3 4 5 6 7 8 9 10

Donation amount

Please select which of the following non-profit organizations you would like to donate $${q://QID17/ChoiceNumericEntryValue/1} of your charity bonus payment to.

- ○ An organization that aims to improve officer safety as well as health and wellness in police.
- ○ An organization that aims to reduce the scope of policing in our society by providing vetted alternatives to policing.
- ○ An organization that advocates to reform the police by increasing accountability, for example, through officer training.

If you had to donate to a non-profit, which of the non-profits below would you choose to donate to.

- ○ An organization that aims to improve officer safety as well as health and wellness in police.
- ○ An organization that aims to reduce the scope of policing in our society by providing vetted alternatives to policing.
- ○ An organization that advocates to reform the police by increasing accountability, for example, through officer training.

Thank you

Thank you for taking part in our survey. Please click the button below to be redirected back to Prolific and register your submission.

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