Mispricing Narratives After Social Unrest *

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Abstract

We examine how negative sentiment toward an industry shapes beliefs and behaviors, focusing on demands for racial justice after George Floyd's murder and the prominence of the "defund the police" movement. Using a survey experiment, we find that laypeople and finance professionals predicted larger stock declines for police-affiliated firms when lacking product details, while exposure to protest narratives further reduced accuracy. In the field, mutual funds in protest-exposed areas were 20% less likely to hold police stocks, and local political support for police funding fell by 4.3 percentage points. Our findings highlight how salience drives financial and behavioral overreactions.

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1 Introduction

When valuing firms, how do stakeholders interpret market reactions to future policies, and how do they respond to narratives surrounding those policies? The interplay between these narratives and industry fundamentals is crucial in shaping investor reasoning and public perception (Shiller, 2017). Events such as elections, wars, coups, and protests lead to diverse interpretations and implications, with the stock market serving as an information aggregator that balances immediate reactions with long-term outcomes. Understanding how stakeholders process and react to available information is essential for accurately assessing firm performance and policy implication.

We examine how stakeholder beliefs adapt to events negatively impacting an industry, focusing on demands for racial justice after the murder of George Floyd, which triggered the largest protests in U.S. history (New York Times (2020)). We perform an experiment to isolate the effects of different types of information on stakeholder beliefs. In the absence of details on the products supplied by firms connected to policing, laypeople and finance professionals forecasted more negative stock outcomes for such firms, and narrative information often reduced their prediction accuracy. In contrast, exposure to product details improved their forecast accuracy. Open-text analysis indicates that respondents overestimated the impact of police budget cuts and declining public trust in police on the market performance of policing suppliers, underscoring the wide influence of "defund the police" narratives. We next show that, in the two years after the protests, investors were substantially less likely to hold police stock, and support for maintaining police funding in protest areas declined by more than 4 percentage points (pp), which was admittedly insufficient to shift the median voter's stance. Overall, the salience of the defund movement impacted policy support and led to overreactions in both forecasting and real-life investment decisions.

Understanding the impact of unforeseen events on firms and industries requires examining the interplay of narratives, expertise, and public opinion. This involves distinguishing between short- and long-term effects while untangling beliefs, preferences, and outcomes. Our aim is to identify significant events that alter societal norms and negatively impact related institutions and firms (Bénabou and Tirole, 2010; Hart et al., 2022). We assess the beliefs and reasoning of key stakeholders—laypeople and finance professionals—using plausibly objective measures of both immediate expectations and long-term outcomes. Finally, we analyze how these stakeholders respond in their investment behavior and policy support.

We tackle this challenge by examining the impact of the 2020 racial justice protests following the murder of George Floyd and the defund movement on policies related to policing (Bursztyn et al., 2020). To gauge the impact on the policing industry, we draw on Ba et al. (2023), who finds that in the short run, public firms connected to the police experienced a 16.5 pp increase in abnormal returns, reflecting optimistic market expectations. In the long run, these firms experienced higher sales and greater reliance on police demand for surveillance and accountability tools, indicating that financial markets anticipated increased resources for law enforcement despite the calls for reduced investment in policing. Our approach aligns with Wolfers and Zitzewitz (2004), who argue that stock markets provide insights into investor expectations, similarly to how market data have been used to understand the impact of the Iraq war on commodity prices (Wolfers and Zitzewitz, 2009).

Second, using the 16.5 pp increase in abnormal returns as a benchmark, we solicited forecasts from over 2,300 nonexperts, namely, citizens who impact policymaking through their votes, and nearly 500 finance professionals on the stock performance of police-connected firms following the murder of George Floyd. Our goal was to understand "who knows what?" (DellaVigna and Pope, 2018) and identify the most influential types of information. We randomly assigned respondents to one of four groups: One received minimal information with a forecast prompt, another received comprehensive background including both narratives and product details, and the other two groups received either narrative information about police defunding and reform or product details about police-related firms.

The information treatments aimed to clarify the effects of narrative and product information on market predictions, given the ambiguous ex ante impact of the protests following the murder of George Floyd on firms contracting with police. The narrative treatments detailed the aftermath of the murder, including the protests, debates over police reform, accountability tools, the "defund the police" movement (Bursztyn et al., 2022), and concerns about increased unrest, crime, and homicides (Premkumar, 2019). The product treatments described a portfolio of twenty publicly traded companies supplying products to police, such as training, body-worn cameras (BWCs), and surveillance equipment (Ba et al., 2023). These treatments were designed to explore how these diverse types of information shape participants' forecasts of police-linked firms' market valuations in the face of complex and uncertain social and policy outcomes.

Our main experimental results show that, among respondents provided with minimal information, only 16% to 29% anticipated an increase in portfolio value following the murder of George Floyd, indicating that both nonexperts and finance professionals generally expected the defund movement to negatively impact police-related firms. The introduction of product information notably shifted these expectations by increasing respondents' likelihood of predicting an increase by more than 30 pp for both groups. However, some uncertainty persisted, and the the accuracy gap did not close. Notably, nonexperts exhibited more prediction errors than experts even when presented with more information, suggesting a precision gap, whereas finance professionals made fewer errors when presented with product information alone.

In addition to collecting their main forecasts, we gathered respondents' probabilistic expectations about their forecast accuracy to gauge their uncertainty levels (Manski, 2004; Hanspal et al., 2021). Nonexperts became more confident when presented with product information or a combination of narrative and product information, while finance professionals' responses were consistently stable, improving mainly with product information. Given these differences in processing product information, we analyze how the forecasts varied with the types of products that firms sell. Nonexperts preferred broad product information, while finance professionals favored detailed information across all types. High-tech and security-focused products had a stronger impact on forecasts because of their relevance to market trends, whereas information on specialized products such as gunshot detection technology and simulation training did not consistently affect stock predictions.

Given that respondents processed information differently depending on the treatment and their expertise, we explored the reasoning behind their predictions to understand belief formation mechanisms. In addition to our experimental sample, we surveyed community organizers and police officers, stakeholders with nuanced insights into policing externalities. We manually coded respondents' explanations into categories such as "defund the police" (*budget cuts*), police *reform*, and a general decline in public trust in the police (*less trust*). Community organizers and police officers were more likely to predict an increase in police stock prices, emphasizing *reform* and accountability measures, given their deep understanding of policing externalities. In contrast, our experimental sample focused on*budget cuts* and *less trust*. This detailed coding helps assess us the qualitative aspects of stakeholders' reasoning and how exposure to different information influences it.

Next, we examine how information exposure impacts reasoning on *reform*, *budget cuts*, and *less trust*. Nonexperts exposed only to product information were less likely to cite *less trust* and shifted toward *reform*. Combined product and narrative information further increased *reform* mentions and decreased mentions of *less trust*. For finance professionals, exposure to product information alone increased the emphasis on *reform*, with minimal changes arising from narrative exposure. Overall, nonexperts responded more to combined information, emphasizing *reform*, while finance professionals relied more on product details. Notably, exposure to product information appears to have reduced the salience of the defund movement by decreasing mentions of *budget cuts* and *less trust*, suggesting different information-processing styles regarding policing and the defund movement.

Before turning to our real-life outcomes, we rationalize the findings from our experimental sample with a simple asset pricing model. Drawing on the Lucas tree model (Lucas, 1978), we model the behavior of survey participants in predicting outcomes in a manner similar to how market participants value assets. This approach involves evaluating how participants discount uncertain cashflows based on their beliefs on different states of the world, in both the short and long run. The model incorporates the impact of specific information treatments—narrative and product—and the expertise level of participants, which affects how they process information and make financial predictions. Our empirical analysis shows that finance professionals make more accurate stock predictions when in possession of detailed product information, aligning with our model's prediction that this leads to higher asset price expectations. Conversely, nonexperts relying on narratives, such as those about protests and defunding the police, focus on short-term impacts, resulting in lower predictions.

As our surveys reveal a strong link between George Floyd's murder and the push to defund the police, which suggests salience-driven explanations (Bordalo et al., 2012, 2013, 2022; Alok et al., 2020; Fisman et al., 2023) that make respondents less likely to associate the event with *reform*, we explore stakeholders' real-life behavior based on their protest exposure. We investigate investor decisions to hold police-associated stocks in the wake of George Floyd's murder and civilian support for maintaining or increasing police funding using their protest exposure in the two election years following the murder. These analyses complement our "information treatment" study by linking it to real-life outcomes for key stakeholder groups, highlighting the impact of information and preferences in critical scenarios.

To explore investors' responses to protests, we use a difference-in-differences strategy to compare mutual funds holding police-related stocks in counties with BLM protests following the murder of George Floyd to those without such exposure. We find a significant 5.3 pp ($p < 0.01$) decrease in holdings of police stocks in protest-affected areas after 2020, indicating that funds exposed to protests were over 20% less likely to hold police stocks, reflecting a shift due to the defund movement. Building on the fact that past experiences matter in investment decisions (Malmendier and Nagel, 2011; Malmendier et al., 2024), we explore the role of county and fund characteristics. Counties with more police per capita, higher murder rates, and prior police killings were less likely to hold police stocks, showing responsiveness to local law enforcement and crime indicators. Changes in fund characteristics (e.g., age, size, diversification) had less clear impacts, suggesting that local dynamics influenced investment decisions. In counties exposed to protests without police killings in 2019, mutual funds were more likely to hold police stocks, interpreting the protests as advocating for reform rather than defunding. In contrast, counties with both protests and recent police killings associated the protests with reduced funding and austerity measures, highlighting distrust and perceived instability.

Finally, we examine whether the emphasis on *budget cuts* and *less trust* in nonexpert reasoning reflects general public preferences. Drawing on the idea that exposure to information related to the financial market impacts policy preferences (Jha and Shayo, 2019), we use nationally representative data from the Cooperative Election Study (CES) and assess how the defund movement influences public sentiment on police reform. Our event-study analysis compares respondents exposed to protests after the murder of George Floyd to those without such exposure. We find that the defund movement led to a significant 4.3 pp ($p < 0.01$) decrease in support for maintaining or increasing police resources in protest-exposed areas after 2020, which stabilized but remained below preprotest levels by 2022. Nevertheless, 93% of respondents in nonprotest areas continued to favor maintaining or increasing police funding, indicating no major shift in the median voter's stance. This suggests that significant defunding of police departments is unlikely and reflects a potential overreaction, while the belief that the defund movement would negatively impact police due to prevailing public opinion remains strong.

Literature Review Our paper explores how beliefs and behaviors respond to policies affecting minority groups (Cascio and Washington, 2013; Haaland and Roth, 2021; Alesina et al., 2021; Bohren et al., 2023), situating recent racial equity movements such as BLM alongside the civil rights movement and earlier policing-related unrest in US cities (DiPasquale and Glaeser, 1998; Cunningham and Gillezeau, 2019; Wasow, 2020), which had lasting effects on political attitudes and resource allocation (Mazumder, 2018; Derenoncourt, 2022). Motivated by the unique influence of BLM and the George Floyd protests on public opinion and voting (Gethin and Pons, 2024),[1] we focus on policing—the core target of activism for BLM (Bursztyn et al., 2023; Ba et al., 2023)—to examine the racial, political and social implications of this activism in the US (Ang and Tebes, 2020; Grosjean et al., 2022; Chenoweth et al., 2022) and its impact on corporate behavior and firm performance (Bogan et al., 2021; Aneja et al., 2023; Denes and Seppi, 2023; Garcia and Ortega, 2024). Our work clarifies public and expert beliefs about the impact of these race-related social movements on policing and their actual support for law enforcement policies.

Second, we contribute to the literature on the role of narratives and information pro-

[1]Other movements focused on environmental protection, gender equality, gun control, immigration, and racial issues have not significantly shifted public opinion or behavior (Gethin and Pons, 2024).

cessing in shaping beliefs (Shiller, 2017; Eliaz and Spiegler, 2020; Schwartzstein and Sunderam, 2021) and decision-making regarding economic outcomes (Perez-Truglia, 2020; Andre et al., 2021, 2022, 2023; Flynn and Sastry, 2022), political behavior (DellaVigna and Kaplan, 2007; Enikolopov et al., 2011), health (Bursztyn et al., 2022), and policy support (Djourelova, 2023; Durante et al., 2024). Our work is particularly relevant to the literature on narratives related to public safety and their implications (Philippe and Ouss, 2018; Grosjean et al., 2022; Mastrorocco and Ornaghi, 2023) for funding allocations and accountability of public servants (Moreno-Medina et al., 2022).

Finally, our paper contributes to the literature examining firm-level exposure to risks and stakeholders' beliefs and responses to these risks,[2] particularly those driven by nonpecuniary motives (Hong and Kacperczyk, 2009; Hart and Zingales, 2017) and social issues(Kumar et al., 2015; **?**; Do et al., 2024). Such motives can lead stakeholders to divest from companies in controversial industries (Bénabou and Tirole, 2010; Fisman et al., 2014). We examine responses to racial uprisings in the US, where the link between protests, financial outcomes, and shifting societal norms——such as debates over "defunding the police" (Bursztyn et al., 2023)——remains underexplored, with preferences often concealed under societal pressures (Kuran, 1995). Moreover, negative publicity typically lowers stock prices by reducing demand, but public services such as policing are insulated from market pressures (Hart et al., 1997). The strong public support for police funding, despite the criticisms, makes cuts unlikely, showing that the industry is less vulnerable to societal disapproval than "sin stocks" such as tobacco, firearms, or private prisons (Hong and Kacperczyk, 2009; Blitz and Fabozzi, 2017; Yegen, 2020).

Plan The remainder of this paper is structured as follows. Next, we provide a brief overview of the year 2020 and the influence of the summer 2020 uprisings on the stock performance of firms contracting with the police. Section 3 examines the impact of an information treatment on the forecasts of nonexperts and finance professionals. Section 4 focuses on the forecasts' underlying reasoning and the mechanism whereby the informa-

[2]Recent studies have explored investors' financial beliefs or preferences using survey experiments (Hanspal et al., 2021; Stroebel and Wurgler, 2021; Giglio et al., 2021a,b) and structural modeling (Baker et al., 2022).

tion treatment shapes this reasoning. The theoretical model that helps explain our results is presented in Section 5. Section 6 investigates how the salience of the defund movement influenced stakeholders' real-life behavior based on their protest exposure. Finally, we conclude with a discussion of the implications of our findings.

2 Background: 2020 Protests and Their Salience

As illustrated in Figure 1 through spikes in Wikipedia pageviews, 2020 was a year of pivotal events that reshaped global and national policies. The COVID-19 pandemic prompted widespread health and economic reforms, while the murder of George Floyd triggered widespread BLM protests and renewed focus on law enforcement and civil rights reforms. The US presidential election, dominated by debates surrounding then-president Donald Trump, further fueled political engagement. Together, these events increased public participation and laid the groundwork for possible policy changes, particularly in response to the calls for police reform.

Floyd's death had a profound impact on public discourse, sparking widespread protests and critical policy debates that underscored the urgency of policing and racial justice reforms. The bottom panels of Figure 1 highlight the influence of the defund movement, as marked by the surge in *New York Times* articles discussing police-related topics and the slogan itself. Similarly, Wikipedia searches for "defund the police" spiked in June 2020, surpassing searches for "police reform," while interest in "police brutality" remained steady. These trends indicate a significant shift in public attention and media coverage toward issues related to reducing police funding.

The heightened salience of "defund the police" may have contributed to overreactions (Bordalo et al., 2022) shaped by media outlets' subjectivity in framing the movement rather than objective descriptions of the policing industry or the policies associated with the protests. In contrast, product-related terms such as "body-worn camera" and "surveillance systems" offer more descriptive insights into what this industry does and the underlying policies that shape it. In the next section, we test how different types of information—–narrative versus product details—–shape beliefs and expectations about police-related industries.

3 Role of Information in Belief Formation

3.1 Experimental Design

Overview and Logistics We conducted an online experiment using Prolific from December 20 to 28, 2022, and registered our hypotheses and analysis design with the AEA registry (`AEARCTR-0010670`) and AsPredicted (`#117117`). The baseline survey ran from December 20 to 23 and was supplemented by a follow-up from December 27 to 28. Participants, who had to be voting-age residents of the United States and fluent in English, received approximately \$0.50 for the baseline survey, which could be completed in less than 3 minutes, and \$1.20 for the 8-minute follow-up, totaling \$1.56 for both surveys, contingent on their completing the survey and passing the attention checks.

Survey Structure To address experimenter demand effect, we designed the Prolific survey in two parts, following the methods of Haaland and Roth (2020, 2021). The baseline survey and a follow-up survey were conducted one week apart, with randomized information treatments applied in the follow-up. We tried to minimize any perceived connection between the two surveys by differentiating style elements such as fonts and backgrounds.

The baseline survey collected demographic information and views on ethical investing, investment experience, and political leaning.[3] In the follow-up, participants completed prediction tasks after randomization into one of four groups defined by a 2×2 factorial design corresponding to $\{$Narrative, No Narrative$\} \times \{$Product, No Product$\}$. Participants predicted stock movements after George Floyd's death and could revise these predictions.[4]

In addition to the Prolific survey, we conducted a parallel survey of professionals in the finance sector. Respondents in this industry were invited via email to participate in a Qualtrics survey. In contrast to the Prolific survey, this survey was administered in a single

[3]The baseline survey questions are available here.
[4]The follow-up survey questions are available here.

phase rather than with 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 based on their prediction accuracy. 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 donate 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, if they wanted to donate, we asked respondents for their choice of nonprofit organization.

Treatment Arms and Randomization Ex ante, it is unclear what sign we should expect for the impact of the protests following George Floyd's murder on the market valuations of firms heavily contracting with police. This ambiguity stems from the interplay of various factors, including the calls for police reform, concerns about rising crime, and the defund movement, in shaping market expectations.[5] Figure 1 indicates that public discourse leans more toward discussion of broad policy and budgetary issues than toward discussion of the application of specific law enforcement technologies or products.[6] 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 influenced participant predictions for the impact of the summer 2020 protests. We employed a 2×2 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 A.2, the participants were first randomly assigned to one of the two narrative conditions that

[5] On narratives associated with viral killings by police in economics, see Rivera and Ba (2018); Premkumar (2019) and Ang et al. (2021).

[6] For instance, from Figure 1, we might conclude that media focus suggests that public discussion was more concentrated on defunding than on police reforms as captured by terms specific to technologies or products utilized by law enforcement agencies.

emphasize the views of various stakeholders:

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

- **Narrative:** *"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)."*

The participants were then randomly assigned to one of the two product conditions, which emphasized the technologies and products used by the 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 results in participants' being randomly assigned to one of four conditions:(1) *No Information*, (2) *Narrative Only* (exposed only to narrative information), (3) *Product Only* (exposed only to product information), and (4) *Narrative and Product* (exposed to both types of information). This design enables us to isolate the separate impacts of narrative and product information on the public's market expectations.

Empirical Specification We analyze the impact of the information treatments on various outcomes using the following ordinary least squares (OLS) specification:

$$y_i = \alpha_0 + \theta_1 Products_i + \theta_2 Narratives_i + \theta_3 Narratives\_Products_i + X_i'\gamma + \epsilon_i \qquad (1)$$

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 $Products_i$ is a binary variable that equals one if the respondent received information about the products in the portfolio and zero otherwise. The variable $Narratives\_Products_i$ designates the respondents who received both the product and the narrative information. The reference group consists of respondents who received neither the narrative nor the product information treatments. We also refer to the omitted group as the reference. In addition, in X_i, we control for the individual covariates collected in the baseline survey. We use robust standard errors because we randomized at the individual level.

Our primary preregistered outcome, y_i, captures the respondents' prediction accuracy. We focus on two main accuracy measures as our primary outcomes. The first is whether the respondent correctly predicted an increase in price, defined as a forecast greater than \$100. The second is the negative absolute prediction error, calculated as the difference between the respondent's forecast and the actual portfolio realization of \$116.5 (Ba et al., 2023).[7]

3.2 Descriptives

Summary Statistics Our study involved respondents who met our eligibility criteria and completed both the baseline and follow-up surveys. For those in the finance industry, the results from the two surveys were combined. Participants who failed the attention checks or did not complete the comprehension question were excluded from the analysis. The

[7] Prediction error is defined as the absolute difference between the actual price and the respondent's forecast.

summary statistics, disaggregated by treatment condition, are detailed in Table 1. Panel A focuses on nonexperts, while Panel B focuses on finance professionals, totaling 2,346 nonexperts and 467 finance professionals. The tables show the average values for each variable across the total sample in Column (1) and for each treatment arm in Columns (2) to (5), with the last column testing for equality of means across conditions.

Demographically, 44% of the nonexpert respondents are women compared to 20% in the finance group. A majority of the respondents (90%) were born in the U.S., and the sample was predominantly white (72% in the nonexpert group and 84% among finance professionals). Nonexperts were generally younger and completed the survey quicker. Over two-thirds of finance professionals checked their investments weekly, versus one-third of nonexperts. While there is a general balance in characteristics across conditions, the "*Narratives_Products*" arm in the nonexpert sample showed lower percentages of women and U.S.-born respondents.

Prediction Distribution Figure 2 displays the portfolio prediction distributions for nonexperts and finance professionals across treatment arms. The finance professionals report predictions with lower variance and higher means, indicating greater consensus than among nonexperts, who exhibit a wider range of predictions. Both groups underestimate stock changes and predict portfolio prices that significantly deviate from the actual prices, often expecting that the murder of George Floyd would have either no impact or a negative impact on the policing industry. The impact of information exposure on the predictions varies between groups. With access to product information, finance professionals tend to predict higher portfolio values, whereas without it, they predict lower values. Those receiving full information or only product information have similar prediction distributions, but the distribution for the latter group features denser peaks. Nonexperts exposed to product information exhibit a bimodal distribution, predicting increases or decreases in portfolio prices.

3.3 Impact of Information on Prediction Accuracy

Accuracy of Portfolio Predictions Table 2 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. For nonexperts, the product information treatment led to a 32.2 pp ($SE = 0.0258$) increase in their likelihood of predicting stock increases (Column (1)), a substantial rise compared to the baseline probability of 0.16. When both product and narrative information were provided, the likelihood increased marginally more to 34.4 pp ($SE = 0.0257$). Interestingly, exposure to only narrative information did not have a large or significant effect on predictions among nonexperts.

Among finance professionals, we observe a different pattern. First, compared to nonexperts, finance experts without information are more likely to predict an increase in the portfolio value with a baseline mean of 0.29. The product-only treatment increased their likelihood of making accurate predictions by 35 pp ($SE = 0.0614$), and the combined narrative–product information treatment yielded a more muted but still large increase of 24.1 pp in the probability of predicting an increase in portfolio value. The narratives-only treatment had a negative impact, reducing the likelihood of correctly predicting a portfolio increase by 5.99 pp, although this was not significant.

The magnitude of errors—negative absolute errors in predictions—also varied (Columns (3) and (4)). Nonexperts had an increase in errors of 10.27 pp in the product information treatment and of 12.76 pp in the treatment with both narrative and product information, indicating that while they were more likely to predict an increase in this treatment, their precision did not necessarily improve. For finance professionals, the errors were significantly lower when they were exposed only to product information (7.18 pp ($SE = 1.862$)).

The influence of the information type on financial prediction is clear from these results. Access to detailed product information substantially improves both nonexperts and finance professionals' likelihood of accurately predicting stock price increases. However, exposure to only narrative information could lead to prediction errors, particularly among nonexperts. Finance professionals, on the other hand, showed enhanced prediction accuracy only when they had access to product information. This highlights a stark difference in how narrative and product information is processed across expertise levels: nonexperts benefit from comprehensive information, while finance professionals rely on specifics about product details to make accurate predictions. The result suggests that precise product knowledge, rather than general narratives, is key to anticipating growth in the policing sector following high-profile grassroots uprisings.

Distribution of Beliefs Motivated by Figure 2, which illustrates that finance professionals' predictions exhibit lower variance and higher means than those of nonexperts, we adopt the methodology of Manski (2004) and Hanspal et al. (2021) to gather respondents' probabilistic expectations regarding the accuracy of their predictions. Table 4 provides an analysis of how the different information treatments affect the distributions of portfolio price predictions among nonexperts (Panel A) and finance professionals (Panel B) relative to the prediction distribution of their counterparts receiving no information. The dependent variables in this analysis are dummy variables that categorize the probability of a stock valuation prediction'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 being the baseline. These findings align with the results presented in Table 2.

For nonexperts, exposure to product information alone significantly reduces negative predictions, particularly in the lowest prediction range (< 81), with a decrease of 15.4 pp ($SE = 0.0184$). The combined narrative–product information treatment generally results in more positive predictions, notably increasing those in the $98 - 102$ range by 12.8 pp ($SE = 0.0120$) and those in the > 120 range by 7.4 pp ($SE = 0.0104$). In contrast, exposure to narrative information alone has a less consistent effect but notably decreases predictions in the lowest range by 3.66 pp ($SE = 0.0187$). In contrast, finance professionals exhibit a more subdued but significant response to different information treatments. The absence of product information notably lowers midrange predictions ($81 - 97$) by 13.4 pp ($SE = 0.0317$), while exposure to product information alone significantly increases higher-range predictions ($103 - 120$ and > 120) by 17.5 pp ($SE = 0.0329$) and 5.82 pp ($SE = 0.0162$), respectively. When narrative information is combined with products, there is a mixed influence; this treatment slightly reduces midrange predictions by

9.24 pp ($SE = 0.0334$) but increases the probabilities of predictions in higher ranges by up to 9.96 pp ($SE = 0.0311$). These findings underscore that both groups—nonexperts and finance professionals—adjust their prediction behaviors based on information exposure, but finance professionals' reactions, although significant, are steadier, with less variance in their response to the information treatments.

Heterogeneity by Type of Prediction Given that nonexperts and finance professionals processed the product information differently, Table 3 explores how the respondents' predictions 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 2 in Column (1) to facilitate comparison with the portfolio prediction.

Nonexperts are significantly more influenced by product information in the broad portfolio context than in evaluating specific stocks, indicating that information is processed differently in general and detailed assessments. In contrast, finance professionals consistently respond more positively to product information across all company types, showing a greater impact of concrete product details over narrative information.

The impact of product information varies notably across companies, particularly for high-tech and security-focused firms such as Axon Enterprise and Teledyne FLIR, which sell advanced technologies such as conducted energy weapons and thermal imaging systems. Valuations of these companies' stock showed a more pronounced response among respondents exposed to product details, likely because of the relevance of the firms' technologies to current market trends. However, firms such as ShotSpotter and VirTra, offering more specialized services such as gunshot detection and simulation-based training, did not show a uniform increase in stock predictions among respondents exposed to product information. This suggests that the specialized nature of their products requires deeper, domain-specific knowledge.

Overall, the effect of product information exposure on stock predictions is closely tied to the nature of the products and services a firm offers, with companies involved in critical and technologically advanced sectors seeing the most significant impact. These results suggest that nonexperts and finance professionals processed the narrative or product information differently depending on the product type.

4 Measuring What Is Top of Mind

This section investigates how various stakeholders interpreted information related to the murder of George Floyd and its implications for police policy. We examine the influence of narratives and product details on their reasoning and assess how information and framing shaped their perspectives. Additionally, we introduce a measure of what was top of mind for these stakeholders (Stantcheva, 2023; Haaland et al., 2024) to identify the mechanisms associated with their involvement in racial justice. This approach helps clarify how different narratives and product information impact stakeholders' views and potentially bridge divides in public discourse on police reform and racial justice.

4.1 Coding Procedures

We exploit the fact that our surveys asked respondents to explain their main prediction to qualitatively analyze their reasoning (Andre et al., 2021, 2022). We opted to hand-code the responses rather than use large-language models because the reasons were often subtly embedded and included in open-ended responses. We manually coded nearly 3,000 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 5 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 independently hand-coded each open-text answer into ten categories.[8] Given a free-text response and a reason, the final categorization was determined

[8]The coders were Duke graduate and undergraduate students and participated in a training session where

by 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.

4.2 Relationship Between Reasoning and Predictions

On-the-Ground Experts' Reasoning In addition to our experimental sample, we conducted a companion survey targeting stakeholders with relevant expertise, particularly community organizers and police officers, who have a nuanced understanding of policing externalities.[9] These experts received comprehensive information, including both narratives and product details, as depicted in the top panel of Figure 3. Both groups exhibited a strong tendency to predict an increase in stock prices for police suppliers following the protests, with 71% of community organizers and 65% of police officers anticipating a rise. The dominant factor influencing their predictions was *reform*, accounting for 40% of responses from community organizers and 46% from police officers. Police officers also placed greater emphasis on *budget cuts* and *unspecified demands* than did community organizers. Police and community organizers were much more likely to predict increases, 65% and 71% respectively, than nonexperts (33%) and finance professionals (42%).

Nonexperts and Finance Professionals The bottom panel of Figure 3 shows that nonexperts primarily linked stock price declines to *less trust* (22%), *budget cuts* (16%), and *reform* (12%), with 63% predicting a drop. Conversely, finance professionals had a more balanced view: 42% forecasted an increase due to *reform* and *unspecified demands*, while

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.

[9]For further details on recruitment, see Section A.2 in the Appendix.

48% anticipated a decrease, largely due to *less trust* and *budget cuts*. Unlike community organizers and police officers who were more optimistic about *reform*, nonexperts and finance professionals focused more on the potential negative impacts. For the remainder of the paper, we concentrate on the themes of reform, budget cuts, and less trust, as these align closely with the rationales provided by community organizers and police officers, who have a deeper understanding of the factors influencing stock prices. Additional reasoning details are provided in Section B.1.2 of the Appendix.

4.3 Impact of Information on Reasoning

Having established the correlation between respondents' beliefs about the negative impact of George Floyd's murder on the policing industry and their reasoning, in Table 6, we examine how exposure to product and narrative information affected reasoning for our experimental samples.

For nonexperts, exposure to product information alone made them 14.8 pp points less likely to mention *less trust* ($p < 0.01$) and shifted their reasoning toward *reform* by 16.8 pp ($p < 0.01$). When both products and narratives were provided, mentions of *reform* increased by 20.2 pp ($p < 0.01$), and mentions of *less trust* exhibited a 21.0 pp ($p < 0.01$) decrease, indicating that exposure to comprehensive information redirected the focus from skepticism to reform. Mentions of *budget cuts* also rose by 7.3 pp ($p < 0.01$) under exposure to combined information, with some nuance visible in the shifts. Finance professionals exposed only to product information were 19.6 pp more likely to emphasize *reform* ($p < 0.01$), with minimal changes in mentions of *less trust* or *budget cuts*. Adding narratives had a modest effect on their emphasis on *reform* and *budget cuts*, indicating greater reliance on product details.

Overall, nonexperts responded more to the combination of narratives and product information, emphasizing *reform* over *trust* or*budget cuts*. In contrast, finance professionals predominantly relied on product details, showing less influence from broader narratives. This highlights the different information-processing styles between these groups concerning policing and the defund movement.

5 Modeling the Role of Information in Beliefs

We model the prediction behavior of survey participants in a framework analogous to one in which market participants price an asset under conditions of limited information regarding future cash flows. The preferences of these participants are influenced by the information they receive. Following the classical Lucas tree model (Lucas, 1978), the asset provides dividends D_1 and D_2 at the end of two respective periods, termed the short run and the long run. The states of the world for these periods are denoted (s_1, s_2), with corresponding physical probability densities $\pi(s_1)$ and $\pi(s_2|s_1)$. The information available to market participants is modeled through a filtration $\{\mathcal{F}_1, \mathcal{F}_2\}$, which captures all accessible information at each stage. Therefore, price predictions at the end of period zero and the beginning of period one are based on the expectations of the discounted cash flows:

$$P = \mathbb{E}\left[\mathbf{m}_1(s_1)D_1(s_1) + \mathbf{m}_2(s_1,s_2)D_2(s_1,s_2)|\mathcal{F}_1\right] \tag{2}$$

where $\mathbf{m}$ is the stochastic discount factor (SDF) as in Cochrane (2009). We model the narrative and product treatments, along with the expertise level (finance professional versus nonexpert), as scenarios that influence the information set $\mathcal{F}$ available to the respondent and the discounting m of cashflows.

Finance Professionals with No Information (O) Consider finance professionals to be agents who discount cashflows, as in standard consumption-based asset pricing, according to the marginal utility of consumption C^{market} of a representative market participant.

$$\mathbf{m}_1(s_1) = \beta_1 \frac{u'(C^{\text{market}}_{s_1})}{u'(C^{\text{market}}_0)}, \quad \mathbf{m}_2(s_1,s_2) = \beta_2 \frac{u'(C^{\text{market}}_{s_1,s_2})}{u'(C^{\text{market}}_0)} \tag{3}$$

where u' is the marginal utility and β_1, β_2 are time preferences. Let agent time preferences in the "No narrative" intervention follow the standard exponential discounting framework with constant time preference $\beta \leq 1$ so that $\beta_1 = \beta$ and $\beta_2 = \beta^2$.

For the period after George Floyd's murder, we expect the immediate dividends $D_1(s_1)$

of the portfolio companies to decline. We denote by $\underline{D}_1$ this low expected level. Let the "No product information" intervention correspond to a scenario where expectations about long-term cashflows are anchored to a baseline level $\tilde{D}_2$ (Tversky and Kahneman, 1974). When we replace expectations with their certainty equivalents for simplicity, the price prediction of finance professionals with no information (O), i.e., with neither narrative or product information, is

$$P_{\text{Finance, O}} = \beta \frac{u'(C_1^{\text{market}})}{u'(C_0^{\text{market}})} \underbrace{\underline{D}_1}_{\downarrow} + \beta^2 \frac{u'(C_2^{\text{market}})}{u'(C_0^{\text{market}})} \underbrace{\tilde{D}_2}_{=} \tag{4}$$

Therefore, we can expect finance professionals not exposed to any narrative or product intervention to predict a decrease in the asset price, as short-term cashflows are expected to decrease, while with limited information on policing products, expectations about long-term cashflows are anchored.

Finance Professionals with Product Treatment (P) Let the "Product" treatment correspond to a scenario with information indicating that future long-term cashflows will substantially increase because of higher demand. We capture this with a certainty equivalent $\overline{D}_2 \gg \tilde{D}_2$, so that the price prediction of finance professionals with product information only (P) is

$$P_{\text{Finance, P}} = \beta \frac{u'(C_1^{\text{market}})}{u'(C_0^{\text{market}})} \underbrace{\underline{D}_1}_{\downarrow} + \beta^2 \frac{u'(C_2^{\text{market}})}{u'(C_0^{\text{market}})} \underbrace{\overline{D}_2}_{\Uparrow} \tag{5}$$

Therefore, if the product intervention manages to induce finance professionals to sufficiently raise their expectations for long-term cashflows $\overline{D}_2 - \tilde{D}_2$, they can predict an overall increase in the price of the asset.

Finance Professionals with Narrative Treatment (N) Let the "Narrative" treatment alter the SDF and the time preference of agents so that they are more fixated on the short term than on the long term. We capture this intervention as transforming agent preferences to the $\beta\delta$-hyperbolic discounting framework (Laibson, 1997) so that $\beta_1 = \beta$ and $\beta_2 = \beta^2\delta$, where $\delta < 1$, and hence the price prediction of finance professionals with narrative information only is

$$P_{\text{Finance, N}} = \beta \frac{u'(C_1^{\text{market}})}{u'(C_0^{\text{market}})} \underbrace{\underline{D}_1}_{\downarrow} + \underbrace{\delta}_{<1} \beta^2 \frac{u'(C_2^{\text{market}})}{u'(C_0^{\text{market}})} \underbrace{\tilde{D}_2}_{=} \tag{6}$$

Therefore, we can expect finance professionals exposed to the narrative intervention to predict a decrease in the asset price, as short-term cashflows are expected to decrease, while they underweight anchored expectations about long-term cashflows.

Finance Professionals with Combined Product and Narrative Treatment (N+P) The combination of the narrative and product information interventions creates two contrasting forces on asset price predictions.

$$P_{\text{Finance, N+P}} = \beta \frac{u'(C_1^{\text{market}})}{u'(C_0^{\text{market}})} \underbrace{\underline{D}_1}_{\downarrow} + \underbrace{\delta}_{<1} \beta^2 \frac{u'(C_2^{\text{market}})}{u'(C_0^{\text{market}})} \underbrace{\overline{D}_2}_{\Uparrow} \tag{7}$$

On the one hand, better product information improves long-term cashflow expectations and drives up price predictions. On the other hand, narratives about protests and defunding the police led to a fixation on short-term cashflows, which could dampen the positive effect on price predictions in the product intervention. On net, we expect the combined narrative and product intervention to lead to a price prediction below that in the product-only intervention and in the scenario without any intervention.

Comparison of Finance Professionals and Nonexperts While financial market experts discount cashflows according to the marginal utility of consumption of the representative market participant,[10] nonexperts of type i discount cashflows according to the marginal utilities of their individual consumption c^i or by accounting for idiosyncratic factors:

$$\mathbf{m}_1^i(s_1) = \beta_1 \frac{u'(c_{s_1}^i)}{u'(c_0^i)}, \quad \mathbf{m}_2^i(s_1, s_2) = \beta_2 \frac{u'(c_{s_1,s_2}^i)}{u'(c_0^i)} \tag{8}$$

The variance of price predictions across nonexperts is thus

$$\text{Var}\left[P_i\right] = \text{Var}_i \left[\mathbb{E}\left[\mathbf{m}_1^i(s_1)D_1(s_1) + \mathbf{m}_2^i(s_1, s_2)D_2(s_1, s_2)|\mathcal{F}_1\right]\right] \tag{9}$$

Therefore, we expect higher variance in the predictions of nonexperts than in those of experts because of disagreement over the pricing kernel. (See Figure 2 and the regression from Table 4 with the information treatment.)

Interpretation Our empirical analysis shows that finance professionals make more accurate stock predictions when provided with detailed product information than nonexperts, who rely more on narratives. This aligns with our model's predictions: professionals adjust their long-term cash flow expectations upward with product information, leading to higher asset price predictions. Conversely, narratives about protests and defunding the police cause a focus on short-term impacts, resulting in lower predictions. Nonexperts exhibit greater variance in their predictions because of inconsistent discounting. The observed higher variance among nonexperts supports our model's assertion that disagreement over the pricing kernel drives prediction discrepancies.

Narratives and Stochastic Discount Rates Here, we present a model where narratives are captured by interventions that affect agents' time discount rate. An alternative model that can generate similar predictions is one in which narratives lead to pessimistic beliefs about likelihood of the state where the police are defunded. Shiller (2017) uses the word

[10]This corresponds to the no-arbitrage assumption and the existence of a pricing kernel (see, e.g., Cochrane (2009)).

narrative to mean "a simple story or easily expressed explanation of events that many people want to bring up in conversation or on news or social media because it can be used to stimulate the concerns or emotions of others". Our intervention is one in which agents are informed about others' beliefs that can induce them to change their predictions. It is well understood that several SDFs can lead to the same asset pricing implication (Cochrane, 2009). Our model does not attempt to disentangle whether the impact of narrative intervention on the SDF comes from changes in time discounting or optimism. Rather, it helps distinguish between interventions that affect the SDF and those that affect the quality of information on cashflows.

6 Salience of Defund for Stakeholder Behavior

Our surveys reveal a strong link between the predicted market response to the murder of George Floyd and the push to defund the police, with up to 80% of respondents predicting a decline in stock values for law enforcement-related companies. Respondents prioritized issues of less trust, budget cuts, and reputation over police reform. This section explores salience-driven explanations for these trends (Bordalo et al., 2012, 2013, 2022; Alok et al., 2020; Fisman et al., 2023), focusing on (1) investor decisions to purchase police-associated stocks based on their exposure after George Floyd's death and (2) civilians' differential support for maintaining or increasing police funding by their protest exposure in the two years following the murder. This complements our information treatment analysis by linking it to real-life outcomes for key stakeholder groups, highlighting the impact of information and preferences in critical scenarios.

6.1 Effect of Protests on Investors' Police Stock Holdings

6.1.1 Research Design

Data and Sample Selection To analyze the impact of the BLM protests on investor behavior, we used data, cleaned and merged from multiple datasets, on mutual funds holding police stocks. Our main data are from the CRSP Mutual Fund database, which provides contact information, summary details, and quarterly holdings.[11] We link fund summary and contact information with quarterly manager holdings records, isolating investments in firms contracting with police departments based on the roster from Ba et al. (2023), creating a balanced panel from January 2018 to December 2022. Additionally, we include fund characteristics such as expense ratio, turnover, and size, calculated quarterly. Funds holding fewer than 10 stocks are excluded to maintain a focus on diversified funds.

Using fund headquarters' zip codes converted to the county level, we pair this information with incident data from the Global Database of Events, Language, and Tone (GDELT) Project[12] and Mapping Police Violence (MPV),[13] to track protests following police killings. We mapped police killings from MPV to corresponding GDELT-recorded protests, identifying relevant law enforcement agencies and protest locations across the US in summer 2020. The main independent variable captures whether the protests were triggered by police killings following George Floyd's murder from May 25 to July 31, 2020. Finally, we supplement our main sample with demographic and socioeconomic data from the American Community Survey (ACS), officer counts from the Law Enforcement Officers Killed and Assaulted (LEOKA) 2019 report,[14] crime rates from the FBI's Uniform Crime Reporting (UCR) Program 2019,[15], police killings from MPV, and party data from the MIT Election Data and Science Lab. Our final sample includes 3,987 fund manager observations, with 2,776 exposed to protests.

Descriptives Table 7 provides summary statistics for mutual funds, comparing those with and without exposure to BLM protests from May 25 to July 31, 2020. Overall, the funds have similar characteristics, such as a low expense ratio and moderate turnover ratio. Funds not exposed to the protests are slightly larger and older with more stocks, whereas

[11]We focus on equity funds, excluding exchange-traded funds and index funds, and include only those with a minimum total net asset value of $1 million. To ensure relevance, we remove funds with Lipper objective classifications related to international, bond, municipal, debt, and government investments.

[12]For an in-depth explanation of the GDELT Project and its methodological approach, see www.gdeltproject.org.

[13]Further details on MPV can be found at mappingpoliceviolence.us.

[14]See Kaplan (2023a).

[15]See Kaplan (2023b).

funds exposed to the protests are somewhat smaller and younger and hold fewer stocks. The average fund manager experience and retail fund percentage are comparable across the two groups.

Empirical Strategy We estimate the impact of the George Floyd protests on mutual fund holdings of stocks connected to police by estimating the following equation:

$$AnyStock_{it}^{police} = \beta_0 + \sum_t D_t \cdot AnyProtest_i \cdot \beta_t + X'_{it-1}\delta + \alpha_i + \gamma_t + \epsilon_{it} \tag{10}$$

where the variable $AnyStock_{it}^{police}$ indicates whether fund i holds police-related stocks in quarter t. The dependent variable equals 1 if a fund holds such stocks during t and 0 otherwise. The variable $AnyProtest_i$ equals 1 if i is located in a county that experienced BLM protests between May 25 and July 31, 2020, and 0 otherwise. We interact this protest indicator with quarter dummies, D_t, using the first quarter of 2020 as the reference period. Control variables, X_{it-1}, include fund-specific covariates from the previous quarter: size, expense ratio, turnover ratio, and manager experience. We also include fund fixed effects, α_i, and quarter fixed effects, γ_t, to account for time-invariant fund characteristics and temporal effects, respectively. The error term, ϵ_{it}, is clustered at the fund level.

The key parameters, β_t, capture the differential changes in the likelihood of holding police-related stocks over time, relative to that in the reference period, between funds exposed to BLM protests and those not exposed. The identification strategy relies on the parallel trends assumption, which posits that in the absence of the events of 2020, funds with and without protest exposure would have followed similar trends in their propensity to hold police stocks.

Moreover, we also present the difference-in-difference β coefficient from the following equation, applicable to both the main sample and the heterogeneity analysis:

$$AnyStock_{it}^{police} = \beta_0 + Post_t \cdot AnyProtest_i \cdot \beta + X'_{it-1}\delta + \alpha_i + \gamma_t + \epsilon_{it} \tag{11}$$

where $Post_t$ equals one for quarters after the murder of George Floyd and zero otherwise.

6.1.2 Results

Main Results Figure 4 shows the impact of the BLM protests in the weeks following George Floyd's murder on mutual funds' holdings of police-related stocks. The coefficient on the dependent variable, indicating whether a fund holds police stocks, shows a significant decline in the postprotest period relative to holdings in the pre-George Floyd period. Specifically, there was a 5.3 pp ($p < 0.01$) decrease in the likelihood of holding police stocks in protest-affected areas after 2020, with the mean for nonprotest areas being 0.23. In other words, mutual funds exposed to the protests were more than 20% less likely to hold police-related stocks after the protests compared to the holdings of funds in areas without protests. This reduction remained consistent but below baseline levels in subsequent quarters, signaling a persistent shift in investment behavior away from police-related stocks. These results suggest that the heightened visibility of protests and the defund movement led fund managers to reduce their propensity to hold police stocks over the two years following the protests.

Heterogeneity by County and Fund Characteristics Figure 5 shows the heterogeneity in the effect of the BLM protests on mutual funds' holdings of police-related stocks, highlighting notable differences based on county (C) and fund (F) characteristics. Notably, funds in counties with more police per capita, elevated murder rates, and a history of police killings in 2019 exhibit more substantial reductions in police-related stock holdings. This implies heightened responsiveness to local law enforcement and crime indicators. In contrast, changes in fund characteristics—such as size, age, manager experience, diversification, and retail or institutional classification—suggest less clear effect heterogeneity, with overlapping confidence intervals. Overall, the analysis suggests that local law enforcement dynamics significantly influenced investment decisions following the protests, while other fund-specific factors show more nuanced effects.

This figure also reveals a distinct pattern for counties exposed to protests without any police killings in 2019, indicating a higher likelihood of holding police-related stocks. This suggests that mutual funds in these areas may have perceived the protests as a push for future police reform rather than defunding the police. Consequently, these funds were more inclined to maintain or increase their investments in police-related stocks, reflecting a belief in the ongoing demand for police reform. In contrast, places with both protests and recent police killings might have associated the protests with reducing police funding and anticipated austerity policies impacting law enforcement agencies. This divergence also highlights underlying distrust in areas with recent police violence, where investors may foresee more drastic measures and instability affecting police-related investments.

6.2 Effect of Protests on Support for Police Funding

6.2.1 Research Design

Data and Sample Selection Drawing on the idea that exposure to information related to the financial market impacts political attitudes (Jha and Shayo, 2019), we use the post-election wave of the CES, a nationally representative survey conducted in November of every election year from 2014 to 2022 (Kuriwaki, 2023; Schaffner et al., 2023). The CES collects data on political perspectives, demographics, and respondents' views on state legislature decisions regarding funding adjustments for sectors such as law enforcement (Mazumder, 2019; Chyn et al., 2022). We exclude observations with missing respondent location information. Additionally, we merge the CES data with the county-level BLM protest data to assess respondents' exposure to protests following the murder of George Floyd, using the respondent's county of residence. Finally, we merge the county characteristic information discussed in Section 6.1. Our final sample includes 233,434 respondents, of whom 133,837 were exposed to protests.

Descriptives We present the characteristics of CES respondents in Table 8, distinguishing between those exposed to BLM protests between May 25 and July 31, 2020, and those not exposed. Overall, the sample includes a balanced mix of married and employed respondents, a range of educational levels from some college to postgraduate degrees, and a distribution across different income brackets. When segmented by protest exposure, those exposed to protests tend to include a higher representation of Black and Hispanic individuals, greater employment rates, and a higher likelihood of reporting incomes above $150K than those not exposed to protests.

Empirical Strategy We estimate the impact of George Floyd's protests on public support for maintaining or increasing funding by estimating the following equation:

$$NoDefund_{ict} = \beta_0 + \sum_t D_t \cdot AnyProtest_c \cdot \beta_t + X_i'\delta + \alpha_c + \gamma_t + \epsilon_{ict} \tag{12}$$

where $NoDefund_{ict}$ denotes the viewpoint of respondent i in county c during year t. This dependent variable reflects whether the respondent endorses action by her state legislature to maintain or increase law enforcement funding. The variable $AnyProtest_c$ equals one if county c has a law enforcement agency that experienced BLM protests between May 25 and July 31, 2020, and zero otherwise. We interact this protest dummy with our year dummies, D_t, with 2018 being the reference year. Additionally, we control for respondent characteristics, denoted by X_i.[16] County and year fixed effects are captured by α_c and γ_t. The error term is captured by ϵ_{ict}, and standard errors are clustered at the county level.

The key parameters, β_t, capture the temporal variations in average outcomes relative to those in 2018 and benchmarked against the outcomes for places without BLM protests. The validity of our identification strategy rests on the parallel trends assumption. Specifically, we assume that, absent the 2020 events, regions with and without protests would have exhibited similar trends in support for police budgets. This implies that areas with protests in 2020 were not inherently different in their historical support for budget increases, as evidenced by data from 2014, 2016, and 2018, from areas without.

For brevity, we also present the difference-in-difference β coefficient from the following equation, applicable to both the main sample and the heterogeneity analysis:

[16] The controls are demographics, marital status, education, income, and employment status. We provide the details in 8.

$$NoDefund_{ict} = \beta_0 + Post_t \cdot AnyProtest_c \cdot \beta + X_i'\delta + \alpha_c + \gamma_t + \epsilon_{ict} \quad (13)$$

where $Post_t$ equals one for the years 2020 and 2022 if the respondent took the survey after the murder of George Floyd and zero otherwise.

6.2.2 Results

Main Results Figure 6 shows the changing sentiment toward maintaining police funding based on Equation 12. The salience of the defund movement, accentuated by the protests, led to a significant 4.3 pp decrease in support for maintaining or increasing police resources in protest-exposed areas after 2020 ($p < 0.01$). This decline stabilized by 2022 but remained below preprotest levels. Despite this shift, a substantial majority—93% in nonprotest areas—continued to favor maintaining or increasing police funding, indicating no major shift in the stance of the median voter. Thus, while support for reducing police funding increased, the overall support for law enforcement funding persisted, suggesting that significant defunding of police departments is unlikely. This reflects a potential overreaction, with the belief that the defund movement would negatively impact police because of prevailing public opinion remaining strong.

Heterogeneity by County Characteristics and Respondent Characteristics Figure 7 presents how the BLM protests influenced support for maintaining police funding, considering heterogeneity across county (C) and individual (I) characteristics. The main specification shows consistent trends across the various characteristics, with the point estimates ranging between -2 and -6 pp. However, the overlapping confidence intervals suggest no substantial differences. For county characteristics, the effect on support is broadly similar regardless of local factors such as racial–ethnic composition, political leaning, unemployment rate, police per capita, murder rate, and prior police killings. Again, the estimates on individual characteristics including gender, race, age, education, marital status, employment, and family income show overlapping confidence intervals. These results suggest that while overall sentiment may have shifted toward reduced support for police funding after the protests, the protests did not have a markedly different impact on support for police funding across diverse county or individual attributes.

6.3 Robustness

This section uses difference-in-difference approaches to compare areas that experienced BLM protests between May 25 and July 31, 2020, with those that did not, relying on the parallel trends assumption. We address potential threats to this identification strategy in Section B.2 of the Appendix. Following Roth (2022), we account for low power and pretesting issues, constructing hypothesized deviations from parallel trends with 80% power and expected event study coefficients if deviations were undetectable. Sensitivity analyses as proposed by Rambachan and Roth (2023) further validate our approach.

We summarize the main results here, with detailed analyses in the Appendix. Funds exposed to protests were less likely to hold police stocks after the murder of George Floyd than those not exposed, even after accounting for low power and pretesting issues. This significant effect relies on the assumption that posttreatment violations of parallel trends are no greater than the worst pretreatment violations. Similarly, areas exposed to protests were less likely to support increasing or maintaining police funding in 2020 and 2022. Sensitivity analyses confirm that our conclusions are robust as long as posttreatment violations of parallel trends do not exceed twice the worst pretreatment violations.

7 Conclusion

This paper studies the impact of narratives and information on stakeholder beliefs and behaviors after the 2020 racial justice protests and the "defund the police" movement. Our findings reveal significant disparities between market outcomes and stakeholder expectations, among both nonexperts and finance professionals lacking detailed product information about police-affiliated firms.

Our experimental information treatments show that exposure to product information substantially improved forecast accuracy, while narrative information often led to overestimations of negative impacts on police-related stocks. This highlights the crucial role of specific, relevant information in shaping accurate market predictions.

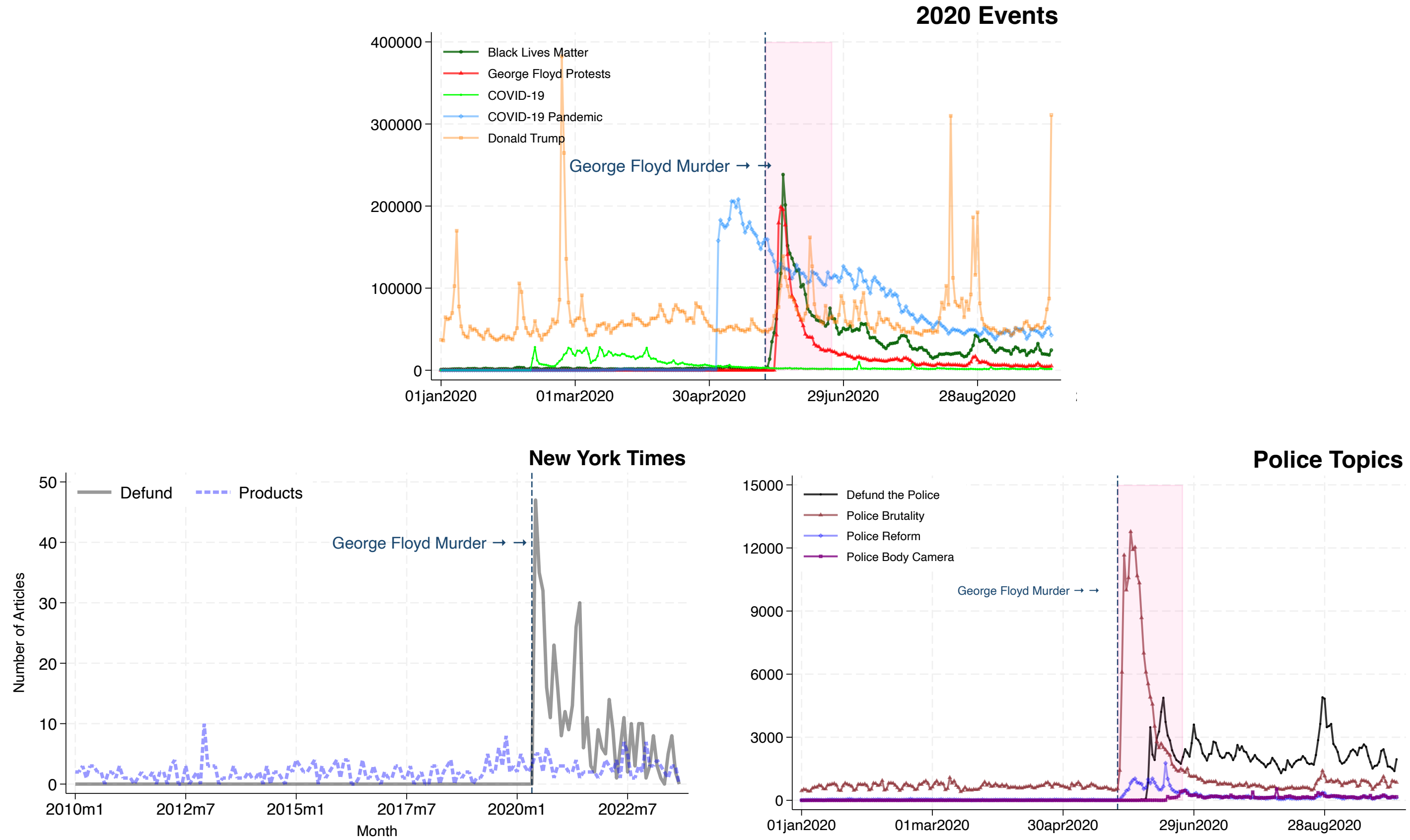
Our analysis of real-world outcomes further supports these findings, showing that mutual funds in protest-affected areas were 20% less likely to hold police stocks after the events of 2020. Additionally, public support for maintaining or increasing police funding decreased by 4.3 percentage points in protest-exposed areas, though this shift was insufficient to alter the median voter's stance.

These results point to the salience of narratives, such as the "defund the police" movement, on both financial predictions, real-life investment decisions, and policy support. They also highlight the importance of providing stakeholders with comprehensive, product-specific information to achieve more accurate market assessments and policy expectations.

Our paper contributes to the growing body of literature on the role of narratives in shaping economic beliefs and decisions, particularly in the context of social movements and their impact on financial markets and public policy. It also offers insights into the complex interplay between information, expertise, and decision-making in times of social unrest and policy uncertainty.

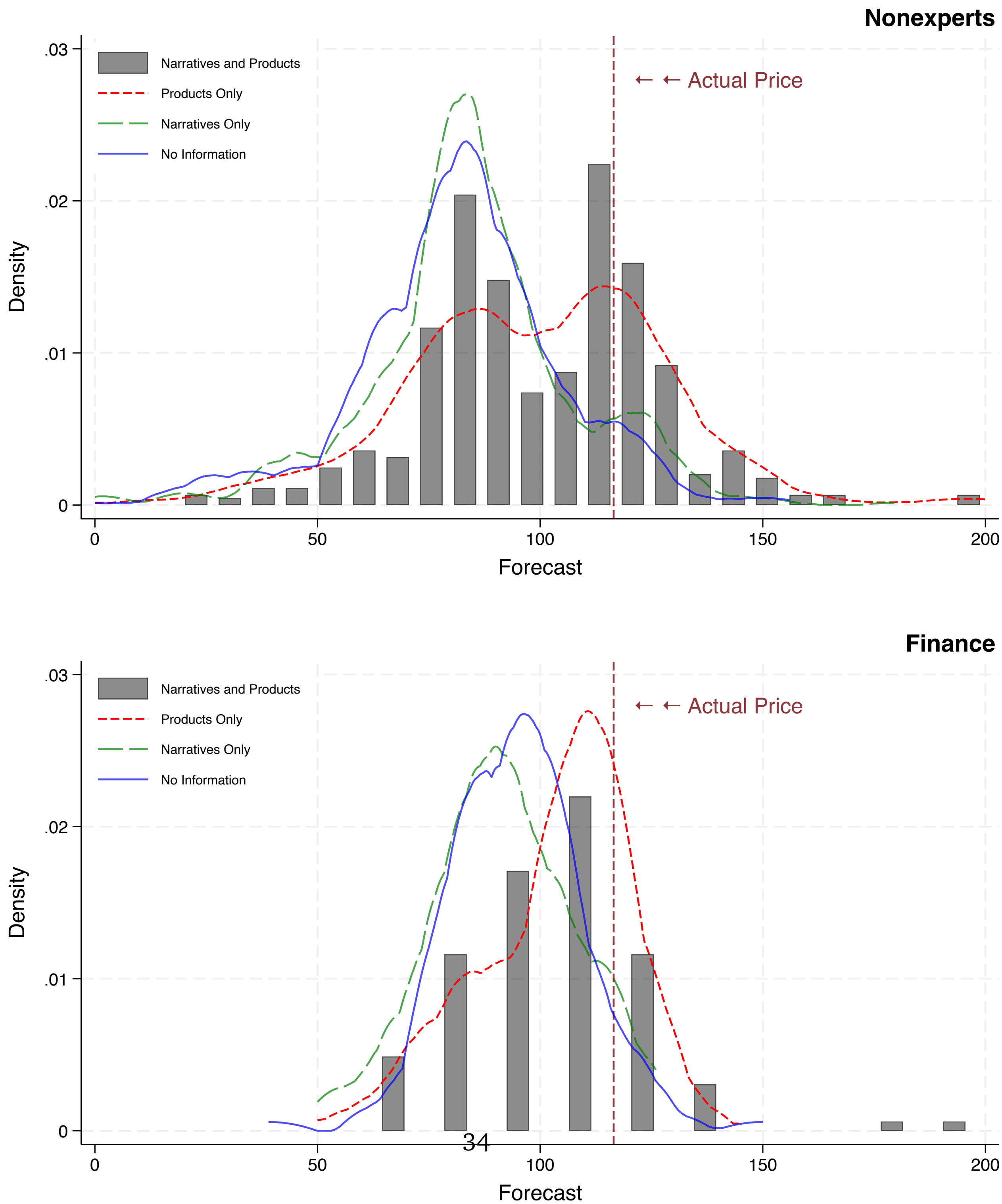
Our findings open up several avenues for future research. It would be valuable to study how the effects of narratives and information exposure on stakeholder beliefs evolve over time, particularly as the immediate impact of social movements can fade. Finally, examining the long-term consequences of misaligned expectations between markets and stakeholders, and how this might impact future social movements and policy debates, could offer valuable insights for both economists and policymakers.

Figure 1: Facts Associated with the Defund Movement and Its Impact



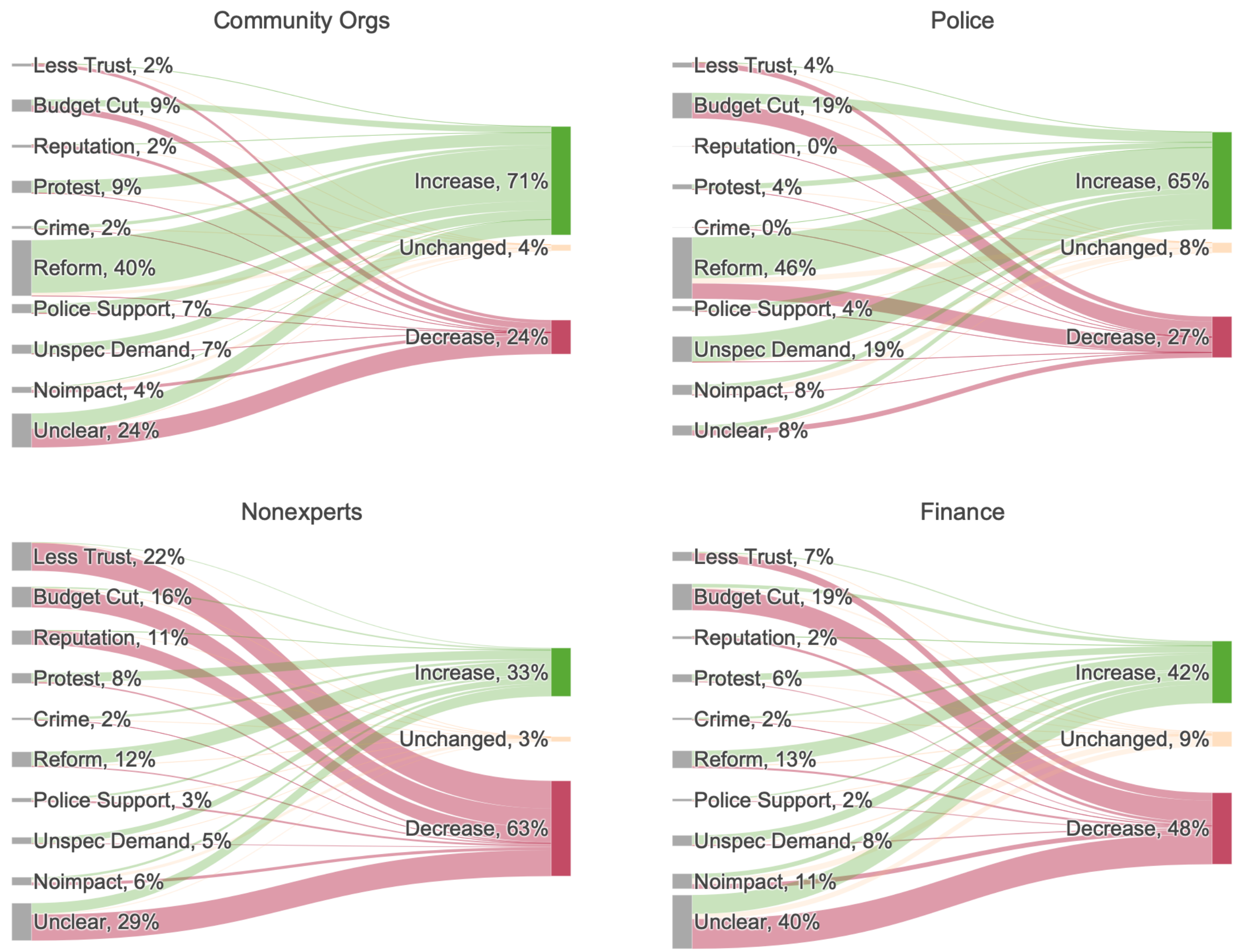
Notes: The top figure presents the daily views of the Wikipedia articles on "Black Lives Matter", "George Floyd Protests", "COVID-19", and "Donald Trump" from January 2020 to September 2020 (Pageviews Analysis (2023)). The shaded vertical sections on the graph represent the 21-day period following the murder of George Floyd. These figures provide insights into the defund the police movement and its impact on the police industry. The bottom-left panel displays the monthly frequency of *New York Times* articles featuring terms related to both "defund the police" and specific police-related products. For police-related products, the terms included are "body-worn camera", "simulation-based training", "gunshot location", "less lethal", "surveillance systems", "thermal imaging systems", "dispatch systems", "firearms training", and "tactical training". For "defund the police," variations such as "defund police", "defunding police", "defunding the police", "police defund", and "funding from police" are also considered. The bottom panel presents Wikipedia searches related to police-related topics based on the Pageviews Analysis (2023).

Figure 2: Distribution of Predictions by Information Treatment



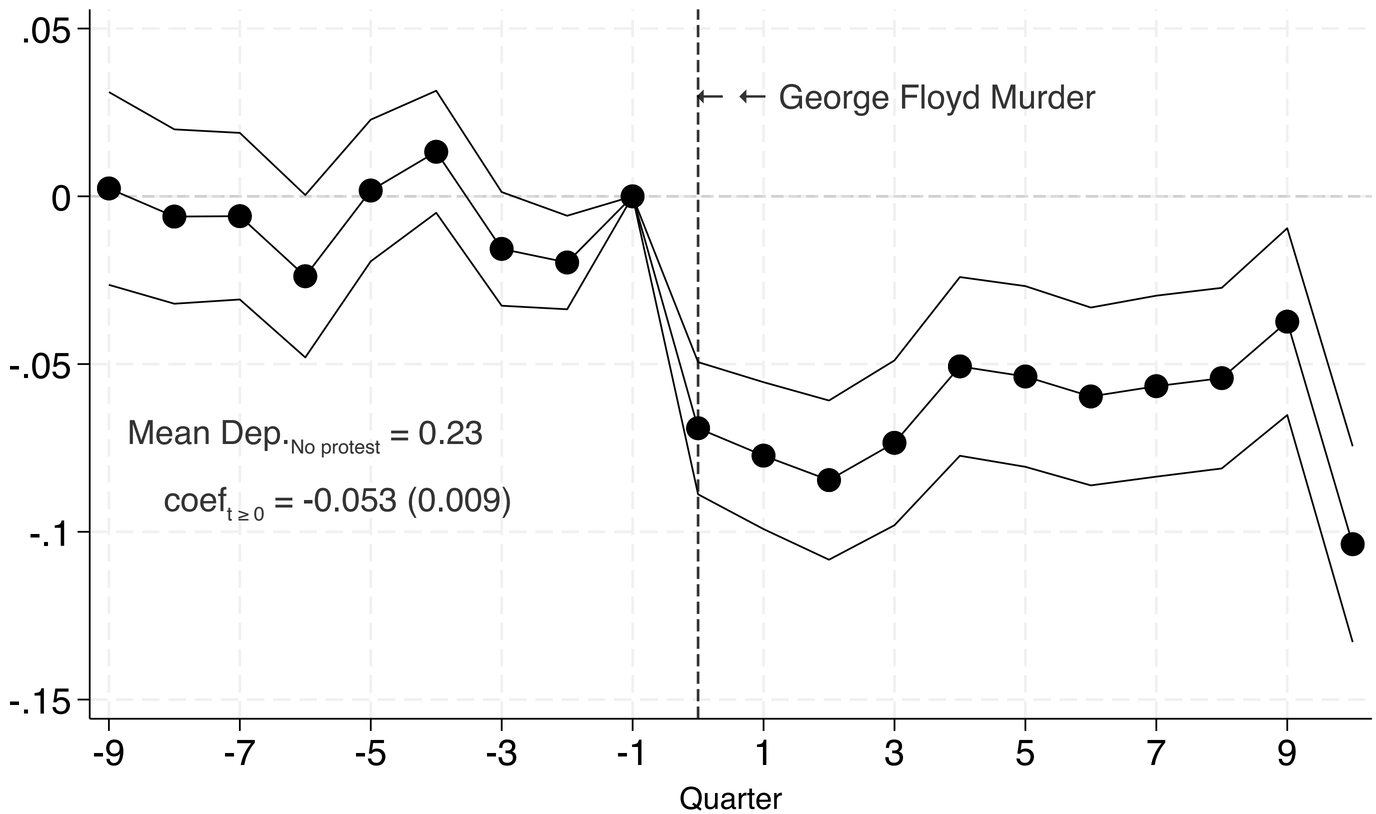
Notes: This figure presents the distribution of the portfolio predictios by treatment arm for nonexperts and finance professionals. Each respondent provided a prediction of the price of a portfolio of firms with ties to policing at 21 days after the killing of George Floyd. The vertical line represents the actual price of the portfolio.

Figure 3: Reasoning and Predictions



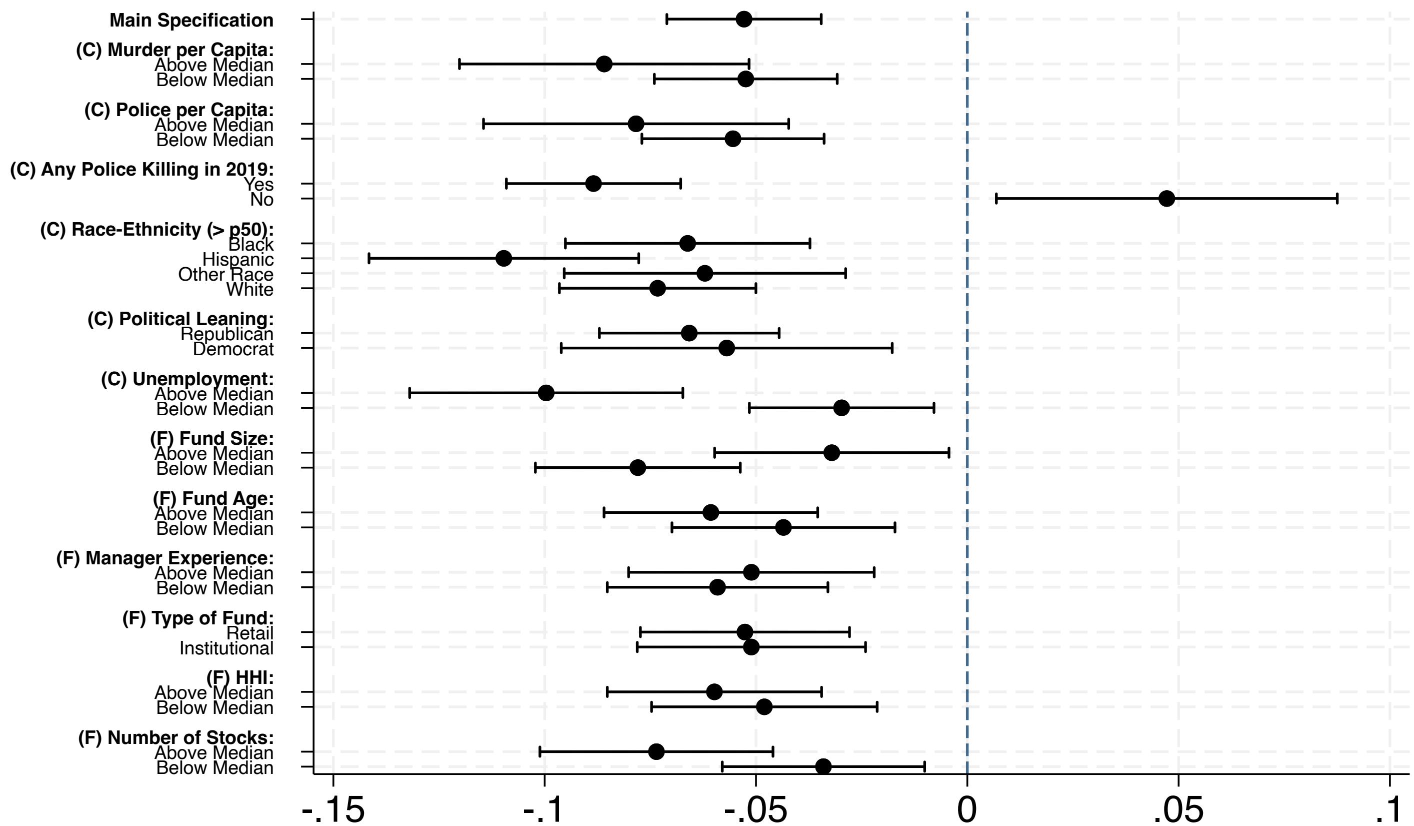
Notes: This figure presents the relationship between respondents' reasoning and stock predictions for community organizers, police officers, nonexperts, and finance professionals. The prediction is of the price of a portfolio of firms with ties to policing 21 days after the killing of George Floyd. The left side of each figure reports the shares of the different reasons invoked by respondents to explain their predictions, and the right side shows the share of respondents who predict an increase, no change, and a decrease in stock prices.

Figure 4: Investor Behavior and the Effect of Protests on Police Stock Holdings



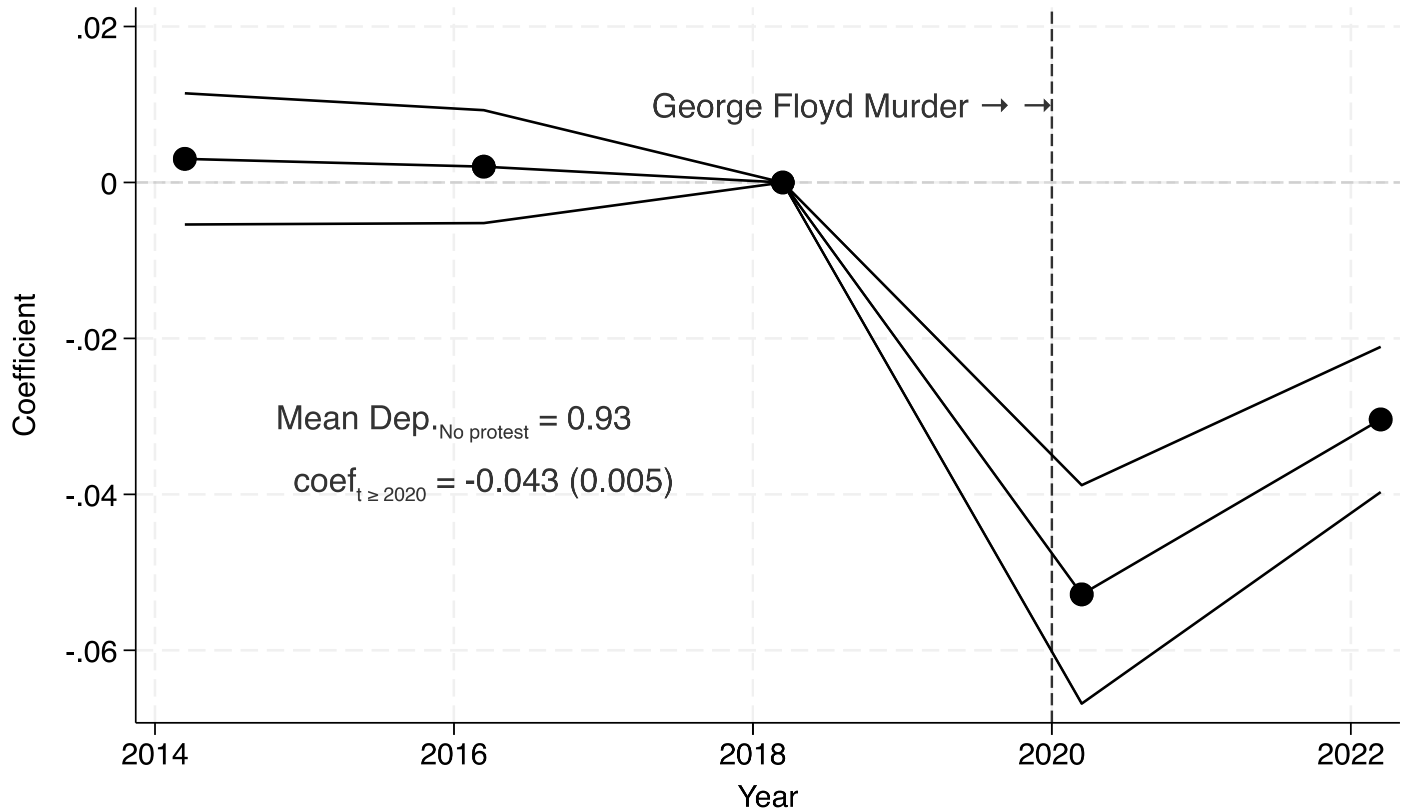
Notes: This figure presents the impact of the BLM protests between May 25 and July 31, 2020, in response to George Floyd's murder on mutual funds' holdings of police-related stock. The dependent variable is set to 1 if a fund holds police-related stock and 0 otherwise. Additionally, the mean of the dependent variable for the omitted category—funds in counties without protests—is provided. We report the difference-in-difference estimate and its standard error in parentheses. We report 95% confidence intervals, with standard errors clustered at the fund level.

Figure 5: Heterogeneity Analysis, Effect of Protests on Police Stock Holdings



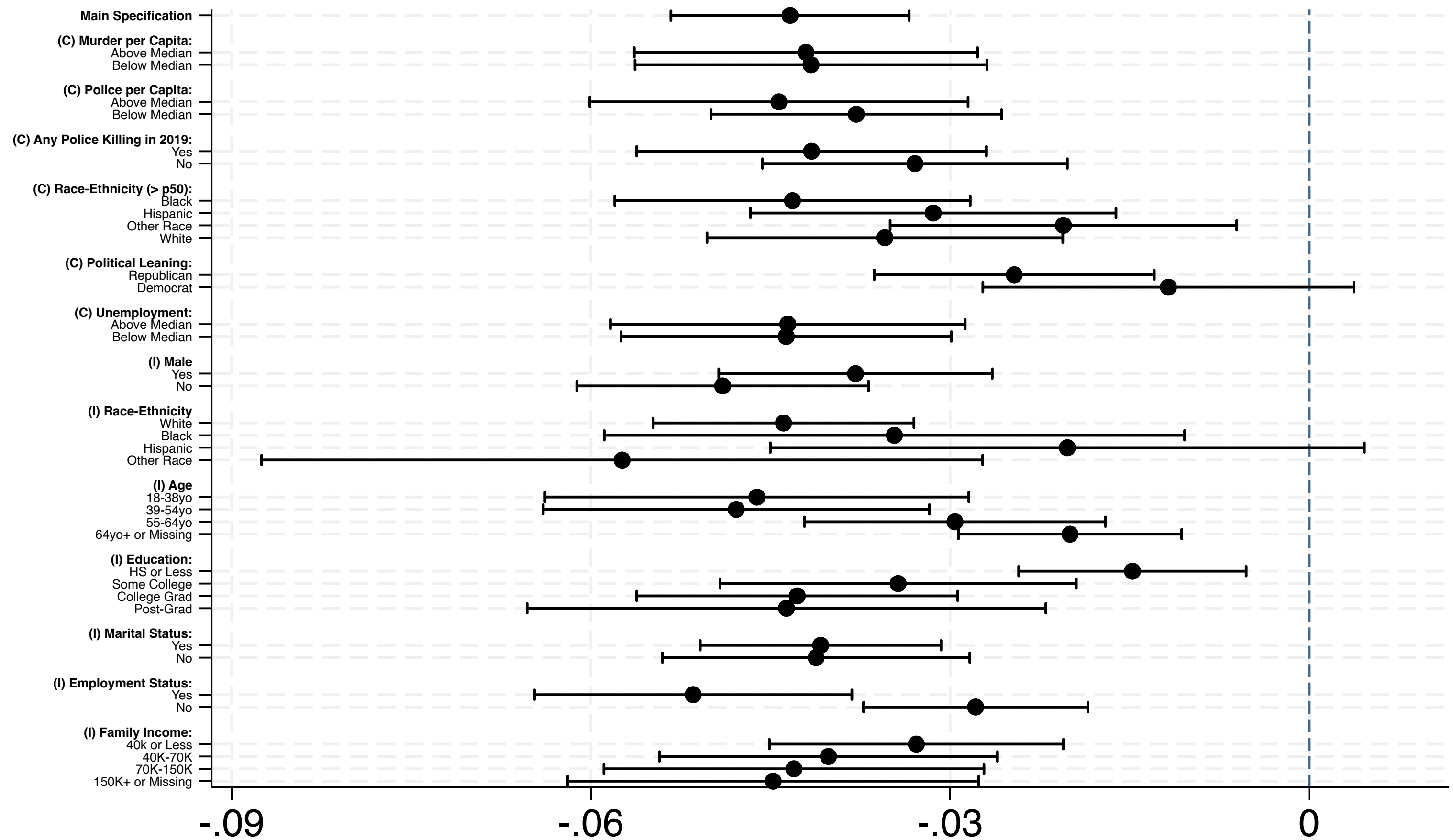
Notes: This figure presents the impact of the BLM protests between May 25 and July 31, 2020, in response to George Floyd's murder on mutual funds' holdings of police-related stock across subgroups with different county characteristics (C) and fund characteristics (F). The dependent variable is set to 1 if a fund holds police-related stock and 0 otherwise. Additionally, the mean of the dependent variable for the omitted category—funds in counties without protests—is provided. We report 95% confidence intervals, with standard errors clustered at the fund level.

Figure 6: Voter Behavior and the Effect of Protests on Support for Police Funding



Notes: This figure presents the impact of the BLM protests between May 25 and July 31, 2020, in response to George Floyd's murder on support for maintaining or increasing police funding. The dependent variable is set to 1 if the respondent supports state legislative action to maintain or increase law enforcement funding and 0 otherwise. Additionally, the mean of the dependent variable for the omitted category—respondents residing in counties without protests—is provided. We report the difference-in-difference estimate and its standard error in parentheses. We report 95% confidence intervals, with standard errors clustered at the county level.

Figure 7: Heterogeneity Analysis, Effect of Protests on Support for Police Funding



Notes: This figure presents the impact of the BLM protests between May 25 and July 31, 2020, in response to George Floyd's murder on support for maintaining or increasing police funding across subgroups with different county characteristics (C) and respondent characteristics (I). The dependent variable is set to 1 if the respondent supports state legislative action to maintain or increase law enforcement funding and 0 otherwise. Additionally, the mean of the dependent variable for the omitted category—respondents residing in counties without protests—is provided. We report 95% confidence intervals, with standard errors clustered at the county level.

Table 1: 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: This 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 2: Impact of Information Treatments on Predictions

	(1) Predict an Increase	(2) Predict an Increase	(3) Neg. Abs Error	(4) Neg. Abs Error
Narratives Only (N)	0.0325	-0.0599	2.276**	-2.786
	(0.0225)	(0.0576)	(1.158)	(1.817)
Products Only (P)	0.322***	0.350***	10.27***	7.180***
	(0.0258)	(0.0614)	(1.211)	(1.862)
Narratives and Products (N+P)	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. (O)	0.16	0.29	-35.66	-23.06
Observations	2346	467	2346	467

Notes: This table presents the impact of exposure to product and narrative information related to policing on the prediction 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 the 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 no information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 3: Impact of Information Treatments on the Likelihood of Predicting a Portfolio Price Increase by Type of Prediction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Nonexperts								
Narratives Only (N)	0.0325	0.0692**	0.0653**	0.0241	0.0260	-0.00989	0.0349*	0.0345*
	(0.0225)	(0.0273)	(0.0277)	(0.0291)	(0.0288)	(0.0294)	(0.0210)	(0.0191)
Products Only (P)	0.322***	0.0219	0.0160	0.0725**	0.0136	0.0531*	0.0354	0.0833***
	(0.0258)	(0.0280)	(0.0283)	(0.0293)	(0.0291)	(0.0293)	(0.0220)	(0.0208)
Narratives and Products (N+P)	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)
Company	Portfolio	Axon	Flir	Motorola	Shotspotter	Virtra	Stocks Only	All
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (O)	0.16	0.64	0.63	0.43	0.58	0.53	0.56	0.49
Observations	2346	2346	2346	2346	2346	2346	11730	14076
Panel B: Finance								
Narratives Only (N)	-0.0599	0.0517	-0.0196	-0.0518	-0.0505	-0.104	-0.0348	-0.0390
	(0.0576)	(0.0600)	(0.0580)	(0.0645)	(0.0631)	(0.0656)	(0.0428)	(0.0408)
Products Only (P)	0.350***	0.162***	0.0683	0.118*	0.120**	0.0504	0.104**	0.145***
	(0.0614)	(0.0566)	(0.0538)	(0.0652)	(0.0588)	(0.0630)	(0.0416)	(0.0412)
Narratives and Products (N+P)	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)
Company	Portfolio	Axon	Flir	Motorola	Shotspotter	Virtra	Stocks Only	All
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (O)	0.29	0.67	0.74	0.45	0.66	0.62	0.63	0.57
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 prediction accuracy of nonexperts (Panel A) and finance professionals (Panel B). Each respondent provided predictions 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., BWCs, 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 no information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 4: Impact of Information Treatments on the Prediction Distribution

	(1) <81	(2) 81-97	(3) 98-102	(4) 103-120	(5) >120
Panel A: Nonexperts					
Narratives Only (N)	-0.0366*	0.0236	-0.00344	0.0139	0.00255
	(0.0187)	(0.0144)	(0.0107)	(0.00979)	(0.00869)
Products Only (P)	-0.154***	-0.0646***	0.0229**	0.119***	0.0763***
	(0.0184)	(0.0137)	(0.0113)	(0.0117)	(0.0102)
Narratives and Products (N+P)	-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. (O)	0.23	0.23	0.18	0.22	0.14
Observations	2346	2346	2346	2346	2346
Panel B: Finance					
Narratives Only (N)	0.0414	0.0217	-0.0486	-0.0196	0.00515
	(0.0355)	(0.0338)	(0.0332)	(0.0263)	(0.0162)
Products Only (P)	-0.0412	-0.134***	-0.0579*	0.175***	0.0582***
	(0.0353)	(0.0317)	(0.0323)	(0.0329)	(0.0162)
Narratives and Products (N+P)	-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. (O)	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 prediction distribution for nonexperts (Panel A) and finance professionals (Panel B). The dependent variables are the percent chance that the prediction 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 no information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 5: Categories of Reasoning Behind Price Predictions

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 predictions with descriptions and examples related to our coding scheme.

Table 6: Impact of Information Treatments on Reasoning

	(1) Less Trust	(2) Less Trust	(3) Budget Cut	(4) Budget Cut	(5) Reform	(6) Reform
Narratives Only (N)	-0.103***	-0.0310	0.0898***	0.0394	0.0410***	-0.00472
	(0.0262)	(0.0353)	(0.0216)	(0.0510)	(0.0109)	(0.0340)
Products Only (P)	-0.148***	-0.0534	-0.0144	0.0571	0.168***	0.196***
	(0.0253)	(0.0360)	(0.0188)	(0.0516)	(0.0168)	(0.0481)
Narratives and Products (N+P)	-0.210***	-0.0553	0.0734***	0.0462	0.202***	0.0231
	(0.0239)	(0.0359)	(0.0211)	(0.0511)	(0.0176)	(0.0369)
Sample	Nonexperts	Finance	Nonexperts	Finance	Nonexperts	Finance
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (O)	0.33	0.10	0.12	0.16	0.02	0.08
Observations	2346	467	2346	467	2346	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 5 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 no information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 7: Summary Statistics of Mutual Funds

	(1) All	(2) No Protest	(3) Any Protest
Size	4.63	4.77	4.57
Expense Ratio	0.01	0.01	0.01
Turnover Ratio	0.58	0.58	0.58
Fund Age	13.26	14.04	12.92
Manager Experience	8.52	8.24	8.64
Retail Fund	0.51	0.52	0.50
HHI	0.02	0.02	0.03
Number of Stocks	232.35	358.39	177.37
Observations	3987	1211	2776

Notes: This table provides the mean values of the covariates for mutual funds in the sample. Column (1) displays the aggregate results for the entire sample. Columns (2) through (5) break down these mean values by exposure to the BLM protests between May 25 and July 31, 2020.

Table 8: Summary Statistics of CES Respondents

	(1) All	(2) No Protest	(3) Any Protest
Male	0.45	0.44	0.46
Black	0.09	0.07	0.11
Hispanic	0.07	0.05	0.08
Other Race	0.07	0.06	0.08
39-54yo	0.25	0.25	0.25
55-64yo	0.25	0.26	0.24
64yo+ or Missing	0.25	0.26	0.24
Married	0.54	0.57	0.52
Employed	0.50	0.47	0.53
Some College	0.22	0.23	0.22
College Grad	0.37	0.34	0.39
Post-Grad	0.15	0.13	0.17
40K-70K	0.24	0.25	0.24
70K-150K	0.23	0.22	0.24
150K+ or Missing	0.23	0.20	0.26
Observations	233434	99597	133837

Notes: This table provides the mean values of the covariates for respondents participating in the Cooperative Election Study 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 by exposure to the BLM protests between May 25 and July 31, 2020.

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Online Appendix

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 com-*

pany 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 Expert Survey Sample

Participation in the expert survey was solicited via email from November 1, 2022 to December 31, 2022. One of the challenges in conducting this survey was that the researchers on this project primarily focus on policing, and hence, 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 (Bertrand and Mullainathan, 2004; Agan and Starr, 2018). 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 from communication. Personalized emails were sent by Duke undergraduate students from the study's email address.

Experts in Police Violence Since our case study focuses on the effect of viral incidents of police violence and the Black Lives Matter movement, it is critical to understand the views of actors involved with the communities most susceptible to various forms of police violence. For this reason, our main experts of interest are individuals connected to community organizations involved in social justice organizing, specifically individuals with ties to nonprofit organizations working on issues concerning racial justice, climate change, and LGBTQ+ rights as well as mutual aid and other relevant grassroots organizations. Our pool of **community organizing experts** was drawn from various mailing lists compiled by our team[1] and from multiple organizations willing to circulate the survey to their networks. The second group of interest is experts from the **police industry**, as they are an essential interest group in any discussion of racial justice in the U.S. To include law enforcement personnel in our survey, we collected email addresses of those who had subscribed to *Police Chief Magazine* between January 2010 to January 2021.

Sample Selection We sent invitations to 23,810 email addresses in the policing expert group and received 46 responses. We then 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 71 respondents: 45 community organizers and 26 police experts.

Table A.6 presents summary statistics on the analysis sample. We also include summary statistics for the finance and nonexpert samples used in the survey experiment. It shows that survey respondents are heterogeneous in demographics across expertise types. Overall, approximately 52% of the expert sample identify as women. However, there is some heterogeneity among experts. Compared to the police expert group, respondents in the

[1]For example, see communityresourcehub.org, surj.org, mutualaidhub.org, and sunrisemovement.org.

community organization group are more likely to be female, less likely to be white, and more likely to be aged 18–34. These differences highlight the demographic heterogeneity within the samples, which could influence the perspectives and responses in the survey experiment

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.4 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.3 repeats this analysis for the proportion of responses where 4 out of the 5 coders agreed. According to Figure A.4, 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 0.49 and 0.95. Given a random response and narrative category, the chance of all five coders agreeing is 0.82. According to Figure A.3, 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 probability 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 attempt 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 Additional Analysis

B.1 Survey Experiment

B.1.1 Impact of Information on Other Outcomes

Willingness to Change Forecasts In Table A.1, we investigate whether survey participants exposed to information about various products associated with the policing industry were willing to revise their portfolio forecasts. Among nonexperts, any exposure to information made them less likely to change their predictions than peers who received no information. Specifically, nonexperts exposed to product information were three times less likely to change their forecasts than those who received narrative information only.

For finance professionals, there is suggestive evidence that those receiving both narratives and product information were less likely to change their predictions than their peers without information. However, the results for the other groups are inconclusive due to noise, with the product-only and narrative-only groups showing similar magnitudes but opposite signs – negative and positive, respectively.

The findings in Columns (3) to (6) of Table A.1 are consistent with those in Table 2, supporting the idea that less information about products and narratives correlates with lower forecast accuracy. Additionally, the results highlight that product information is more critical than narrative information in enhancing forecast accuracy. The coefficients in Table A.1 are smaller in magnitude than those in Table 2, indicating that respondents update their beliefs after exposure to product information, as shown in Table 3. This updating process helps reduce, but does not entirely eliminate, the accuracy gap between respondents with varying levels of information.

Support for Policies We investigate the impact of information on nonexperts' support for various policing-related policies in Table A.2. 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 Tables A.3 to A.5 present 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 heterogeneity analysis supports the main results, indicating that the absence of product information leads to less accurate forecasts. However, we cannot definitively rule out statistical differences between the main sample and the subsample analysis. Among nonexperts, those not exposed to product information are less likely to predict a portfolio increase than those treated with full information, although this effect is smaller for male, younger, and nonwhite respondents and those who check their investments weekly.

For finance professionals, narratives alone do not significantly impact prediction accuracy and sometimes have a negative effect, especially for nonwhites and younger professionals. Product information, on the other hand, significantly improves prediction accuracy across all subgroups, similar to the findings for nonexperts. The combination of narratives and products further enhances accuracy, particularly for females, whites, and those who frequently check investments, showing a strong preference for detailed product information among finance professionals as well.

Table A.5 investigates the role of preferences and perceptions of respondents regarding policing and regulation. Among nonexperts, those who view the police as unethical or prefer more regulation show improved prediction accuracy with product information and the combination of narratives and products. However, narratives alone have negligible or mixed effects. For finance professionals, those who consider the police unethical show no significant improvement with product information alone, and narratives have a negative impact. However, those favoring less regulation and viewing the police as not unethical benefit more from product information and the combination, indicating that perceptions of ethics and regulation influence how different groups respond to various types of information.

Overall, the analysis highlights that detailed product information significantly enhances prediction accuracy across all groups, whereas narratives alone are less effective. The findings emphasize the importance of combining tailored information based on the audience's background and perceptions, with both nonexperts and finance professionals benefiting most from comprehensive product details. Additionally, the results suggest that past experiences and preferences, such as views on policing and regulation, play a critical role in shaping beliefs and responses to information.

B.1.2 Impact of Information on Reasoning

Tables A.7 and A.8 report the impact of all the reasons cited by nonexperts and finance professionals. A key observation for the nonexpert sample is high sensitivity to both narrative and product information, especially regarding *less trust*, *reputation*, *budget cut*, *reform*, and *unspecified demand*, while topics such as *crime* and *police support* seem to be less of a concern. Notably, the narrative-only treatment led to a significant decrease in mentions of *less trust* of 10.3 pp and of *reputation* of 5.53 pp, whereas mentions of *budget cuts* increased by 8.98 pp, with all these changes being significant at the 1% level. Exposure solely to product information triggered substantial increases in mentions of *less trust*, *reputation*, and *protests* of 14.8, 8.74, and 9.01 pp, respectively, along with notable reductions in mentions of *reform* and *unspecified demand*. The absence of both narrative and product information leads to even more pronounced changes: an increase in mentions of *less trust* and *reputation* of 21.0 and 12.1 pp, respectively and a decrease in mentions of *reform* and *unspecified demand*.

Compared to nonexperts, finance professionals demonstrated a distinct response pattern to information exposure. Specifically, when exposed solely to product information, they exhibited significant shifts in their reasoning, with increases in mentions of *reform* and *unspecified demand* of 19.6 pp and 8.02 pp, respectively, both significant at the 1% level. This treatment also led to a substantial reduction in mentions of *reputation* and *no impact* of 4.97 pp and 13.6 pp, respectively, both changes also significant at the 1% level. Additionally, mentions of *protest* decreased by 9.91 pp, a significant change at the 1% level. Exposure solely to narrative information significantly elevated mentions of *unclear* reasons by 13.9 pp, indicating increased ambiguity in responses, a change significant at the 5% level. The absence of both narrative and product information subtly decreased mentions of *reputation* and *no impact* by 3.59 pp and 7.57 pp, respectively, both significant at the 10% level, while mentions of *unclear* reasons increased by 12.1 pp and *unspecified demands* decreased by 6.49 pp, again significant at the 10% level.

This analysis highlights that exposure to product information specifically predisposed respondents to associate the movement with *reform* rather than *budget cuts*, likely leading them to give more weight in their forecasting to the technology adoption, spending, and potential budget reallocation associated with police reform than to the budget cuts advocated by police abolitionists or the "defund" movement.

B.2 Robustness Checks in Stakeholder Behavior Analysis

The results from Section 6 use difference-in-difference approaches to compare areas that experienced BLM protests between May 25 and July 31, 2020, with those that did not. This relies on the parallel trends assumption, which posits that, absent the 2020 events, both protest and nonprotest areas would have followed similar outcome trends—specifically, mutual funds' propensity to hold police stocks and voters' support for police funding. We perform several tests to address potential threats to this identification strategy.

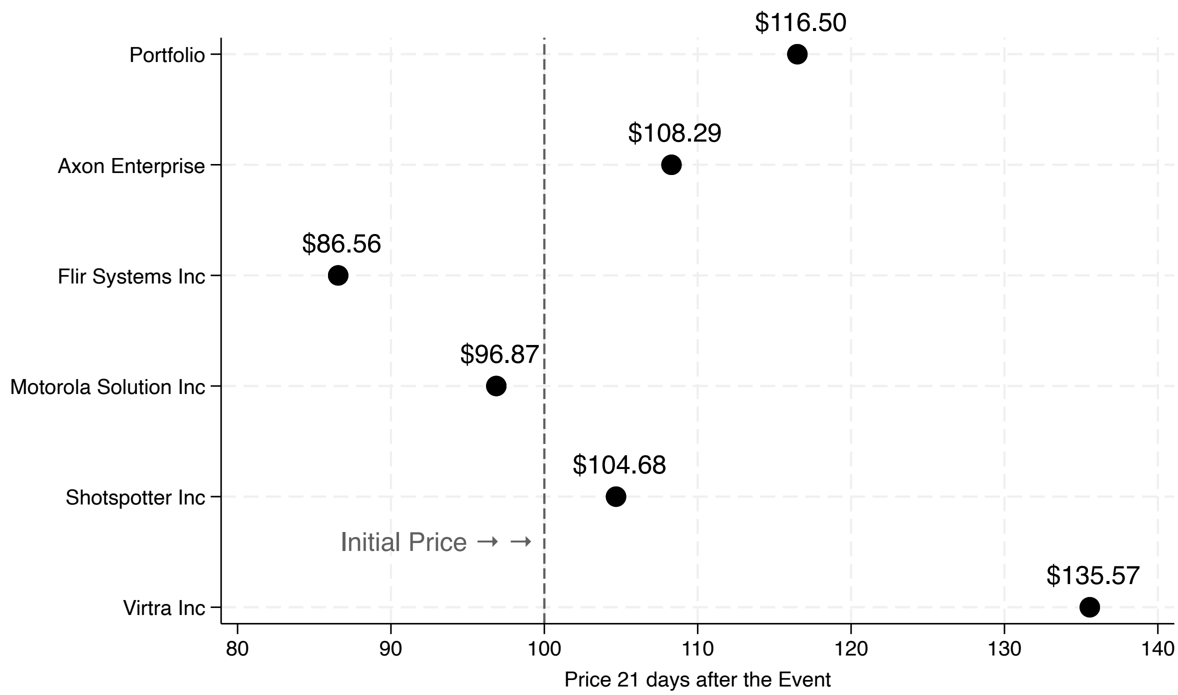
Following Roth (2022), we account for low power and pretesting issues in testing the parallel trends assumption. Low power implies that nonzero pretrends may not be detected statistically. The method constructs hypothesized linear deviations from parallel trends with 80% power. To address pretesting issues, it constructs expected event study coefficients if deviations existed but were undetectable using conventional methods, indicating how the coefficients should look if the true pretrend followed the hypothesized trend. Additionally, we perform sensitivity analyses as proposed by Rambachan and Roth (2023), allowing for potential parallel trends violations, which helps identify how different the counterfactual trend would need to be from the pretrends to overturn our conclusion.

Effect of Protests on Investors' Police Stock Holdings The top panel of Figure A.5 illustrates the counterfactual trends for the outcome of interest, showing that funds exposed to protests were less likely to hold police stocks after George Floyd's murder than their peers not exposed to protests, even after accounting for low power and pretesting issues. The bottom panel of Figure A.5 presents the confidence sets for the treatment effect of the protests in the quarters following George Floyd's murder, using various values for the magnitude restriction parameters. Setting $M^* = 1$, which limits the posttreatment violations of parallel trends to be no larger than the maximum pretreatment violation, yields a robust confidence set excluding 0, with bounds $[-0.187; -0.001]$. For higher values, we converge to the "breakdown value" for a null effect. Thus, our conclusion of a significant effect of protests on mutual funds holding police stocks hinges on the assumption that posttreatment violations of parallel trends are no greater than the worst pretreatment violations.

Effect of Protests on Support for Police Funding Similar to the investor analysis, the top panel of Figure A.6 generates the counterfactual trends for support in maintaining or increasing police funding. We confirm that areas exposed to protests were less likely to support increasing or maintaining police funding in 2020 and 2022, even after accounting for the potential problems of low power and pretesting in evaluating pretrends. Additionally, the sensitivity analysis indicates that for any values $M^* = \{0.5, ..., 2\}$, we obtain a robust confidence set that always excludes 0. Therefore, our conclusion of a significant effect of protests on support for police funding is reliable as long as we assume that the posttreatment violation of parallel trends is no more than twice the worst pretreatment violation of parallel trends.

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: Flow of the Experiment Design

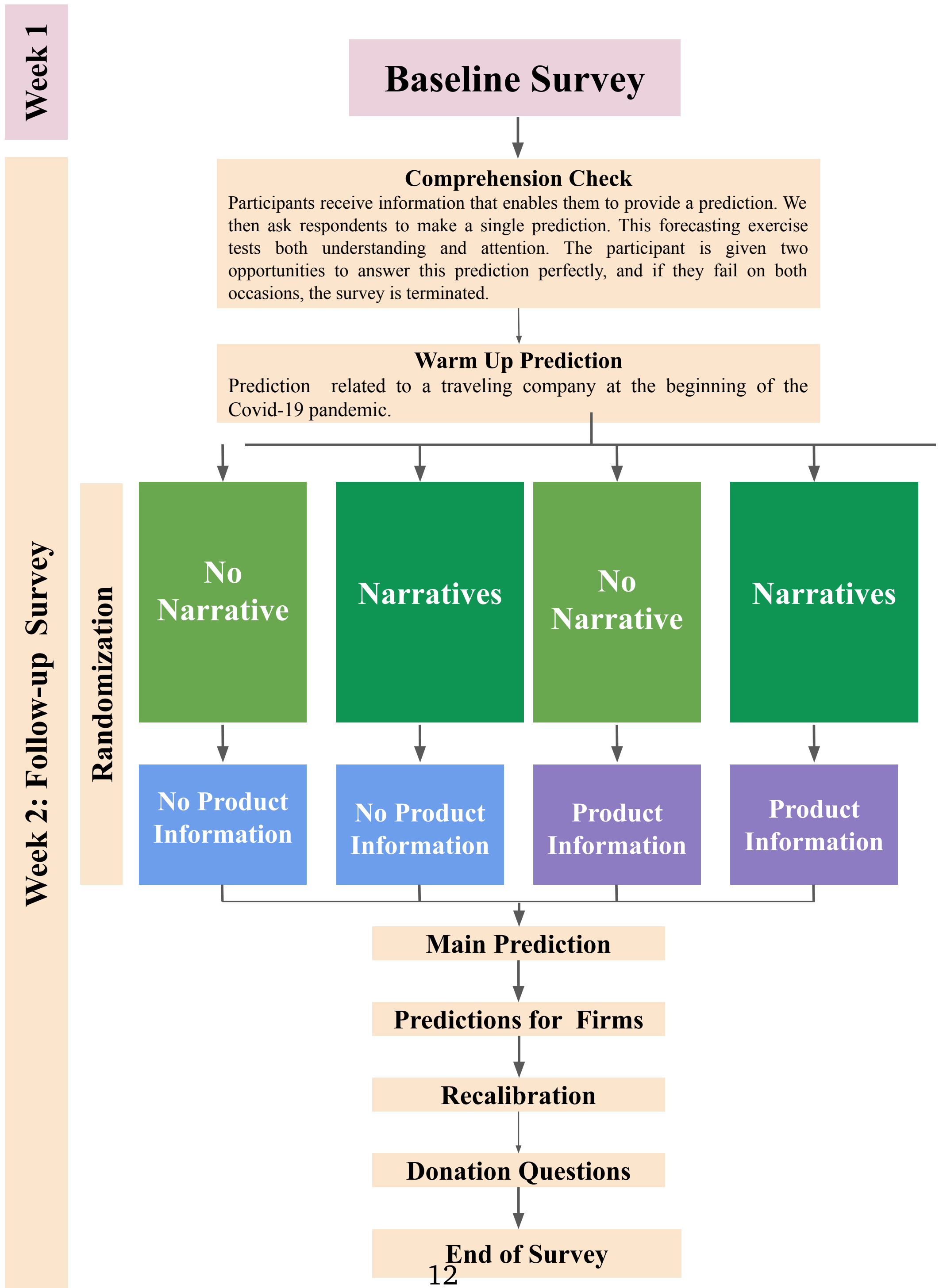
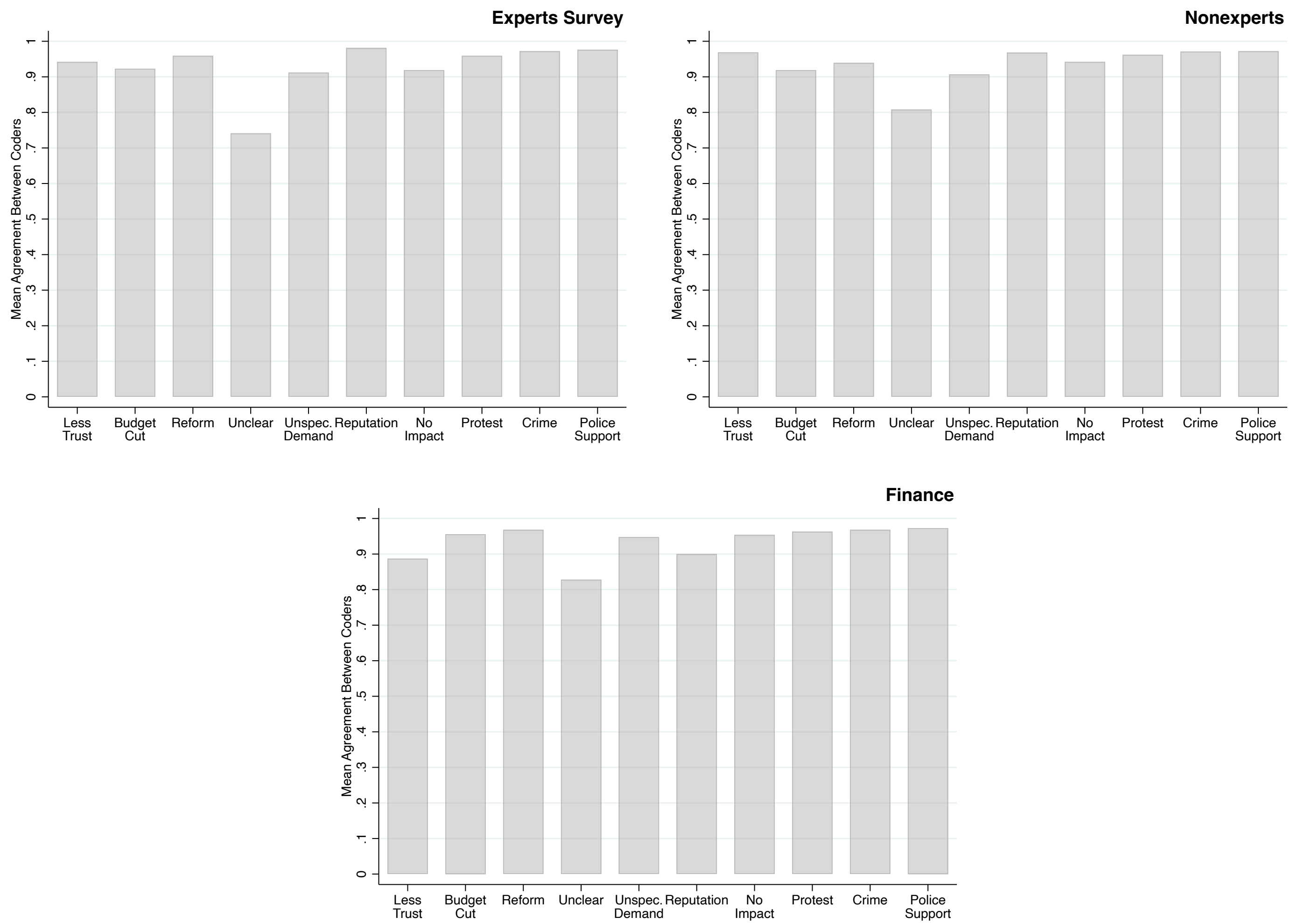
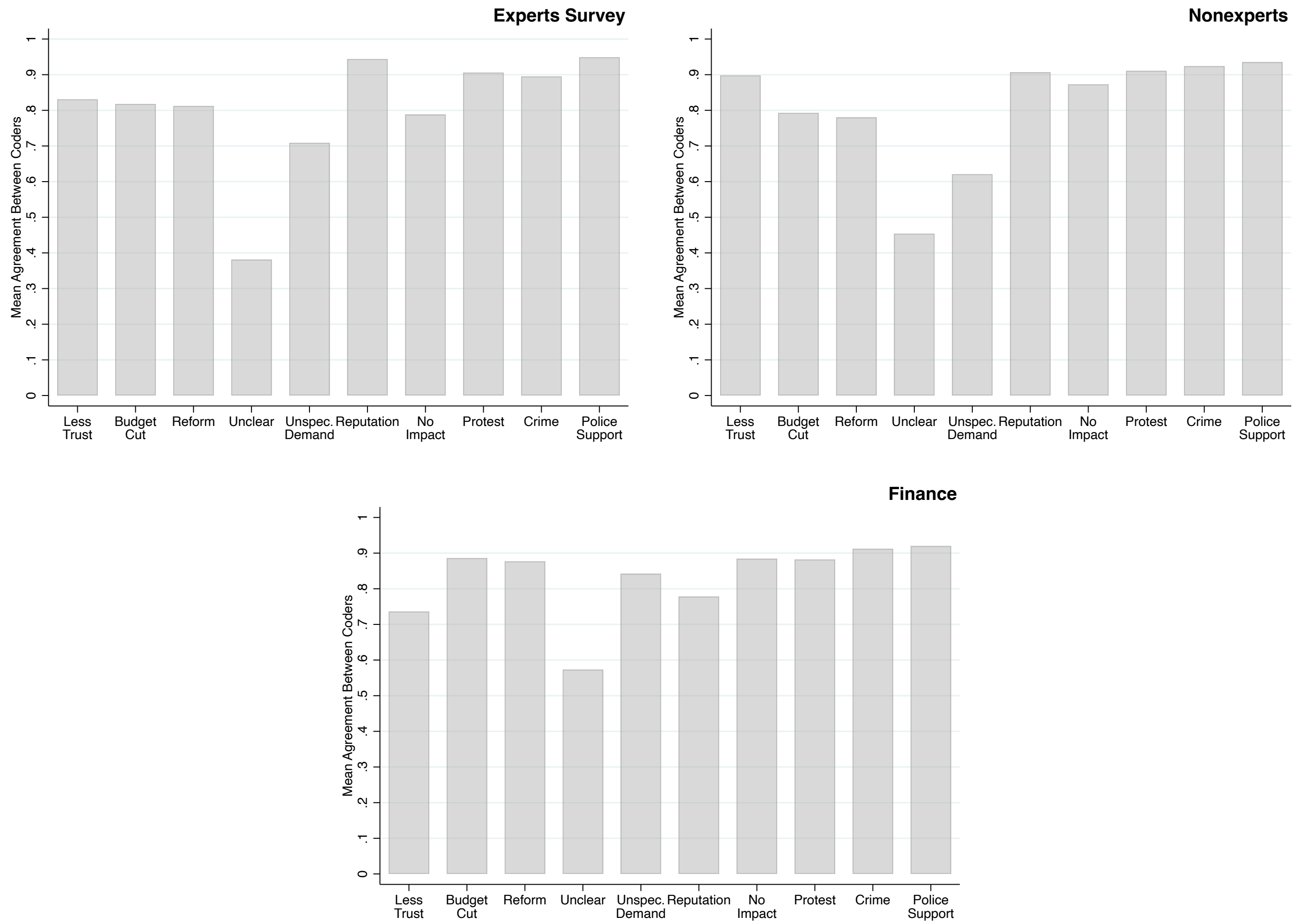


Figure A.3: Categorization Agreement Across Four of the Five Coders



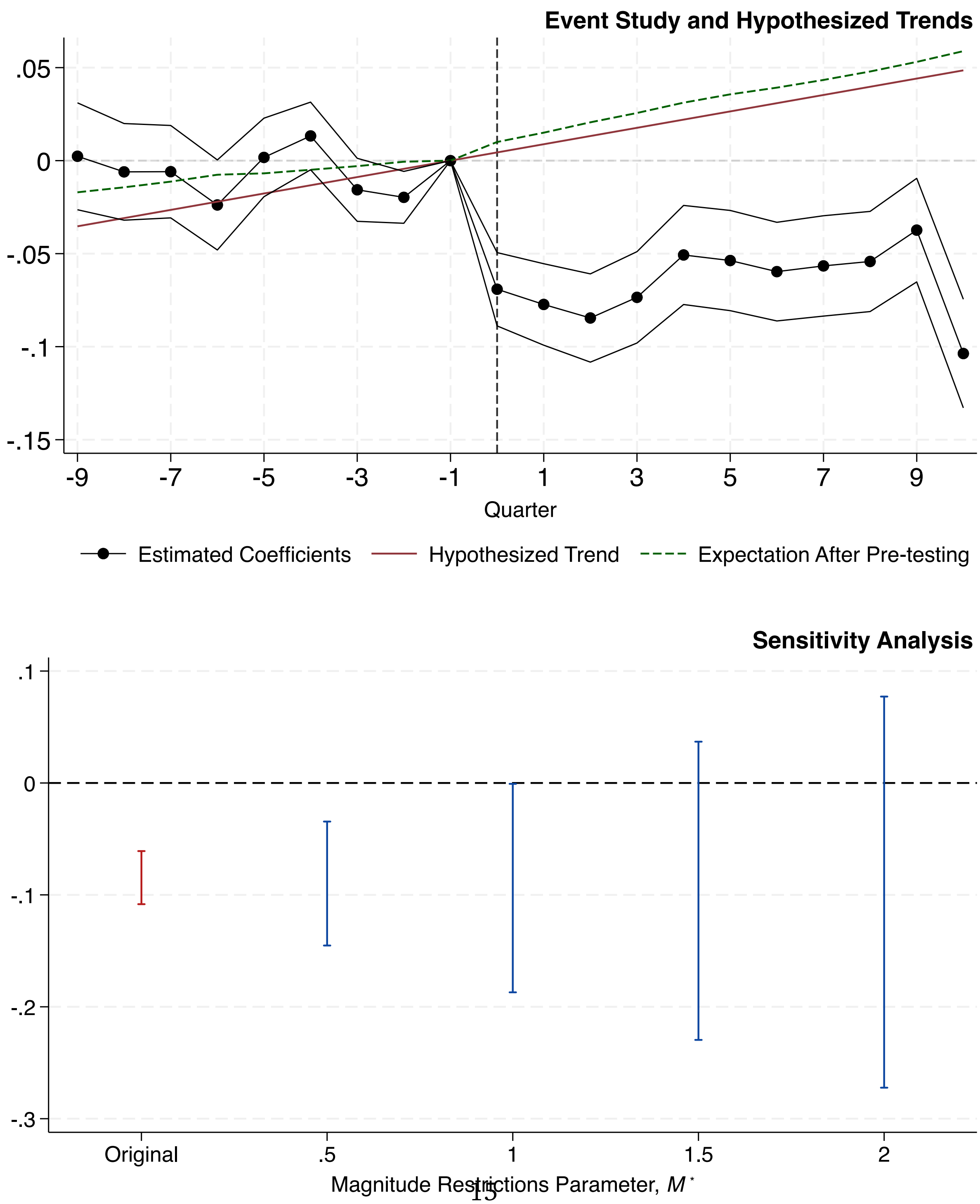
Notes: This figure reports the agreement by coders across categories for the expert survey, nonexpert experiment and the finance experiment. Given a sample (e.g., expert survey) and a category (e.g., *less trust*), the bar height represents the proportion of responses where at least 4 out of 5 coders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

Figure A.4: Categorization Agreement Across All Coders



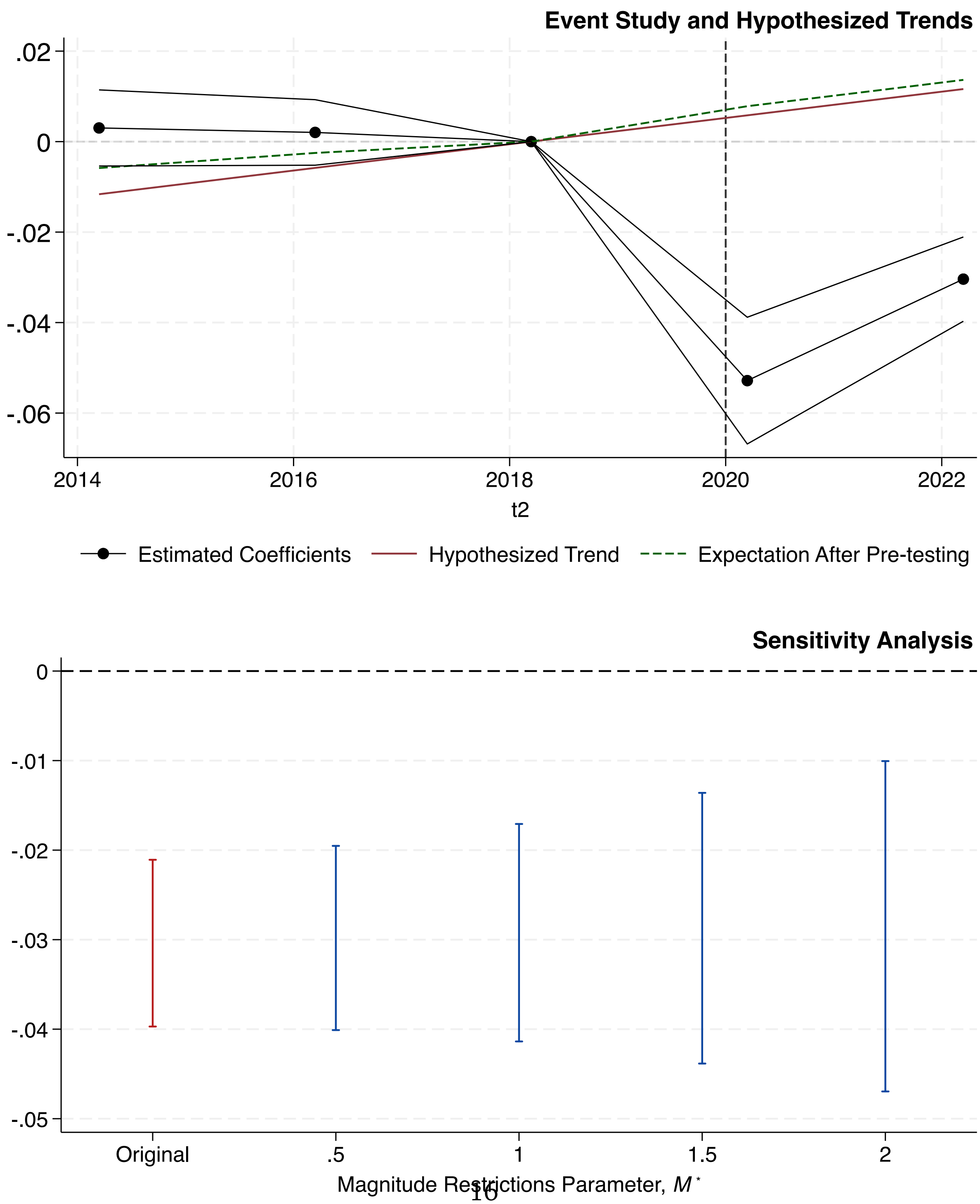
Notes: This figure reports the agreement by coders across categories for the expert survey, nonexpert experiment and the finance experiment. Given a sample (e.g., expert survey) and a category (e.g., *less trust*), the bar height represents the proportion of responses where exactly 5 out of 5 coders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

Figure A.5: Robustness: Effect of Protests on Police Stock Holdings



Notes: These figures present various specification checks on the impact of the BLM protests in response to George Floyd's murder on mutual funds' holdings of police-related stock. The dependent variable is set to 1 if a fund holds police-related stock and 0 otherwise. The top figure plots potential violations of parallel trends based on Roth (2022). We report the event study coefficients from Figure 4 and 95% confidence intervals, with standard errors clustered at the fund level. The solid line indicates the hypothesized linear deviation from parallel trends with 80% power. The dashed line shows the expected values of event study coefficients if the deviation existed but was undetectable using conventional methods. The bottom figure presents the bounds on relative magnitudes associated with a 95% robust confidence interval from Rambachan and Roth (2023).

Figure A.6: Robustness: Effect of Protests on Support for Police Funding



Notes: These figures present various specification checks on the impact of the BLM protests in response to George Floyd's murder on support for maintaining or increasing police funding. The dependent variable is set to 1 if the respondent supports state legislative action to maintain or increase law enforcement funding and 0 otherwise. The top figure plots potential violations of parallel trends based on Roth (2022). We report the event study coefficients from Figure 6 and 95% confidence intervals, with standard errors clustered at the fund level. The solid line indicates the hypothesized linear deviation from parallel trends with 80% power. The dashed line shows the expected values of event study coefficients if the deviation existed but was undetectable using conventional methods. The bottom figure presents the bounds on relative magnitudes

Table A.1: 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
Narratives Only (N)	-0.0468*	0.0399	0.0202	-0.0841	1.876	-1.578
	(0.0248)	(0.0534)	(0.0269)	(0.0626)	(1.187)	(1.913)
Products Only (P)	-0.123***	-0.0365	0.240***	0.285***	6.958***	6.187***
	(0.0233)	(0.0479)	(0.0278)	(0.0632)	(1.209)	(1.939)
Narratives and Products (N+P)	-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. (O)	0.28	0.19	0.30	0.39	-30.89	-21.62
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 no information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.2: 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
Narratives Only (N)	-0.000955	0.0745	0.0249	-0.0183	-0.00754	0.000955
	(0.0290)	(0.171)	(0.0255)	(0.0204)	(0.0209)	(0.0290)
Products Only (P)	-0.0245	0.0480	0.0256	-0.0319	-0.0182	0.0245
	(0.0292)	(0.173)	(0.0257)	(0.0200)	(0.0207)	(0.0292)
Narratives and Products (N+P)	-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. (O)	0.56	2.36	0.25	0.15	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. In addition, we report the mean of the dependent variable of the omitted category, i.e., individuals receiving no information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

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

	(1) Female	(2) Male	(3) White	(4) Nonwhite	(5) Age: 18-34	(6) Other Age	(7) Check Invt. Weekly	(8) Does not Check Invt. Weekly	(9) Liberal	(10) Conservati
Narratives Only (N)	0.0102	0.0515*	0.0454*	0.00123	0.00878	0.0461	0.0432	0.0237	0.00478	0.0599*
	(0.0331)	(0.0307)	(0.0272)	(0.0409)	(0.0337)	(0.0302)	(0.0383)	(0.0281)	(0.0311)	(0.0326)
Products Only (P)	0.339***	0.311***	0.332***	0.297***	0.259***	0.363***	0.295***	0.335***	0.251***	0.406***
	(0.0390)	(0.0344)	(0.0301)	(0.0510)	(0.0404)	(0.0335)	(0.0434)	(0.0323)	(0.0356)	(0.0371)
Narratives and Products (N+P)	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	Nonexpert
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. (0)	0.15	0.17	0.17	0.16	0.15	0.18	0.15	0.17	0.19	0.14
Observations	1028	1318	1689	657	935	1411	807	1539	1248	1098

Notes: This table reports the heterogeneity in the treatment effects for the nonexpert sample. The dependent variables are measures of accuracy given by a binary variable that equals 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 characteris (gender, race, age, investment patterns, and political leaning). In addition, we report the mean of the dependent variable of the omitted category, i.e., individuals receiving no information. $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.4: 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
Narratives Only (N)	-0.139	-0.0387	-0.0235	-0.167	-0.0575	-0.0584	-0.0591	-0.0543
	(0.104)	(0.0666)	(0.0630)	(0.142)	(0.202)	(0.0599)	(0.0986)	(0.0700)
Products Only (P)	0.362***	0.364***	0.371***	0.292*	0.397	0.357***	0.311***	0.384***
	(0.133)	(0.0690)	(0.0673)	(0.150)	(0.403)	(0.0629)	(0.0950)	(0.0797)
Narratives and Products (N+P)	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. (0)	0.22	0.31	0.26	0.42	0.30	0.29	0.38	0.23
Observations	95	372	378	89	28	439	203	264

Notes: This table reports heterogeneity in the treatment effects for the finance professional 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 no information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.5: Heterogeneity Analysis by Preferences: Likelihood of Predicting a Price Increase

	(1) Police is Unethical	(2) Police is not Unethical	(3) More Regulation	(4) Less Regulation	(5) Police is Unethical	(6) Police is not Unethical	(7) More Regulation	(8) Less Regulation
Narratives Only (N)	0.0183	0.0284	0.0180	0.0486	-0.457*	-0.0305	-0.0972	-0.00624
	(0.0514)	(0.0249)	(0.0315)	(0.0322)	(0.255)	(0.0595)	(0.0888)	(0.0758)
Products Only (P)	0.227***	0.350***	0.328***	0.312***	-0.0252	0.372***	0.280***	0.425***
	(0.0566)	(0.0290)	(0.0354)	(0.0374)	(0.230)	(0.0626)	(0.0900)	(0.0846)
Narratives and Products (N+P)	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. (0)	0.24	0.14	0.18	0.14	0.67	0.27	0.36	0.22
Observations	591	1755	1256	1090	28	439	222	245

Notes: This table reports heterogeneity in the treatment effects for the finance professional 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 no information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.6: Summary Statistics of Stakeholders in Our Sample

	(1) Community Organization	(2) Police	(3) Finance	(4) Nonexperts
Female	0.71	0.19	0.20	0.44
Born in the U.S.A.	0.87	0.92	0.93	0.92
White	0.56	0.69	0.81	0.72
Age: 18 to 34	0.49	0.04	0.06	0.40
Age: 55+ or missing	0.47	0.58	0.70	0.45
Check Investment Weekly/Daily	0.09	0.12	0.43	0.34
7-13 min	0.53	0.58	0.46	0.43
14+ min	0.38	0.38	0.47	0.13
Observations	45	26	467	2346

Notes: This table reports summary statistics for the community organization and police expert samples, as well as for the nonexpert and finance expert experimental samples.

Table A.7: 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
Narratives Only (N)	-0.103***	0.0898***	0.0410***	0.00487	0.0103	-0.0553***	0.0133	-0.0348***	-0.00744	0.0136
	(0.0262)	(0.0216)	(0.0109)	(0.0273)	(0.00791)	(0.0206)	(0.0157)	(0.0128)	(0.00607)	(0.0108)
Products Only (P)	-0.148***	-0.0144	0.168***	-0.0819***	0.0587***	-0.0874***	-0.0123	0.0901***	0.0170*	-0.00866
	(0.0253)	(0.0188)	(0.0168)	(0.0260)	(0.0117)	(0.0197)	(0.0145)	(0.0184)	(0.00870)	(0.00894)
Narratives and Products (N+P)	-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	Nonexpert
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. (O)	0.33	0.12	0.02	0.31	0.01	0.17	0.07	0.07	0.01	0.03
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 predictions. The depende variable equals one if the respondent provided a reason associated with the respective category and zero otherwise. Table 5 provides details of the categories with descriptions and exampl 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 receivi no information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.8: 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
Narratives Only (N)	-0.0310	0.0394	-0.00472	0.139**	0.0245	-0.00628	-0.0847*	-0.0991***	-0.0166	0.0353*
	(0.0353)	(0.0510)	(0.0340)	(0.0650)	(0.0283)	(0.0252)	(0.0447)	(0.0273)	(0.0177)	(0.0209)
Products Only (P)	-0.0534	0.0571	0.196***	-0.0636	0.0802**	-0.0497**	-0.136***	0.0100	0.00405	-0.00106
	(0.0360)	(0.0516)	(0.0481)	(0.0613)	(0.0339)	(0.0212)	(0.0431)	(0.0383)	(0.0206)	(0.0121)
Narratives and Products (N+P)	-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. (O)	0.10	0.16	0.08	0.35	0.03	0.04	0.18	0.10	0.03	0.01
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 5 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 no information. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

C Survey Information

Figure A.7: 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.

Figure A.11: 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.

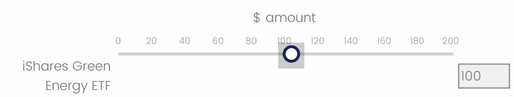
Example 2
If $100 decreases by 6%, its value becomes $100 - $6 = $94.

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.



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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