NBER WORKING PAPER SERIES

UNDERSTANDING DEMAND FOR POLICE ALTERNATIVES

Bocar A. Ba
Meghna Baskar
Tony Cheng
Rei Mariman

Working Paper 32418
http://www.nber.org/papers/w32418

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02139
May 2024, Revised August 2024

Special thanks to Mallory Sepler-King for allowing us to use her website for research purposes and providing general expertise on police alternatives. We are grateful to Abi Adams-Prassl, Amna Akbar, Randy Akee, Dionissi Aliprantis, Marcella Alsan, Isaiah Andrews, Manuela Angelucci, Peter Arcidiacono, David Autor, Pat Bayer, Peter Blair, Marika Cabral, Sylvain Chassang, Zoe Cullen, Janet Currie, Jeff DeSimone, Jennifer Doleac, Joe Doyle, Martha Eies, Samantha Eyler-Driscoll, Rob Garlick, Jonah Gelbach, Arkadev Ghosh, Felipe Goncalves, Jonathan Gruber, Nathan Hendren, Anjelica Hendricks, Mitch Hoffman, Justin Holz, Kalila Jackson-Spieker, Larry Katz, Desire Kedagni, Dean Knox, Jonathan Kolstad, Phil McHarris, Robert Moffitt, Jonathan Moreno-Medina, Ismael Mourifie, Aurelie Ouss, Michelle Phelps, Laura Pilossoph, Michael Pollman, James Poterba, Roman Rivera, Chris Roth, Viviana Rodriguez, Felwine Sarr, Todd Sarver, Craig Sylvera, Duncan Thomas, Cody Tuttle, Nastasia Watkins, Huseyin Yildirim, and seminar participants at JPAL Design Within Reach, MIT, UCSB, Minneapolis Fed, Cleveland Fed, and the HBS Inequality in the Digital Age Conference. Patton Chen, Omar Farrag, Mary Ann Fahmy, Elizabeth Johnson, Lily Levine, Della Maggio, Pushkar Nimkar, Judicaël Waounwa, Alex Whitefield, and the Woodman Scholars from the Duke Economic Analytics Lab—Harika Amineni, Sanjit Beriwal, Jack Duhon, Alicia Gong, Justice Hatcher, Julia Ma, Melissa Sandoval, and Audrey Wang—provided outstanding research assistance. The study is approved by the IRB at Duke (IRB 2023-0369 and 2024-0214 and registered at the AEA RCT Registry for the survey experiment (AEARCTR-0014096) and the field experiment (AEARCTR-0013061). We gratefully acknowledge financial support from JPAL North America's Social Policy Research Initiative and Duke Economics Department. This work was completed during Ba's visit to the Opportunity Inclusive Growth Institute at the Minneapolis Fed. Any errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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May 2024, Revised August 2024
JEL No. H10, K0, P0

ABSTRACT

In a series of experiments, we present evidence of bipartisan public demand for police alternatives, contrasted with persistent policy resistance from key stakeholders. First, our survey experiment demonstrates that introducing U.S. respondents to dontcallthepolice.com (DCTP), a database of non-governmental emergency response options, significantly reduces reliance on police for nonviolent situations. However, this effect does not extend to violent scenarios where no police substitutes exist. Second, our follow-up survey reveals enduring impacts, including heightened recall of the 988 hotline as an alternative during suicidal crises. Third, our field experiment and qualitative interviews find police resistance to embracing DCTP, despite widespread public support for nonviolent police substitutes.

Bocar A. Ba
Department of Economics
Duke University
213 Social Sciences
Durham, NC 27708
and NBER
bocar.ba@duke.edu

Meghna Baskar
Duke University
meghna.baskar@duke.edu

Tony Cheng
Duke University
tony.cheng@duke.edu

Rei Mariman
Duke University
rachel.mariman@duke.edu

1 Introduction

After George Floyd's death in 2020, the momentum of the campaign advocating alternatives to traditional policing surged (Kaba et al., 2021; Akbar, 2020; Phelps, 2024). Advocates called for a shift toward community-based, public health–focused safety measures for the various situations in which social workers might effectively substitute for police (Dee and Pyne, 2022; Davis et al., 2024).[1] This shift could also be cost-effective—using BLS data, Figure 1 shows that police officers earn approximately 29% more per hour than mental health and substance abuse social workers, such that a police response is likely to be costlier than other response options in certain emergencies. However, so far, the movement to reduce the societal scale of policing in favor of nonpolice alternatives has not achieved broad successes (Ba et al., 2023a,b). In this paper, we address three central questions: First, is the limited adoption of police alternatives driven by a lack of public demand? If so, does the limited demand stem from insufficient information among the public about the availability of such alternatives? Third, could resistance from key policymakers be hindering the shift away from traditional policing?

Using a survey experiment presenting respondents with scenarios ranging from armed robbery to mental health crises—most of which are based on real incidents involving a police response that devolved into civilian fatalities—we find that exposure to the information on the website dontcallthepolice.com (DCTP) significantly reduces demand for police in nonviolent situations but not in violent ones where no police substitute exist, with this effect remaining consistent across political lines. A follow-up survey shows that those informed about alternatives are likelier than the control group to recall the 988 helpline and less likely to call 911 in suicidal crises in the medium term, indicating a lasting impact of the information intervention. We then conduct a large-scale, nondeceptive field experiment to assess how stakeholders in policing respond to these results. Despite our finding that the information effect on the likelihood of relying on police and nonpolice alternatives holds across both Republican and Democrat respondents, our experiment reveals that police engage more than other stakeholders with DCTP, signaling potential resistance. In-depth qualitative interviews further explore police perspectives, revealing skepticism toward DCTP. Our findings suggest that while better information on the availability of police alternatives has a bipartisan impact on demand for police in nonviolent situations, resistance from police as key policymaking stakeholders remains a significant barrier to reducing the scale of policing in favor of alternative forms of emergency response.

Developing an empirical understanding of different constituencies' views on police alternatives presents significant challenges. The introduction of police alternatives and the reallocation of resources from police in some jurisdictions have sparked a polarizing debate, complicating efforts to

[1]More generally, social scientists are increasingly interested in conceptualizing new and alternative models of public safety (Bell et al., 2020; Glazer and Sharkey, 2021; Western, 2019) as part of a broader reckoning with the limitations of the American criminal justice system (Lee, 2024). For example, Bell (2021) calls for a next generation of policing research that does not assume that more or better policing is the only pathway to public safety.

evaluate both the effectiveness of these alternatives and public sentiment toward them (Bursztyn et al., 2023). Additionally, evaluation of public responses to new policies requires careful consideration of potential selection bias in policy adoption and of the preferences of key stakeholders (Hjort et al., 2021; DellaVigna and Kim, 2023). Furthermore, police departments might strategically collaborate with researchers whose work aligns with the departments' own interests, further complicating the task of objectively evaluating police alternatives and demand for them (Bell, 2021; Davies et al., 2021).

We address these challenges in several steps. First, we design a survey to evaluate participants' likelihood of turning to law enforcement as first responders in various crisis scenarios. The survey includes four real-life incidents—all of which ultimately ended in likely preventable civilian deaths at the hands of police—and one fictional scenario. These scenarios range from violent incidents, including armed robbery and domestic violence, to nonviolent situations involving mental health vulnerabilities and homelessness. This approach provides insights into respondents' attitudes toward policing and police alternatives, highlighting patterns in public perceptions across diverse contexts. All scenarios are phrased to position the respondent as a bystander, measuring the propensity to call the police as a witness rather than as a victim.

Second, we partner with dontcallthepolice.com (DCTP), a website listing community-based crisis intervention services as alternatives to a law enforcement response. We randomly assign over 2,700 respondents to one of three animated educational videos (Alesina et al., 2018; Bernstein et al., 2023) to introduce nondeceptive experimental variation. The first video, which we label the *Government* treatment, provides information on government services that can serve as police alternatives (211, 311, 988), acting as an active control to ensure that all participants receive relevant information, allowing us to measure the average causal impact on beliefs (Bottan and Perez-Truglia, 2022; Haaland et al., 2023). The *DCTP* treatment contains the *Government* treatment information, but adds vetted information on nongovernmental emergency response options to minimize police involvement, as highlighted on the DCTP website. Last, we implement a *Control* treatment using definitions of economic indicators, such as full-time and part-time employment rate, as a placebo. We then assess respondents' inclination to call the police across scenarios and their demand for and interest in police alternatives.

We begin our analysis by documenting that individuals overwhelmingly consider police involvement essential in situations involving violence. Pooling the scenarios together, we find that the *DCTP* treatment significantly reduces overall demand for police services, especially in nonviolent situations. In contrast, the *Government* treatment does not significantly change police demand from the level in the *Control* group. Analyzing likelihood of calling the police in specific scenarios, we observe that the *DCTP* treatment does not significantly alter the demand for police in high-stakes, violent scenarios where there is no substitute for police, such as armed robbery. However, the treatment significantly reduces demand for police in nonviolent scenarios such as encountering a naked man, a person experiencing suicidal ideation, or someone engaged in disruptive begging. The results indicate that while alternative response options are valued for nonviolent crises, the public still recognizes the role of police in handling violent emergencies as critical.

Next, motivated by the higher costs of police relative to that of social workers and the potential benefits of a greater reliance on more specialized alternative first responders, we explore respondents' demand for police substitutes, (Dee and Pyne, 2022; Davis et al., 2024). We find that the *DCTP* treatment significantly increases the preference for a social worker response in nonviolent situations. This suggests that providing information about community-based alternatives is more effective at reducing reliance on police than presenting information about *Government* resources alone. Given the cost disparity between social workers and police, this shift could also lead to substantial savings for local governments.

Much research finds that partisanship significantly influences attitudes toward policing and reallocation of police budgets (Bursztyn et al., 2023; Sances, 2023c,b,a). Surveys show that Republicans are likelier than Democrats to support police and oppose movements such as "Defund the Police," which proposes reallocation of funds to nonpolice public safety resources. Surprisingly, however, we find that both Democrats and Republicans show decreased demand for police in nonviolent scenarios under the *DCTP* treatment, while their responses to the *Government* treatment are more muted. This suggests broad openness to community-based police alternatives across political lines. We also evaluate the impact of each treatment on preferences for different names of websites presenting police alternatives. We consider dontcallthepolice.com and 911alternatives.com, which host identical content, and assess how the treatments influence preferences by partisanship. Contrary to expectations, both Democrats and Republicans show heightened interest in the DCTP site after exposure to information about it, despite conservatives typically being more pro-police and opposed to police reform efforts. This suggests bipartisan support for nonpolice resources when viable alternatives are presented, highlighting the potential for community-based interventions to gain broad acceptance.

In the final section of our survey experiment, we evaluate the lasting impact of our educational intervention on the availability of the 988 helpline, a crucial but underrecognized emergency resource for suicide prevention (PEW (2023)). The results of a follow-up survey conducted a week after participants were shown the three-minute educational video reveal that those informed about police alternatives continued to significantly prefer the 988 helpline over a police response for suicidal ideation crises. Treated respondents were twice as likely to recall the availability of 988 as the *Control* group, only 9% of which knew of this option. Additionally, those exposed to the *DCTP* and *Government* treatments were 21 and 15 pp less likely, respectively, to dial 911 in these scenarios ($p < 0.01$ for both). These results underscore the significant and lasting influence of targeted information interventions on emergency response decision-making, highlighting the effectiveness of the DCTP website and educational efforts in promoting the use of specialized crisis resources such as the 988 helpline over traditional police intervention in high-stakes situations.

While our survey experiment findings show a bipartisan effect on respondents' likelihood of turning to police alternatives and their interest in the website dontcallthepolice.com, implementing these resources would benefit from agreement among policymakers and stakeholders, including law enforcement, who may resist changes to the status quo (Hjort et al., 2021; Goerger et al., 2023; Cheng, 2023). To explore the policy implications and gauge receptiveness among key stakeholders in the U.S. responsible for shaping policies on police alternatives (police, sheriffs, local officials, and Department of Justice grantees), we conducted a large-scale field experiment disseminating a summary of our survey experiment results to these stakeholders via email and inviting feedback.[2] We tested the hypothesis of localized institutional resistance by randomizing counties into two conditions with different subject lines and evaluating stakeholders' interest based on their responses to an email with different subject lines, with one version featuring dontcallthepolice.com and another 911alternatives.com, both of which link to the same content. The results show no difference in engagement with the email among nonpolice stakeholders, but police respondents engaged more with the emails with "dontcallthepolice.com" in the subject line. This heightened engagement suggests that police could either be supportive, resistant, or be indifferent to nonpolice alternatives.

In a final exercise, we conducted in-depth qualitative interviews with key stakeholders to complement our survey and field experiments (Finkelstein et al., 2021; Bergman et al., 2024). These interviews aimed to understand policymakers' and influential stakeholders' perceptions of police alternatives. Our goal was to capture the perspectives of those who can shape policy, providing insights that quantitative methods alone might miss. These semistructured interviews, averaging over 45 minutes each, revealed insights that complement our quantitative findings. Despite the bipartisan effect of information about police alternatives on the demand for police, greater institutionalization of these alternatives faces challenges, especially from law enforcement. Stakeholders generally supported 911 alternatives for their potential to reduce police workload, improve efficiency, and prevent escalation in nonemergency situations. However, DCTP received mixed reactions, with skepticism rooted in concerns about its connotations and practicality. Police stakeholders, in particular, associated DCTP with defunding the police and expressed concerns about public confusion about who to call for crisis incident and inadequate emergency responses.

Our findings suggest that while police stakeholders were interested enough in DCTP to agree to interviews, their involvement was often driven by a desire to voice concerns about the potential for confusion and negative outcomes, indicating strong skepticism. This suggests that, even with broader public support, successful implementation of initiatives such as DCTP and police alternatives in general will require careful framing and the active engagement of law enforcement. Without their buy-in, police may resist or block these efforts, regardless of the broader openness to change.

[2] We note that the emails summarized findings from a previous version of the survey experiment by Ba et al. (2024), which is replicated in the current paper.

Literature Review Our study intersects with diverse strands of research. First, our work contributes to the literature studying the dynamics and risks of police involvement with vulnerable and at-risk groups, such as young men of color and economically disadvantaged individuals (Bor et al., 2018; Ang, 2020),[3] individuals experiencing gender-based violence (Miller and Segal, 2019; Cunnigham and Shah, 2018; Adams-Prassl et al., 2023) such as domestic violence (Aizer and Dal Bo, 2009; Leslie and Wilson, 2020; Adams et al., 2024), individuals experiencing homelessness (Evans et al., 2016, 2021), and individuals struggling with mental health vulnerabilities or substance abuse (Dee and Pyne, 2022; Davis et al., 2024). By delving into the determinants of police–civilian encounters (Ba, 2018; Rivera and Ba, 2023; Ang et al., 2024), our work can inform policies aimed at mitigating the fears and risks inherent in these critical interactions (Pickett et al., 2022). Moreover, to the best of our knowledge, no survey has yet quantified the demand for police services, particularly in situations for which alternatives exist (e.g., crises affecting homeless people, mental health crises), or gauged public awareness of these substitutes.[4]

Second, our research sits at the intersection of literature on partisanship, polarization, and policy adoption, as highlighted by recent work such as DellaVigna and Kim (2023). Recent studies have revealed significant externalities from the politicization of policies, spanning areas such as health insurance and outcomes (Sances and Clinton, 2021; Bursztyn et al., 2022, 2023), perceptions of racial gaps (Alesina et al., 2018; Haaland and Roth, 2021), and redistribution (Cascio and Washington, 2013; Cullen et al., 2021). While political affiliations often shape beliefs and behaviors in areas such as policing (Ang and Tebes, 2023; Grosjean et al., 2022; Ba et al., 2023; Goncalves and Tuttle, 2024), our research highlights an area with limited evidence of polarization. Specifically, we uncover a surprisingly stable effect of our information intervention across political lines on demand for police alternatives in nonviolent crises and interest in dontcallthepolice.com.

Third, our research contributes to the literature on policy adoption and how policymakers respond to evidence-based research (Hjort et al., 2021). Our work relates to research documenting positive experimentation site selection in evaluations of new programs (Allcott, 2015; DellaVigna and Linos, 2022; Wang and Yang, 2023), which is particularly relevant when we consider the role of police departments in policy design. Police departments may join studies to ensure favorable outcomes or control the narrative, indicating positive selection (Bell, 2021; Goerger et al., 2023). Given the literature on the generalizability of evidence-based policies (Vivalt, 2020; DellaVigna and Kim, 2023), our field experiment highlights how stakeholders, particularly those whose autonomy or image may be affected, play a crucial role in the adoption of new policies.

Finally, our paper contributes to a growing literature in economics that uses in-depth qualitative interviews to deepen our understanding of context and uncover potential mechanisms driving

[3] See also Tucker et al. (2019), Robinson (2020), and Shields (2021).

[4] We further document the heterogeneity in constituents' responses to the information about police alternatives, which is also crucial for understanding their willingness to engage with law enforcement to report a crime (Jácome, 2022; Goncalves et al., 2023; Golestani, 2023; Graef et al., 2023) or police wrongdoing (Ba, 2018; Hendricks, 2021).

observed findings (Finkelstein et al., 2021). This approach has been employed to complement the interpretation of quantitative results across various topics, including housing (Bergman et al., 2024), health economics (Alsan et al., 2019), public finance (Bustos et al., 2022), crime (Bruhn. et al., 2024), and development economics (Jayachandran et al., 2023). At the same time, we contribute quantitative evidence about the demand for and challenges to institutionalization of police alternatives, an area in which research thus far has primarily been restricted to qualitative studies and legal scholarship (e.g., Bell et al., 2020; Chaudhary et al., 2021; Simonson, 2020). Our paper overall provides an example of how sociological insights from interviews can be integrated into an economics framework as both a source of data and a means of enhancing respondent engagement and the timeliness of policy feedback.

Plan The remainder of this paper is structured as follows: Section 2 provides a brief background on police alternatives in the U.S. Section 3 presents a simple conceptual framework supporting our hypotheses. Section 4 details our survey experiment evaluating the impact of information on the demand for police alternatives. Section 5 discusses the lasting effects of our intervention on demand for the 988 Suicide & Crisis Lifeline. Section 6 covers our field experiment testing stakeholder responses. Section 7 presents qualitative interviews with stakeholders, and Section 8 concludes.

2 Background on Police Alternatives

Governmental Resources The United States has several government-administered hotlines that serve as integral components of its public service infrastructure; these resources can serve as potential alternatives to a traditional policing response in specific scenarios. The 988 hotline, launched in July 2022, serves as a critical resource for suicide prevention and mental health emergencies, offering a direct line to mental health professionals who can offer immediate assistance. Similarly, the 211 hotline, launched in 2000, is a government-supported service directing individuals to essential social assistance services such as housing aid, food assistance programs, and employment support. Last, the 311 hotline connects residents with municipal services, addressing inquiries and issues about city regulations, public works, sanitation, and transportation. These hotlines represent government-provided resources designed to offer support and guidance in specific circumstances that may not require law enforcement involvement. They provide specialized assistance for non-criminal emergencies and other situations where such services are applicable.

Nongovernmental Resources In this study, we collaborate with the platform dontcallthepolice.com to evaluate the demand for various community-based alternatives to traditional law enforcement services. In the U.S., the conventional response to a broad spectrum of crises, from minor disturbances to emergencies, is to contact emergency services through 911. This reflexive action often results in armed law enforcement officers responding to situations for which they may lack appropriate training or resources, potentially exacerbating conflicts and leading to violent outcomes.

Against this backdrop, DCTP provides a repository of community-based resources offering support for youth, runaways, LGBTQ+ individuals, and elderly people and resources for those facing homelessness, mental health vulnerabilities, sexual assault, domestic violence, substance abuse issues, or nonviolent crimes. DCTP vets each listed resource to ensure that the information is current and accurate, including assessments of the potential for any law enforcement involvement, with notes on whether the resource is a mandatory reporter. Moreover, the website name, dontcallthepolice.com, is designed to encourage individuals to reconsider reflexively relying on police as first responders for every crisis.

Since its launch, the website, which lists over 500 organizations across North America, has attracted over 1.17 million visits. Figure 2 shows that a notable traffic spike on dontcallthepolice.com occurred around the conviction of Derek Chauvin—the police officer responsible for George Floyd's death. This surge contrasts with the steady traffic on communityresourcehub.com and the varying visits to defundthepolice.com and highlights an increase in public interest in alternative crisis resources in the context of major police-related scandals, a topic that has so far remained neglected in literature focusing specifically on police behavior (Prendergast, 2001, 2021), civilian responses (Ang et al., 2024), or both (Rivera and Ba, 2023).

Hourly Police Costs and Potential Subsitutes In the context of these governmental and nongovernmental resources, it is important to consider the financial implications of the relative reliance on traditional policing versus community-based alternatives. Police officers earn approximately 29% more per hour than mental health and substance abuse social workers, making them a costlier option for handling crises that could be managed by specialized nonpolice services. This wage disparity suggests the potential cost-effectiveness of redirecting some public safety tasks in nonviolent situations toward social workers. Specifically, police officers earn an average of $28.99 per hour, compared to $22.43 for mental health social workers—below the national average of $23.30 per hour—and $26.96 for other social workers.

3 Conceptual Framework

We investigate the role of information in demand for police by testing three hypotheses: (1) that exposure to information about police alternatives, especially the *DCTP* information, will increase demand for these substitutes in nonviolent situations, (2) that information about police alternatives does not necessarily reduce demand for police in cases for which there are no police alternatives, e.g., armed robberies, and (3) that informing individuals about police alternatives will significantly and lastingly increase their likelihood of recalling the availability of the 988 government hotline for suicidal crises.

We present a simple model rationalizing individuals' baseline willingness to call the police. More details can be found in Section A of the appendix. In this framework, a bystander decides whether to call the police or choose an alternative based on the situation's nature. For instance, the bystander might encounter a violent situation like an armed robbery, or, in a nonviolent scenario, someone experiencing suicidal ideation. The probability of each type of situation is predetermined.

The decision process considers the utility gained from making the correct choice—calling the police when they are necessary and avoiding them when they are not—and the penalty for making an error, such as calling the police when an alternative is preferable. Callers may affirmatively prefer alternatives (e.g. specialized services tailored to the situation) or be disincentivized from calling the police (e.g. concern about armed responders). Additionally, the bystander must consider the cognitive effort involved in remembering when not to call the police, which incurs a cost. This cost influences the likelihood of choosing the alternative. The bystander aims to maximize her expected payoff by balancing utility against the effort cost, finding the optimal level of cognitive effort.

Our framework and empirical design examine how different levels of information about police alternatives influence decision-making. The model predicts that, in nonviolent scenarios, the perceived severity of the consequences of calling the police in error increases across different treatments, leading to greater cognitive effort and a higher likelihood of opting for nonpolice options. This progression shows that, as the potential mistake becomes more severe, bystanders are more motivated to remember alternatives, resulting in a higher probability of choosing nonpolice options. We hypothesize that the *DCTP* information, highlighting that police should not be the default option, notably enhances this propensity, demonstrating the importance of detailed and specific information in guiding public decisions toward more appropriate emergency responses.

4 Demand for Police and Alternatives: A Survey Experiment

4.1 Experimental Design

Overview and Logistics We surveyed an online sample of 2,745 U.S. adults to gauge their baseline preferences for police involvement in specific scenarios. Participants were recruited via Prolific in July and August 2024. We used the platform to target a representative sample by sex, gender, and political affiliation. Respondents were randomized into treatments in which they viewed educational videos on both governmental and nongovernmental police alternatives. Our research protocol was preregistered with the AEA registry (AEARCTR-0014096). The eligibility criteria were that the respondent be a U.S. resident, of voting age, and proficient in English. Participants received a $2 payment, contingent on their completing the study and passing the attention checks. The median completion time was approximately 13 minutes.

Survey Structure The survey began by collecting participants' zip code of residence and presenting an attention check question. Any respondents failing the attention check were screened out at this stage. We then collected respondents' baseline opinions on how important a police response is in scenarios involving (1) crime, (2) domestic violence, (3) homelessness, (4) mental health issues, (5) sexual assault, and (5) substance abuse.

Participants were then randomly assigned to view concise informational videos describing resources that can serve as alternatives to traditional policing in the United States. The experiment consisted of three distinct treatment groups: (1) *Control*, (2) *Government*, and (3) *DCTP*. Subsequently, participants were presented five hypothetical situations and asked to rate their own propensity to contact the police for assistance in the corresponding cases, with responses measured on a scale ranging from 0 to 100%. The presentation of all scenarios is phrased such that the respondent is cast as a bystander to the incident. Hence, the survey measures the propensity to call the police for assistance as a witness rather than as a victim.

We then presented another attention check to ensure that participants were still reading and answering carefully. Next, to assess how messaging might affect receptiveness to police alternatives, we asked respondents which of the two names for the site about police alternatives was more appealing to them. Finally, we collected demographic information, such as birth year, gender, race, education, income, and political leaning. The complete survey text can be found here.

Experimental Variation To introduce nondeceptive experimental variation, we used animated videos similar to those in the studies of Alesina et al. (2018), Alesina et al. (2018), and Bernstein et al. (2023), all presenting truthful information. The *Control* treatment served as a placebo, providing information about unemployment, a topic unrelated to police. The second treatment, which we refer to as the *Active Control* or *Government* treatment, offered information on alternative governmental services (211, 311, and 988) to help disentangle the effects of priming from genuine belief updating (Haaland et al., 2023). The final arm, the *DCTP* treatment, presented information about vetted nongovernmental options prioritizing minimizing police involvement.

We maintained consistency by ensuring that each video was of similar duration, such that respondents across all treatment arms performed tasks of similar length. Complete transcripts of the videos are provided in Appendix C, and screenshots from the videos are displayed in Appendix Figures A.1, A.2, and A.8. The conditions are as follows:

- **Control** video: This treatment provided information about unemployment and various definitions related to economic outcomes (e.g., labor force, who counts as unemployed). [5]
- **Government** video: The treatment for this experimental arm provided information on government resources that can serve as viable alternatives to a police response, such as 988 for

[5] The link to the *Control* video can be found here.

suicide and mental health crises, 211 for community assistance, and 311 for city services. To maintain consistency in video duration across the experiment, supplementary, nonpertinent content on environmental issues was included as filler material.[6]

- **DCTP** video: The treatment for this experimental arm emphasized that police are often the default emergency responders in the U.S. even though most calls for service do not involve violent crimes. It then introduced dontcallthepolice.com and presented the website as a vetted database of community resources suitable for attending to nonviolent crises and providing specialized intervention. The website advocates reliance on these alternatives to minimize unnecessary interactions between civilians and law enforcement. The end of the video also presents the *Government* video information on the 988, 211, and 311 hotlines.[7]

Scenarios Our primary outcome measure is respondents' reported propensity to contact law enforcement in crisis situations. We evaluate their reactions to four scenarios mirroring real incidents that resulted in civilian fatalities during police encounters, as cataloged in the Mapping Police Violence database (see Appendix D). Although the scenarios are inspired by fatal incidents, such interactions often occur without casualties.[8] These scenarios provide real-world examples, while a fifth, fictional scenario extends the inquiry into the hypothetical. This approach identifies respondents' beliefs about the appropriateness of relying on police as first responders in various situations and has been used in other contexts, such as labor economics research (Cortés et al., 2022).

The scenarios are as follows: (1) "armed robbery" (*"Two men attempt an armed robbery of a jewelry store"*), (2) "screaming woman" (*"A woman screams and cries while a man makes threats"*), (3) "naked man" (*"A naked man walks down the street near a music festival"*), (4) "suicidal ideation" (*"A neighbor seems really upset and says he is 'thinking about ending things'"*), and (5) "disruptive begging" (*"A man begs in front of a restaurant and curses at people who ignore him"*). The first two scenarios are violent incidents, while the other scenarios correspond to nonviolent situations. The order in which the scenarios were presented to respondents was randomized to prevent ordering effects.

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

$$y_i = \alpha + \beta_D DCTP_i + \beta_G Government_i + X_i'\gamma + \epsilon_i \tag{1}$$

[6] The link to the *Government* video can be found here.
[7] The link to the *DCTP* video can be found here.
[8] The press has documented similar cases of police responses to armed robbery, a screaming woman, a naked man, and suicidal ideation that did not result in fatalities.

where outcome y_i of respondent i is a function of each treatment condition. The outcomes are presented in Table 1. The variable $DCTP_i$ is a binary variable that equals one if the respondent received the *DCTP* video treatment and zero otherwise. The variable $Government_i$ is a binary variable that equals one if the respondent received the *Government* video treatment and zero otherwise. The omitted group corresponds to the *Control* treatment. In addition, in X_i, we control for individual covariates. The covariates include age dummies, race-ethnicity dummies, a male dummy, education dummies, political affiliation dummies, income dummies, single dummy, and baseline demand for police. We use robust standard errors, as we randomized at the individual level. The parameters on the treatment indicators identify the intent-to-treat effects under randomization. The analysis was performed in Stata and R.

Outcome Variables Table 1 defines the outcomes used in our analysis. The primary measure is the likelihood of calling the police across the five scenarios, quantified on a scale of 0 to 100. We employ the Kling–Liebman–Katz (KLK) index (Kling et al., 2007) to synthesize these responses, generating composite z-scores that encapsulate overall, violent scenario–specific, and nonviolent scenario–specific demand for police.[9] Additionally, we created binary variable to capture respondent's preferred responders (police, social workers, or none) for each scenario. Interest in alternative resources is gauged with a binary variable reflecting engagement or no engagement with the dontcallthepolice.com or 911alternatives.com website. Note that although the websites have different names, they have identical content.

4.2 Validation of Design

Descriptives Table 2 shows demographic distributions for the overall sample and the subdivisions of the *Control*, *Government*, and *DCTP* experimental conditions. Respondents' demographics are consistent across these groups—except for less than high school, there are no significant differences ($p > 0.1$) by age, race, gender, political affiliation, marital status, or baseline value on our index of policing demand. This indicates that the randomization led to balanced characteristics across treatment arms.

Our sample is 60% White. Less than half of the sample is male, and the average age of respondents is 47. Respondents' education levels mostly exceed high school, with a modest fraction holding graduate degrees. A majority are Democrats, and less than a fifth have no party affiliation. Over half of the sample is not single. Income levels are mixed, with a small portion in the high-income bracket. We do not find significant differences along these demographic characteristics in the baseline police preferences index, as further confirmed by the similar distributions of pretreatment demand for police services across groups.

[9] We compute the z-score by subtracting the control group's mean and dividing by its standard deviation.

Moreover, we show in Table A.1 that the Prolific sample closely mirrors the U.S. population in several key demographics, including gender distribution, educational attainment for those with some college, high-income levels, and marital status. However, notable differences exist: the Prolific sample is slightly older, has a higher proportion of Black and other racial groups, and fewer Hispanic respondents. Additionally, the sample is more educated, with more individuals holding graduate degrees, and it leans more Democratic in political affiliation while having fewer respondents with no party affiliation. These differences should be considered when interpreting the survey results. To ensure accurate interpretation, we will present the results disaggregated by group in subsequent sections, as some groups may not be fully representative in our main analysis.

Time to Watch Video and Complete Survey Figure A.10 presents the cumulative distribution functions (CDFs) for the time participants spent watching the informational video and completing the survey, broken down by treatment arm. The survey design ensured full engagement: Respondents were required to have audio enabled and could not proceed until the entire video had played. Participants also had to actively select responses for each question, with numerical entries mandatory where applicable. The top graph, which includes the time spent watching the video, reveals statistically significant differences across the treatment groups, with the control group taking the least time. However, these differences are minor—approximately 5 to 10 seconds—and are neither economically nor statistically significant when we compare means. The bottom graph, which tracks the time spent completing the survey, shows negligible differences across treatment arms, indicating that the varying video lengths did not meaningfully affect survey completion time.

Preliminary Evidence Figure A.11 provides initial evidence that exposure to the educational videos is associated with reduced demand for police. This is illustrated by the CDFs for police demand across the control and the two treatment groups before and after the intervention.

Pretreatment demand for police, as shown in the left panel, appears similar; this is indicated by the overlapping CDFs and insignificant Kolmogorov–Smirnov (KS) test results. In contrast, after treatment, as shown in the right panel, there is a clear divergence for the *DCTP* respondents, with the CDF shifting leftward, signaling lower postintervention demand for police among respondents. However, the differences between the *Control* treatment and the *Government* treatment are more muted. Thus, these preliminary results indicate that information provision may influence public preferences concerning police involvement.

4.3 Main Results

Demand for Police Table 3 presents our main results using equation 1 to assess the effect of the educational videos on demand for police. Columns (1) to (3) show the KLK index results. Respondents exposed to the *DCTP* video exhibit a 0.178σ ($SE = 0.0254$) decrease in overall demand for police, with a more pronounced reduction of 0.244σ ($SE = 0.0303$) for nonviolent scenarios. In contrast, the *Government* treatment does not significantly change police demand from that for the *Control* arm, where respondents received information about unemployment.

Moreover, columns (4) to (8) in Table 3 analyze respondents' likelihood of calling the police in different scenarios to determine whether the treatment effects vary by situation. The *DCTP* treatment leads to a nonsignificant 1.124 pp ($SE = 0.759$) increase in the likelihood of calling the police for "armed robbery", suggesting that respondents prioritize police intervention in high-stakes situations regardless of exposure to the *DCTP* information. Conversely, the *DCTP* treatment significantly reduces demand for police in the nonviolent scenarios: for "naked man" by 6.818 pp ($SE = 1.640$), for "suicidal ideation" by 17.01 pp ($SE = 1.535$), and for "disruptive begging" by 2.602 pp ($SE = 1.255$). The 5.490 pp ($SE = 1.186$) decrease for the "screaming woman" scenario suggests a caveat in respondents' views on the appropriateness of a police response in violent scenarios, consistent with the widespread reluctance to call the police in domestic violence cases (Iyengar, 2009). There is no strong evidence that the *Government* treatment changes demand for police relative to that of the control group.

Moreover, the p-value between the effects of *DCTP* and *Government* rejects the null hypothesis of equality for the "screaming woman" scenario and the nonviolent scenarios. These findings suggest that *DCTP* information is more effective than the *Government* information in reducing respondents' demand for police when alternative options are presented. This indicates that governments might consider naming interventions in a way that makes it clear police should not be the default option and that alternatives such as 988, 311, or 211 should be considered instead.

Preferred First Responders in Crises Table 4 investigates the impact of the information treatments on preferences for who should respond in each scenario: police, a social worker, or no one. The *DCTP* treatment significantly reduces the preference for a police response in the "screaming woman" situation by 6.61 pp ($SE = 1.71$), and nonviolent scenarios such as "naked man" by 12.0 pp ($SE = 2.20$), "suicidal ideation" by 4.75 pp ($SE = 1.74$), and "disruptive begging" by 11.3 pp ($SE = 1.92$). In contrast, there is no significant change for the "armed robbery" scenario.

Conversely, the *DCTP* treatment significantly increases the preference for a social worker response in nonviolent scenarios: "screaming woman" by 6.71 pp ($SE = 1.56$), "naked man" by 11.4 pp ($SE = 2.04$), "suicidal ideation" by 4.71 pp ($SE = 1.87$), and "disruptive begging" by 14.6 pp ($SE = 2.28$). In contrast, there is no significant change under the *Government* treatment in social worker preference for all scenarios.

Finally, the near-zero coefficients for the "no one" category across both treatments suggest that the information does not increase the desire for no response but rather leads respondents to prefer that someone other than a police officer, particularly a social worker, respond.

4.4 Does Partisanship Matter?

Much existing research finds that partisanship significantly influences attitudes toward police alternatives and reallocating police budgets (Bursztyn et al., 2023; Sances, 2023c,b,a). Political stances shape beliefs about law enforcement's role in society (Ang and Tebes, 2023) and officer behavior (Grosjean et al., 2022; Ba et al., 2023; Goncalves and Tuttle, 2024). Surveys generally show that Republicans are likelier than Democrats to support police and oppose movements such as "Defund the Police" and "Black Lives Matter" (BLM). [10] Given these findings, we might expect Republicans' demand for police to be less elastic to changes in their level of information about police alternatives. This section explores how partisanship influences our results.

Demand for Police Table 5 shows the impact of the *DCTP* and *Government* information treatments on demand for police, segmented by partisanship. The *DCTP* treatment significantly reduces demand for police across all groups, with Democrats showing a decrease of 0.199σ ($SE = 0.0366$), Republicans a decrease of 0.180σ ($SE = 0.0425$), and independents a decrease of 0.173σ ($SE = 0.0607$). This effect is even more pronounced for nonviolent scenarios, with reductions of 0.303σ ($SE = 0.0429$) for Democrats, 0.252σ ($SE = 0.0540$) for Republicans, and 0.156σ ($SE = 0.0670$) for independents.

In contrast, the *Government* treatment does not significantly change demand for police in either violent or nonviolent scenarios for any partisan group. These results indicate that the *DCTP* treatment effectively reduces demand for police, particularly in nonviolent scenarios, across all political affiliations. Interestingly, Republicans exhibit a notable decrease in demand, suggesting that when presented with alternatives, they may, similarly to Democrats, be receptive to reducing their reliance on traditional policing methods. This highlights a bipartisan openness to reconsidering police involvement in the presence of viable alternatives.[11]

Interest in dontcallthepolice.com The domain name dontcallthepolice.com might intuitively resonate more with liberals who support police reform or reduction, while it might deter conservatives who support traditional law enforcement models. To examine such a potential political divide, Table 6 investigates the effect of the information treatment on the response to the different website domain names, specifically, dontcallthepolice.com versus the (identical) 911alternatives.com, by respondent partisanship.

[10] See the 2021 PEW poll on police spending, 2021 Ipsos/USA Today on defunding the police and trust in police, and 2023 PEW poll on BLM.

[11] In Table A.8 of the appendix, we analyze the impact of information treatments on the demand for police across various scenarios by interacting the treatments with partisanship status, rather than using subsample. Our key findings show that the *DCTP* treatment significantly reduces the demand for police in nonviolent scenarios, such as those involving a naked man, suicidal ideation, and disruptive begging. Importantly, the interaction terms between the treatment and partisanship (Democrat, No Party) are generally not statistically significant and are much smaller than the main treatment effects. This suggests that the effects of the information treatments are consistent across different political affiliations.

Democrats show a notable increase in interest in the *DCTP* website following the information exposure, with an increase of 45.1 pp ($SE = 0.0310$). Republicans also demonstrate a significant rise of 42.2 pp ($SE = 0.0323$), showing substantial interest in the DCTP site once informed about it, in contrast to our initial expectations. Similarly, independents show a significant increase in interest in DCTP of 46.8 pp ($SE = 0.0435$). Conversely, interest in the 911 alternatives website diminishes across all political categories post-treatment, with the declines ranging from 42.1 to 32.0 pp and being most pronounced among Democrats. The *Government* information treatment, however, does not significantly shift interest in either site across different political affiliations, with negligible coefficient values indicating a uniform response irrespective of party affiliation. These findings reveal that the branding of dontcallthepolice.com effectively discourages respondents from viewing the police as default responders. Once individuals are informed about police alternatives, there is a bipartisan shift toward reliance on nonpolice resources in situations where substitutes exist. This underscores the role of branding in shaping perceptions and the potential for information campaigns to foster broad-based support for police alternatives.[12]

4.5 Additional Analysis

Experimenter Demand Effect The possibility of respondents' altering their answers to align with their perceived expectations of the experimenters is a concern.[13] While this could influence respondents in the *DCTP* or *Government* groups to reduce their reported likelihood of calling the police, the findings for the "armed robbery" scenario, although not statistically significant, suggest otherwise. After viewing the *DCTP* or *Government* video, respondents were *more* or *less* likely to report that they would call the police in this scenario, indicating that the scenario's perceived severity may have overridden any experimenter demand effects.[14]

Impact of Information Using Within Variation To complement Figure A.11 and ensure comparability between pre-treatment and post-treatment questions, we ran a regression in Table A.2 using a modified dependent variable that captures changes in respondents' likelihood of calling the police, without controlling for the pre-baseline index since it is now part of the dependent variable.

[12] Table A.9 of the appendix use the interaction of the treatments with partisanship status, rather than using subsample. We find that the *DCTP* treatment significantly increases interest in the dontcallthepolice.com website (Column 1) and decreases interest in the 911alternatives.com website (Column 2). Column 3 shows a reduction in the proportion of respondents who express no interest in either website under the *DCTP* treatment. When examining the interaction terms, we find that most are not statistically significant, indicating that the effect of the *DCTP* treatment on website interest does not differ meaningfully between Democrats and Republicans. This lack of significant interaction effects highlights that the *DCTP* treatment has a broadly consistent impact across political affiliations, suggesting that the influence of the treatment is not driven by partisan differences. Overall, the *DCTP* treatment effectively increases engagement with the dontcallthepolice.com website, with no substantial variation in response based on political affiliation.

[13] Recent evidence, however, suggests limited experimenter demand effects in some online surveys (de Quidt et al., 2018; Mummolo and Peterson, 2019; Haaland et al., 2023).

[14] Moreover, the "don't call the police" name implies that any experimenter demand effect would likely bias the reported likelihood of calling the police downward in that it directly discourages respondents from doing so (Haaland et al., 2023).

This variable measures the change in the likelihood of calling the policebefore and after treatment, with adjustments for baseline demand by aligning each scenario with its respective category. The results are consistent with our main analysis: the *DCTP* treatment significantly reduces the likelihood of calling the police in nonviolent scenarios, such as those involving a naked man, suicidal ideation, and disruptive begging, while slightly increasing it in a robbery scenario. The Government treatment shows no significant impact across most scenarios.

Confidence in the Likelihood of Calling the Police Our motivation for examining respondents' confidence in their reported likelihood of calling the police stems from a broader concern about the role of self-selection in decision-making. Researchers argue that conclusions drawn from average behavior in experiments, which often ignore self-selection, may not accurately reflect the biases present in real-world institutional outcomes. We follow the approach of Enke et al. (2023), who suggest that asking respondents about their confidence in their responses can capture the extent to which individuals' self-assessed decision quality correlates with their actual behavior. Hence, Table A.3 investigates the role of respondents' confidence in their reported likelihood of calling the police across various scenarios.

First, the mean confidence levels in the reference group, which received information about unemployment, show that people are more confident about their reported likelihood of involving police in violent scenarios and less confident about this likelihood for nonviolent crises. Second, we observe no significantly differential confidence for the "armed robbery" and "suicidal ideation" scenarios. Finally, the *DCTP* treatment significantly reduces respondents' confidence in their reported likelihood of calling the police for the "screaming woman" and "naked man" situations, while under the *Government* treatment, their confidence in their response increases for the "screaming woman" scenario but decreases for the "disruptive begging" scenario.

Heterogeneity Tables A.5, A.6, and A.7 present the heterogeneity in our findings across various respondent characteristics and indices in Appendix E. For the nonviolent scenarios, the trend shows a consistent decrease in demand for police, with female, White, and older respondents displaying the largest declines relative to the effects in the main sample. For violent scenarios, the patterns are mixed, with White and Black respondents notably reducing their demand for police after exposure to the *DCTP* information, diverging from the main sample's response, although this result is only marginally statistically significant. In contrast, Hispanic respondents exposed to the *DCTP* information are 0.231σ likelier to call the police for the violent scenarios; although statistically nonsignificant, these results are in line with the finding of (Jácome, 2022). Overall, the findings align with the main sample's tendency toward reduced police demand for the nonviolent situations.

Baseline Demand In Table A.4, we investigate the influence of the *DCTP* and *Government* treatments on the propensity to call the police, segmenting the results by respondents' baseline reliance on police services. Respondents are categorized into low-, moderate-, and high-reliance groups based on their position within the quartiles of the baseline police demand index.

In the "armed robbery" scenario, the *DCTP* treatment increases the likelihood of low-propensity callers contacting the police more than that of moderate- and high-propensity callers, though not significantly. The *Government* treatment's impact is minimal across all groups. Moderate- and high-propensity groups show heightened responsiveness to the treatments for nonviolent crises. The *DCTP* treatment significantly decreases the likelihood of police involvement in the "screaming woman," "naked man," "suicidal ideation," and "disruptive begging" scenarios. The *Government* treatment similarly affects demand for police, notably in the "disruptive begging" scenarios for low propensity groups. Overall, the *DCTP* treatment has a more substantial impact, especially in reducing police contact for nonviolent situations among groups with moderate and high baseline propensity to call the police.

5 Impact on Demand for the 988 Suicide & Crisis Lifeline

This section examines the lasting impact of our intervention on respondents' recall of the availability of the 988 Suicide & Crisis Lifeline. Launched on July 16, 2022, and offering free and confidential support 24/7, the lifeline replaces the 10-digit National Suicide Prevention Lifeline number with the more accessible 988 code. The effectiveness of this resource depends on public awareness of it, and uptake has so far been modest; a Pew study found that only 13% of the public is aware of 988 (Pew, 2023). This section explores how our educational intervention affected recall of the availability of the 988 lifeline.

Incentivized Follow-Up Survey We assess the persistent effects of our intervention on awareness of the 988 helpline for emotional crises. This survey evaluated respondents' recall of key messages from our three-minute educational videos shown a week earlier. We compared the response of informed groups with that of their uninformed counterparts for the "suicidal ideation" and "armed robbery" scenarios. Participants could earn $0.10 for correctly identifying the relevant government resources. The survey included a question on which emergency hotline to call, allowing only 20 seconds to respond, simulating the response time in a real-life crisis. Our objective was to see whether our information treatment could foster sustained awareness of the availability of alternatives such as the 988 hotline.

Results In the follow-up survey, over 85% (2,342 respondents) of the initial sample participated. Figure 3 shows that the *DCTP* treatment significantly boosts the likelihood of dialing 988 in the "suicidal ideation" scenario, doubling the rate from 9% to 17%. The decrease in likelihood of dialing 911 is more pronounced under the *DCTP* treatment than under the *Government* treatment

(21 vs. 16 pp, both $p < 0.01$). This suggests that provision of specific alternative numbers to call, along with an explicit prompt to consider alternatives, leads to a sharper decline in 911 usage. In contrast, respondents overwhelmingly reported that they would dial 911 in the "armed robbery" scenario, and virtually none of them said that they would dial 988, regardless of their knowledge of alternatives, as shown in Figure 4.

These findings highlight the importance of how information is conveyed, showing that educating the public about specialized crisis services such as 988 can lead to a behavioral shift toward reliance on these services in mental health crises while ensuring that police remain the primary responders for violent crimes such as armed robbery.

6 Stakeholders' Response to Our Findings: A Field Experiment

While our survey experiment findings show a bipartisan turn toward police alternatives and the website dontcallthepolice.com in response to our information treatment, policymakers and stakeholders involved in discussions related to policing, such as law enforcement, may show support or resistance to their implementation. To explore the policy implications and gauge receptiveness among key stakeholders, we conducted a large-scale field experiment. Despite the potential of our insights to inform policy, decision-makers such as local officials and law enforcement might be reluctant to embrace them due to political considerations (Hjort et al., 2021; Goerger et al., 2023). We tested this hypothesis by evaluating stakeholders' interest based on the email subject line, where we included "911alternatives.com" in the subject line in one treatment arm and "dontcallthepolice.com" in another, with both sites linking to the same content. The next section provides details on our design.

6.1 Experimental Design

Setup Our large-scale field experiment, conducted from February to March 2024 and preregistered with the AEA registry (AEARCTR-0013061), targeted key stakeholders influencing policies on access to police alternatives. Invitations were sent via Qualtrics from the Duke Economic Analytics Laboratory email (informing.policy.research@duke.edu) to avoid priming effects.[15] The email summarized our findings, informing recipients that informing the public about the resources available on dontcallthepolice.com reduced the likelihood of calling the police for nonviolent encounters.

Recipients could request the report and provide feedback by clicking a link or replying, "Yes, send me the report so I can learn more and provide feedback." No reply after four attempts, spaced eight days apart, was recorded as a "no" response. Respondents who requested more information

[15] The principal investigator's Black-sounding name could impact the response rate (Jowell and Prescott-Clarke, 1970; Bertrand and Mullainathan, 2004; Kline et al., 2022), especially among providers of local public services in the U.S. (Giulietti et al., 2017).

received an email with a brief report, illustrated in Figure 5, summarizing the key findings of a previous version of the paper by Ba et al. (2024). This report replicates our core results, highlighting the bipartisan shift toward reliance on police alternatives in nonviolent situations under our information treatment.

Counties were the randomization unit in our experimental design, allocated to one of two conditions: *911 alternatives* or *DCTP*. Both email variants included identical content and a video link about Don't Call the Police, but the *DCTP* condition used specific language from the Don't Call the Police website. The subject lines of the emails varied as follows:

- **Subject line for "911 alternatives"**: "New research: bipartisan support for police alternatives - receive information about the findings and 911alternatives.com"
- **Subject line for "DCTP"**: "New research: bipartisan support for police alternatives - receive information about the findings and dontcallthepolice.com"

Data Source and Sample Selection We compiled our contact list from various expert groups including law enforcement, DOJ grantees, and local officials using three main sources. First, we acquired law enforcement and correctional facility contacts from the National Public Safety Information Bureau. Next, we sourced data on DOJ grantees from public DOJ records. Finally, we gathered local official contacts from an online resource, keeping only those with valid emails and counties identifiable via zip codes.

The list was categorized into groups such as "police," "sheriff and detention facilities," "other law enforcement," "local officials," and "DOJ grantees." We supplement these contacts with demographic and political data from the ACS 2017–2021 and MIT Election Data and Science Lab, along with law enforcement metrics from LEOKA 2022 and crime statistics from the FBI UCR 2022. We also used data on fatalities caused by law enforcement from Mapping Police Violence, excluding counties with insufficient data or fewer than five contacts for privacy. Initially, we reached out to 48,597 email addresses. After removing invalid contacts, our final sample included 45,163 valid addresses. Our main analysis focuses on the 11,623 recipients who opened the email, spanning 2,368 counties.

Empirical Specification Our main specification analyzes the impact of the *DCTP* subject line relative to *911 alternatives* subject line on the response rate using the following specification:

$$Send_i = \beta_0 + \beta_D DCTP_i + \beta_P Police_i + \beta_{DP} Police_i \cdot DCTP_i + X_i'\gamma + \epsilon_i \tag{2}$$

Our main outcome $Send_i$ equals one if the respondent wanted to receive information about the study and zero otherwise. The variable $DCTP_i$ is a binary variable that equals one if the respondent received the *DCTP* treatment and zero otherwise. The variable $Police_i$ equals one if the respondent is in a police agency and zero otherwise. In addition, X_i controls for county covariates, state fixed effects, and respondent type. We clustered the standard errors at the county level, i.e., the level of randomization. The main variable of interest is the interaction between $Police_i$ and $DCTP_i$, with coefficient β_{DP} capturing whether police departments are more or less likely to request information on police alternatives when exposed to the *DCTP* subject line. Note that we also report the results without interaction as a benchmark for equation 2 to provide a clearer understanding of the main effects of the treatment and the police affiliation independently.

Geographical Distibution and Balance Table Figure 6 illustrates the geographic spread of email recipients in our field experiment, delineated by the treatment status assigned at random to their counties. The visualization underscores a broad distribution of participants across the United States, with denser populations in more urbanized areas reflecting a higher number of recipients.

Table 7 presents summary statistics by treatment arm, detailing the covariates of respondents' counties. This table shows that the demographic and political compositions of the counties is consistent across treatment arms, with approximately 11% of recipients being Black, 12–14% Hispanic, and 7–8% from other racial groups. Respondents' political affiliations are uniform, with Republicans accounting for 45–47% in each arm. Most respondents are in urban areas, ranging from 83% to 84%. Panel B, which focuses on respondents who opened the email, similarly reveals no significant differences across the same set of variables. Moreover, respondents in both panels have similar characteristics. Overall, the findings suggest that the treatment and control groups are balanced. The F-test for the equality of covariates between the two arms confirms that groups assigned to 911alternatives.com versus dontcallthepolice.com are not significantly different from each other.

6.2 Results

Main Table 8 shows the impact of the *DCTP* subject line on responding and willingness to receive information about police alternatives. Among email openers, 5% in the reference group wanted more information, and 6% replied. The *DCTP* subject line has a negligible effect on nonpolice stakeholders. However, police respondents are 2 pp less likely to request additional information ($p < 0.01$). The interaction between *DCTP* and police status is positive, at 3.12 pp ($p < 0.01$), indicating increased engagement among police respondents. Thus, the *DCTP* subject line modestly impacts nonpolice stakeholders but significantly boosts engagement among police respondents, showing a divergent reaction.

These findings reveal important implications for introducing 911 alternatives and the differing responses of stakeholders, particularly the police. Nonpolice stakeholders show no difference in engagement between the *911 alternatives* and *DCTP* subject lines, indicating that the framing does not affect their willingness to engage. In contrast, police respondents are indifferent to *911 al-*

ternatives but become more engaged with the *DCTP* framing. Considering the interview evidence presented in the next section, we surmise that this differential engagement is attributable to police resistance to models of alternative response that would challenge their role: The increased engagement highlights the police's resistance to models of alternative response that vested interest in countering narratives around alternative emergency responses. These findings reveal important implications for introducing 911 alternatives and the differing responses of stakeholders, particularly the police. Nonpolice stakeholders show no difference in engagement between the *911 alternatives* and *DCTP* subject lines, indicating that the framing does not affect their willingness to engage. In contrast, police respondents are indifferent to *911 alternatives* but become more engaged with the *DCTP* framing. Considering the interview evidence presented in the next section, we surmise that this differential engagement is attributable to police resistance to particular framings of alternative response models that would symbolically or substantively challenge their roles.

Heterogeneity Analysis Figure 7 presents an analysis of the demand for information on police alternatives, focusing on the impact of police status and the *DCTP* subject line across various county characteristics. Police officers generally show lower engagement in counties with high search intensity for "Defund the Police," a higher number of police officers per capita, higher crime and unemployment rates, and a lower share of Republicans. Conversely, the *DCTP* subject line significantly boosts engagement in these counties, especially where police feel more strain due to higher unemployment rates and majority-Democrat populations. The *911 alternatives* subject line tends to reduce engagement. This suggests that subject line responsiveness varies with the local sociopolitical context, with the *DCTP* subject line being more effective in areas with heightened sociopolitical pressures.

Survey Results Table A.12 evaluates the relationship between the *DCTP* subject line and respondents' perceptions of police alternatives and willingness to be interviewed. Assignment to *DCTP* or police status alone does not significantly change views on police alternatives. However, *DCTP* assignment increases interview willingness by 17 pp, and police status boosts it by 29 pp. Conversely, the interaction of *DCTP* treatment with police status decreases interview willingness by 32 pp. These results suggest that while the *DCTP* subject line encourages engagement, its combination with police identification deters interview participation, likely because of hesitation rather than a rejection of police alternatives.

Robustness Our main sample focused on respondents who opened the email. This section explores factors affecting the likelihood of opening the mail, with results in Table A.11. The dependent variable is one if the respondent opened the email and zero otherwise. Approximately a quarter of the reference group opened the email. We find that the *DCTP* subject line has a positive but statistically insignificant effect on open rates. Police respondents are significantly likelier to open the email, with coefficients ranging from 2.7 to 3.5 pp ($p < 0.01$). The interaction between *DCTP* and police status is positive but not significant. Most covariates, such as race, unemployment rate, urban status, and crime statistics, show no significant effects, except urban status and share of Republicans, which have positive and negative significant effects, respectively. These findings imply that while the *DCTP* subject line alone does not significantly increase engagement, targeting police respondents enhances email open rates.

Table A.13 presents a robustness check of the main results from Table 8, showing the impact of the *DCTP* subject line without conditioning on whether recipients opened the email. The results are consistent with the main findings: Police respondents are significantly more engaged with the *DCTP* framing, with the coefficient on the interaction term being 0.95 to 0.97 pp. This effect size is substantial when benchmarked against the mean engagement rate of nonpolice stakeholders in the *911 alternatives* group, which is only 1%. The results highlight a nearly 95% increase over this baseline, indicating that police are notably more responsive to the *DCTP* framing, reinforcing our intuition about potential resistance or strategic engagement on the part of law enforcement in discussions around police alternatives.

7 Qualitative Interviews with Stakeholders

7.1 Overview

How do key stakeholders perceive police alternatives? This section uses in-depth, semistructured interviews to complement our survey and field experiments (Finkelstein et al., 2021; Bergman et al., 2024).[16] The use of interviews has two key advantages in this context. First, interviews provide insights into unobservable factors, such as perceptions, motivations, and thought processes, which are not evident when participants interact with materials independently. While we aimed to minimize selection into our interview sample by using centralized contact information from the Duke Economic Analytics Laboratory, the goal of our interviews nonetheless was to uncover new mechanisms, logics, and processes that may not be anticipated (Boyd and DeLuca, 2017; Small, 2009). Second, the interviews, conducted in the study's final stage, allowed us to probe comparative perceptions of both the DCTP and 911 alternatives framing.

After receiving the study's summary report, respondents were invited to provide feedback through interviews with the Duke Economic Analytics Laboratory. Of the 150 interested, 60 participated. Interviews were conducted by four research assistants and averaged 47 minutes with a range of 17 minutes to over two hours. While we interviewed each of the respondents who opted in, we are also confident that we reached saturation—the point at which no new information or themes are

[16] The use of qualitative tools to complement quantitative methods in economics is growing, providing better insights into the context, implementation, and interpretation of policies in health economics (Alsan et al., 2019), public finance (Bustos et al., 2022), crime (Bruhn. et al., 2024) and development economics (Jayachandran et al., 2023).

observed in the data, a conceptual yardstick for when a "sufficient" number of interviews have been completed (Guest et al., 2006).[17]

The interviews covered participants' motivations, associations with *DCTP* and *911 alternatives*, and reactions to our findings on bipartisan responsiveness to information about police alternatives. Conducted online and transcribed via Zoom, the transcripts were cleaned and coded by a principal investigator and research assistants to identify emergent and unexpected patterns (Glaser and Strauss, 1967; Timmermans and Tavory, 2012). Intercoder reliability was established for the structured questions. Appendix B provides further details on sampling, recruitment, and analysis. In the subsections below, we first examine stakeholders' motivations for participating in the interviews and then evaluate their perceptions of police alternatives.

7.2 Why Participate in an Interview?

We identify the reasons that motivated respondents to participate to our in-depth interviews.

***Reason 1: Learn About the Study Results.* —** Respondents participated in interviews driven by either open curiosity or opposition, reflecting varying perceptions of the study's legitimacy. They viewed the interviews as opportunities to provide feedback, motivated by the perceived validity or invalidity of the research. Participants often highlighted their desire to learn, seeing policing as an evolving practice and valuing academic research for establishing best practices. A department chief noted, "our law enforcement profession is always changing and evolving... I'm always trying to stay up on all the latest trends and what best practices are" (Interview, 2024 April 25).

***Reason 2: Inform the Study.* —** Participants did not just seek to learn; they wanted to inform. Specifically, participants highlighted their expertise on policing and public safety—obtained, for example, directly on the job or as a policymaker, an organizational partner, or an elected official—and wanted to contribute to the study's findings. A stakeholder from the DOJ grantee group described how this study "lined up with a lot of the work that we do in our state" and so "thought it would be a good opportunity to hopefully learn from you all, and also help inform some of the work that you're doing" (Interview, 2024 May 10). Among those with the motivation to inform the study were also stakeholders seeking to publicize "first-of-their-kind" programs within their own jurisdictions, such as various corresponder models, crisis intervention programs, and counselor programs on university campuses. Several participants also highlighted their own academic pursuits, ranging from current teachers and master's students to their past undergraduate studies, as a rationale for participating in this study.

***Reason 3: Police Reservations about DCTP.* —** Police stakeholders in the *DCTP* condition expressed concerns about study bias and unqualified participants. For instance, one participant said, "I came to this decision to provide unbiased feedback. I wasn't sure how many other participants

[17] For additional context, 60 interviews is approximately the median number of interviews conducted in studies published across several American Sociological Association–sponsored journals (Deterding and Waters, 2021). Boyd and DeLuca (2017) characterize studies with 50 or more interviews per fielding period as large-N interview studies.

were going to be involved and pretty much transparent" (Interview, 2024 April 12). Another, with expertise in mental health counseling and law enforcement, explained, "Anytime that I can participate in a study where we can lend my years of expertise into any type of data collection process, I'm gonna participate" (Interview, 2024 May 9). These participants felt their engagement would ensure at least one unbiased perspective was included, a sentiment not expressed by those in the *911 alternatives* condition. These concerns over participant quality, which were not expressed among police stakeholders assigned to the *911 alternatives* condition, are particularly salient given the self-selection of those willing to engage with academic research into interview participation (Davies et al., 2021).

7.3 Perceptions of Police Alternatives

Immediate Reactions Participants' perceptions of police alternatives were gauged through two key exercises. First, they identified up to three words or phrases associated with "DCTP" and three with "911 alternatives," beginning with their assigned condition. Figure 8 presents word clouds of their responses sized by frequency and colored by stakeholder.[18] Stakeholders across groups identified negative words such "distrust" and "fear" more frequently in response to "DCTP" than to "911 alternatives," the associations to which were dominated by "mental health." In response to DCTP specifically, however, the words that only police stakeholders identified (e.g., "concerning," "disconnect," "embarassment," "don't," and others colored in red) generally appear more negative than those identified by nonpolice stakeholders only, which were more mixed in sentiment (e.g., "people of color," "safety", "diffused fear", "doing what's right", and others colored in black).

Coding each word in the context of their explanations confirmed these patterns in Table 9: Police stakeholders associated "DCTP" with more skeptical terms (43%) than supportive ones (63%), whereas the opposite was the case for nonpolice stakeholders (64% supportive vs. 42% skeptical). For "911 alternatives," stakeholders across groups expressed strong support (95% supportive vs. 7% skeptical for police and 94% vs. 11% for nonpolice).

Explanations of Perceptions We analyzed explanations for these words using a grounded theory approach (Charmaz, 2006; Glaser and Strauss, 1967) (see Table A.15 for code definitions and frequencies). Stakeholders associated police alternatives with specific intervention models, best-trained responders, and budgetary efficiency. By raising minority groups more frequently, however, the stakeholders also understood "DCTP" more often through a racialized lens. Specifically, police stakeholders (28% in relation to "DCTP" vs. 2% in relation to "911 alternatives") highlighted trust,

[18]To construct the word clouds, we conservatively standardized the 316 words or phrases identified into 271 by reducing synonyms to their root words. For instance, responses such as "community leaders" and "community policing" were reduced to "community," and "mental health professional" and "mental health services" to "mental health." Our goal was to preserve the words that respondents identified.

fear, and other issues tied to racialized communities more often than nonpolice stakeholders (14% in relation to "DCTP" vs. 2% in relation to "911 alternatives").

Rationales for Support Participants approved of the availability of 911 alternatives for several reasons:

1. *Reducing Police Overload:* Many believed 911 alternatives would alleviate police workload by handling nonemergency calls, allowing officers to focus on more critical tasks and improving efficiency.[19] One stakeholder explained, "If a police officer is not spending 90 minutes taking a stolen auto or working a burglary, they can apply their attention and their energies in the areas that are more important" (Interview, 2024 April 18). The interviewee clarified that the outcome in stolen auto cases is likely the same regardless of whether a rookie cop, veteran officer, or even a private officer files a report.

2. *Partitioning Expertise:* Stakeholders valued labor specialization, arguing that police should focus on criminal activities while trained professionals should handle other issues. One stakeholder explained how attending trainings does not equate to having professional expertise: "We can go through a 40-hour class and learn alternative measures to be able to talk to somebody that's in crisis, but that doesn't make us a mental health professional—and so we need to find alternative ways to respond to those" (Interview, 2024 April 19).

3. *Avoiding Escalation:* Interviewees noted that police presence could exacerbate situations, such as mental health crises, and believed the availability of alternatives would reduce such risks. Several stakeholders raised the scenario of suicide-by-cop and suggested that nonpolice responses would reduce the likelihood of lethal outcomes.

Ambiguity and Support The broad definition of "911 alternatives" allowed stakeholders to envision complementary programs. For instance, stakeholders considered the following programs to be 911 alternatives: major retailers deputizing asset protection officers for shoplifting enforcement (Interview, 2024 April 26), hospitals hiring their own law enforcement for involuntarily committed patients (Interview, 2024 May 6), and drivers coordinating with private companies to document automobile accidents (Interview, 2024 April 26). Multiple participants also referred to community policing as a 911 alternative (e.g., Interivew, 2024 May 08).[20] The variety of programs that came to mind for participants is an important element in explaining their widespread support for 911 alternatives.

[19] The potential for 911 alternatives reducing police overload aligns with historical research documenting the role of 911, call centers, and related communication technologies in expanding policing's scope (Gillooly and Thacher, 2024).

[20] Referring to community policing as a 911 alternative aligns with research documenting how police support community initiatives to resist broader institutional reforms (Cheng, 2022).

Skepticism Toward DCTP Participants expressed skepticism toward the "DCTP" framing that they attributed to negative connotations and practical concerns. They associated "DCTP" with defunding the police: "In general, 'don't call the police' sounds a lot to me like 'defund the police,' and a belief that the police are bad or have bad intentions" (Interview, 2024 April 30). Participants warned that the "DCTP" framing would "demonize" or "villify" the police (Interview, 2024 May 13). They believed that the DCTP campaign would confuse the public, leading to inappropriate or inadequate responses in emergency situations. Several warned against putting community members in the decision-making role of whether and whom to call when they lack expertise on who may be the appropriate responder: "[DCTP] puts the wrong decision-makers with insufficient information in the position of making decisions that they're not prepared to make" (Interview, 2024 April 17). Many preferred improving the training of 911 operators or reframing "DCTP" as a collaborative initiative with the police.

Summary In summary, participants were generally supportive of the "911 alternatives" framing due to the potential of nonpolice alternatives to reduce police overload, partition expertise, and avoid escalation. In contrast, they were skeptical of the "DCTP" framing, associating it with impracticalities and negative connotations. Police stakeholders were particularly skeptical, which aligns with their expression of concern over the study's potential bias from unqualified participants as an additional motivation for participating. The qualitative findings highlight practical obstacles expressed by police in particular, ranging from symbolic framing to substantive roles, in the policy implementation of police alternatives.

8 Conclusion

Despite the heightened momentum of campaigns to institutionalize police alternatives after George Floyd's death in 2020 (Kaba et al., 2021; Akbar, 2020; Phelps, 2024) and the potential cost-effectiveness of shifting certain tasks to social workers, the scale of policing has not been significantly reduced. This study investigates whether the limited adoption of police alternatives is due to a lack of public demand, insufficient information, or resistance from key policymakers. First, we evaluate the impact of information treatments on the likelihood of calling the police in various scenarios, revealing that exposure to police alternatives—particularly through the DCTP website—significantly reduces the demand for police in nonviolent situations while maintaining or increasing reliance on police in violent cases, with consistent effects across political lines. Our study also highlights the lasting impact of our educational intervention, as respondents informed about alternatives were likelier to recall the 988 helpline for suicidal crises a week later. However, our field experiment and interviews uncovered a key barrier: resistance from police as critical policymaking stakeholders, who, despite the public shift toward a greater likelihood of relying on nonpolice responders in nonviolent crises under our information treatment, remain skeptical and may resist the implementation of alternatives. Specifically, we note that the DCTP framing—which is most effective in shifting preferences among respondents in our survey experiment—also inspires the highest degree of resistance from police in our field experiment—despite the fact that they are generally supportive of police alternatives if framed differently—underscoring the need to carefully consider the language and framing used to introduce police alternatives for successful policy adoption. Our results have several salient policy implications.

First, our research stands out for its proactive approach, in that we intervene *before* 911 calls are made: This represents a significant departure from most of the related literature, which largely focuses on post-911 call interventions (Ang et al., 2024; Goncalves et al., 2023). By both explicitly discouraging reflexive reliance on police and informing individuals about viable alternatives to police intervention, the study influences decision-making at a critical juncture, potentially reshaping public reliance on law enforcement.

Second, the consistency of the impact of our information treatment on demand for police across party affiliations presents an opportunity for policymakers to collaborate across party lines in advancing comprehensive crisis response strategies. Interestingly, despite the political divide on police reform and funding (Bursztyn et al., 2023; Sances, 2023c,b,a), our findings suggest a surprisingly uniform perception across party lines of the website dontcallthepolice.com. This may indicate a broader, shared understanding of the need for context-appropriate crisis response strategies. It underscores the potential for bipartisan collaboration in developing comprehensive policies that respect individual preferences and societal needs, even in a politically charged context.

Finally, these findings suggest that while the public would be amenable to reducing police involvement in nonviolent crises, resistance from law enforcement could hinder the success of alternatives. Policymakers need to carefully frame police alternatives as complementary to traditional policing and actively engage law enforcement to address their concerns. Without this buy-in, such initiatives could face resistance, limiting their effectiveness. This underscores the importance of considering how powerful stakeholders, such as law enforcement, influence the adoption of evidence-based policies.

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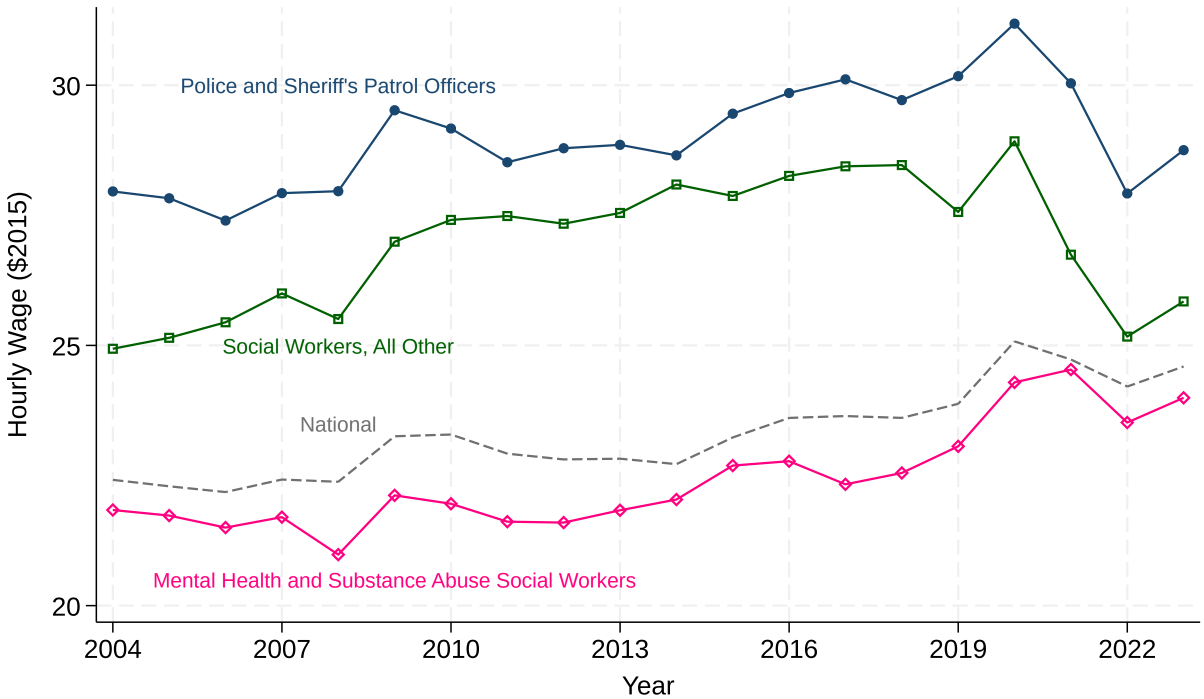
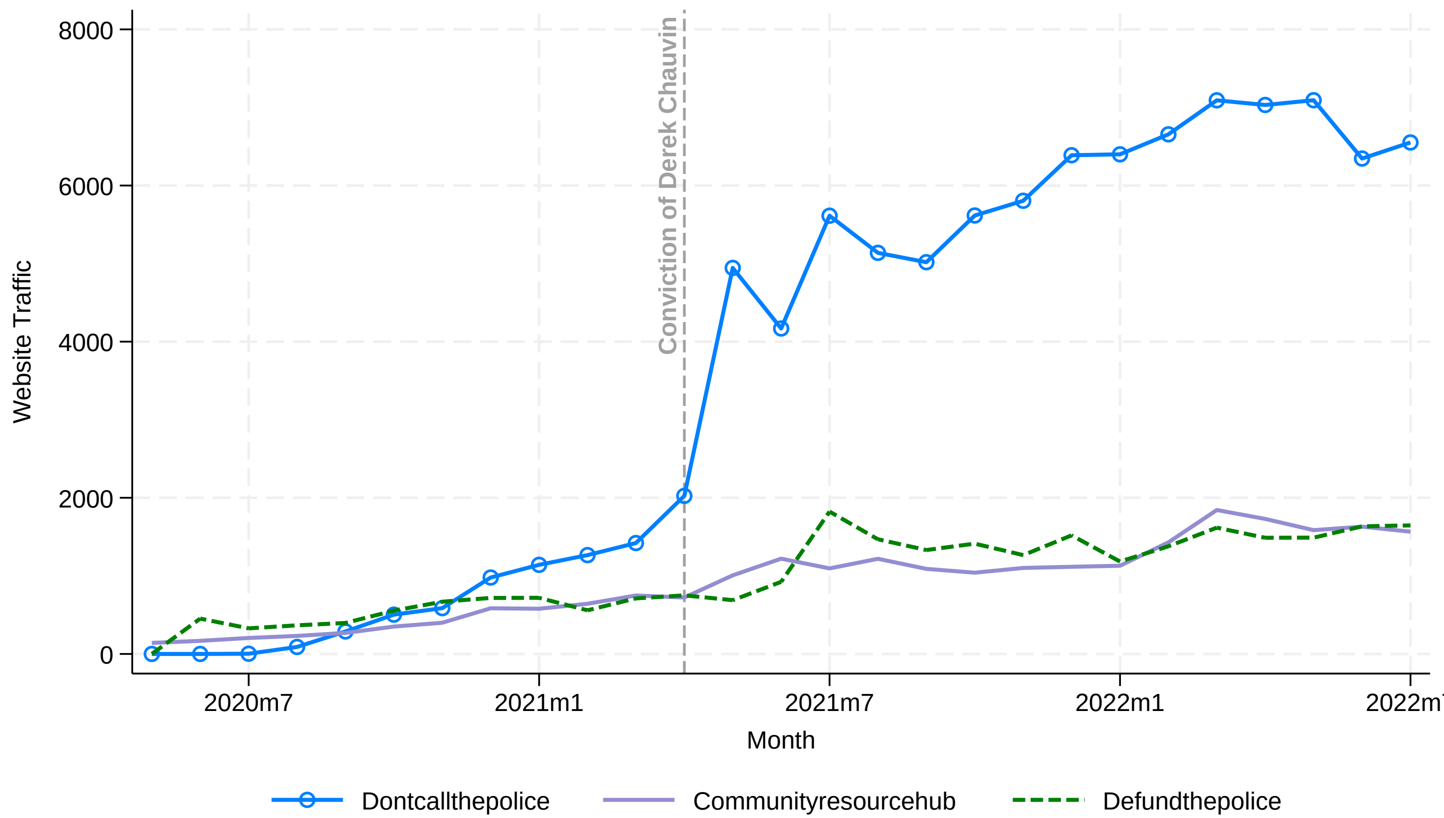
Figure 1: Average Hourly Wages of Police Officers and Their Alternatives



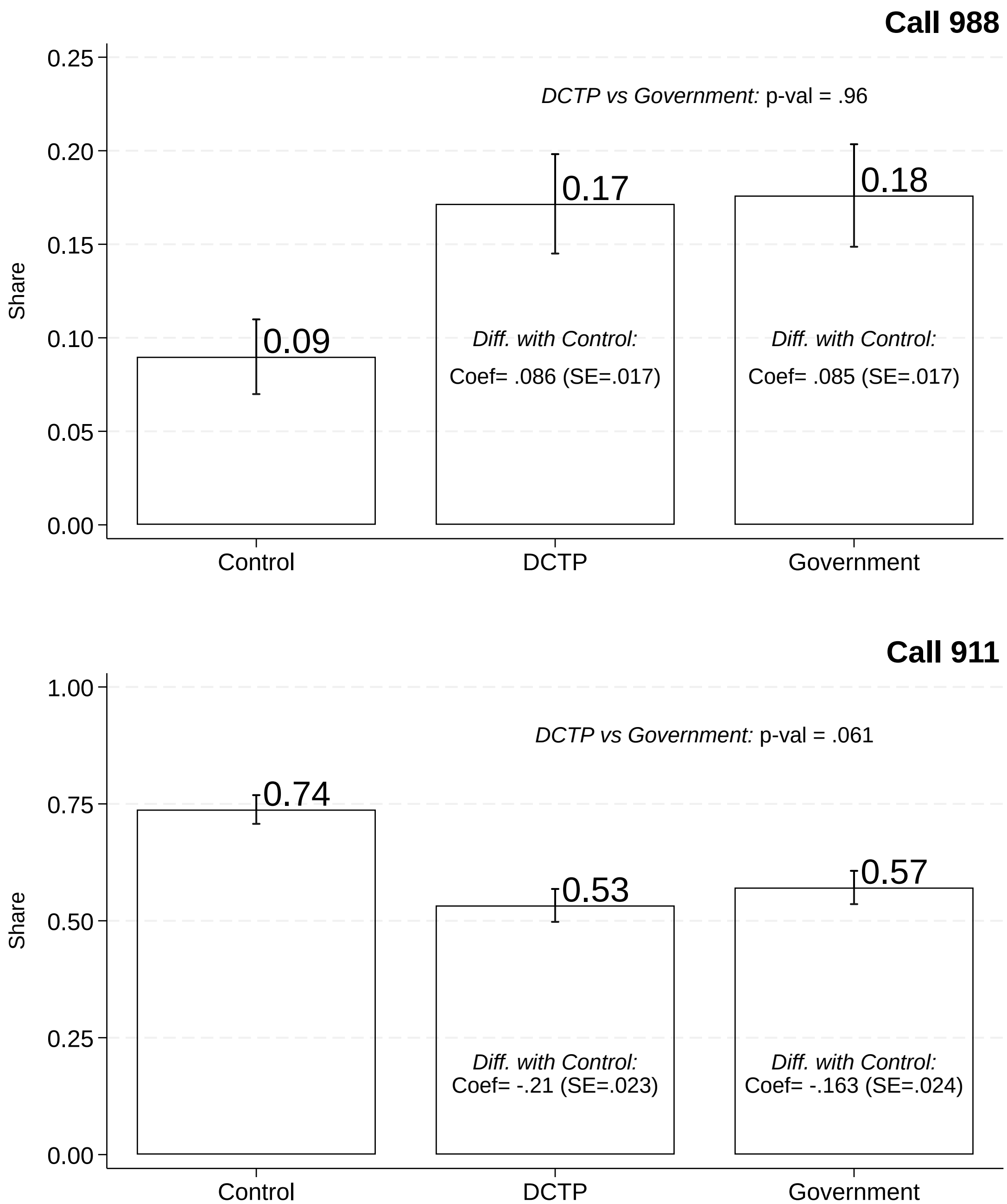
Notes: This figure displays hourly wage trends by occupation from 2004 to 2023. It compares wages for police and sheriff patrol officers, mental health and substance abuse social workers, and other social workers against the national average. All wages are adjusted to 2015 dollars.

Figure 2: Website Traffic over Time



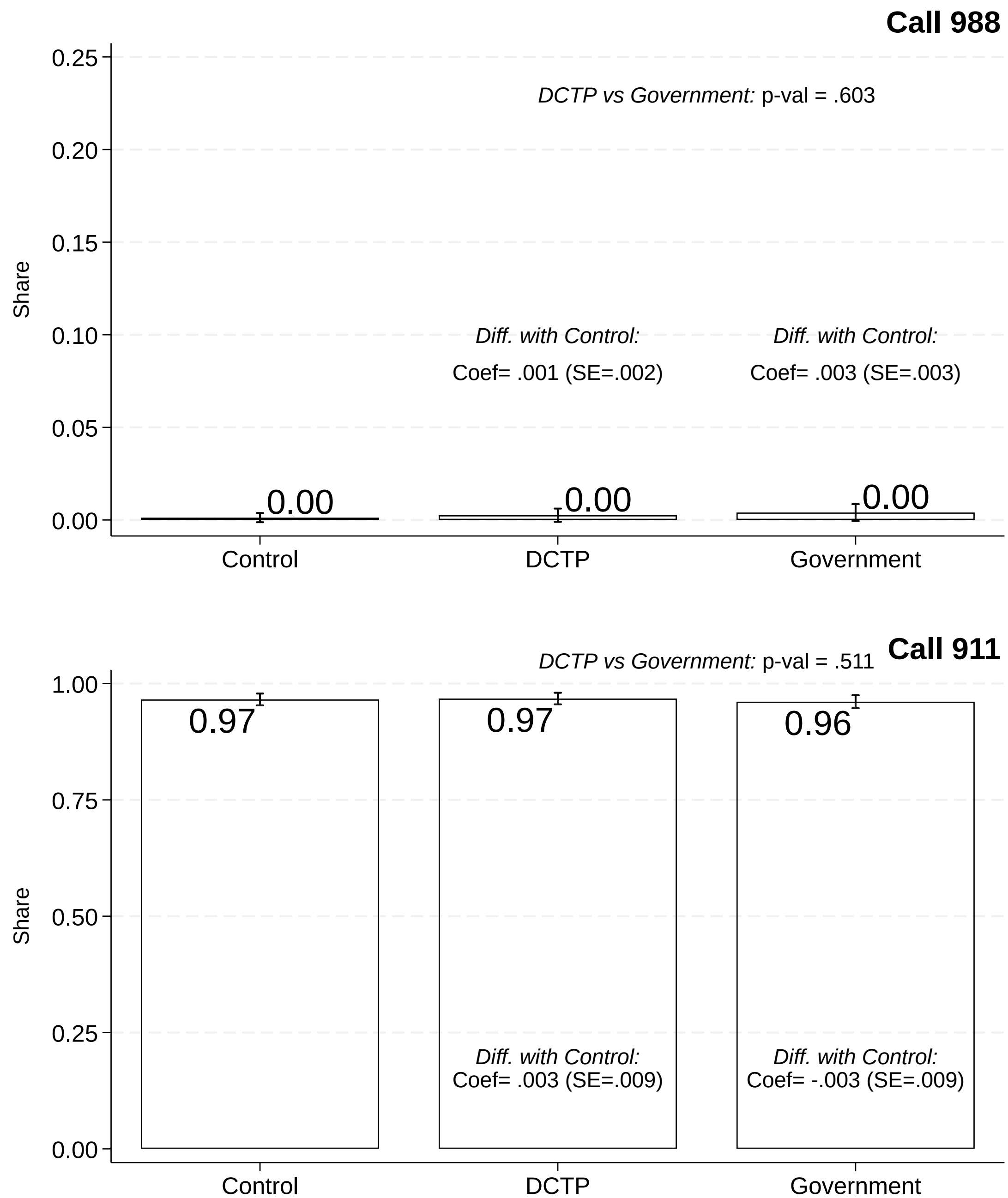
Notes: This figure presents website traffic trends for three different resources related to police and community services over time: (1) dontcallthepolice.com, a website offering alternatives to law enforcement to call in crisis situations; (2) communityresourcehub.com, a site providing a range of community support resources; and (3) defundthepolice.com, a site associated with the movement to reallocate police funding to other community services. The vertical line corresponds to the month of the conviction of Derek Chauvin, the officer who murdered George Floyd.

Figure 3: Impact of Information on Likelihood of Recurrence to Emergency Response Resources for the "Suicidal Ideation" Scenario



Notes: This figure shows the share of respondents who reported that they would dial 988 or 911 services in the "suicidal ideation" scenario, differentiated by treatment arm (*DCTP*, *Government*, and *Police Alternatives*), in the follow-up survey administered one week after the launch of the baseline survey. We present the differences between the treatment and control responses using Equation 1 with robust standard errors. Additionally, we report the p-values for the differences between the coefficients of *DCTP* and *Government*. The mean of each treatment arm and the 95% confidence intervals are also reported.

Figure 4: Impact of Information on Likelihood of Recurrence to Emergency Response Resources for the "Armed Robbery" Scenario



Notes: This figure shows the share of respondents who reported that they would dial 988 or 911 in the "armed robbery" scenario, differentiated by treatment arm (*DCTP*, *Government*, and *Police Alternatives*), in the follow-up survey administered one week after the launch of the baseline survey. We present the differences between the treatment and control responses using Equation 1 with robust standard errors. Additionally, we report the p-values for the differences between the coefficients of *DCTP* and *Government*. The mean of each treatment arm and the 95% confidence intervals are also reported.

Figure 5: Educational Summary of Research Showing Bipartisan Openness to Police Alternatives

Understanding the Demand for Police Alternatives

Duke Economic Analytics Laboratory

Short educational videos on police alternatives can shift public reliance away from police in nonviolent contexts and potentially enable more effective police responses to violent incidents.

Duke TRINITY COLLEGE OF ARTS AND SCIENCES | DEPARTMENT of ECONOMICS

Summary

In an online experiment, we surveyed over 2000 U.S. residents about their willingness to rely on the police for several violent and non-violent scenarios. After being introduced to community-based police alternatives (DontCallthePolice.com) through a short educational video, participants rated their likelihood to call the police for the given scenarios on a 1-100 scale.

We find that exposure to the DCTP video creates variability in participants' likelihood to call the police, conditional on if the scenario described is violent or non-violent in nature. Notably, we observe a decrease ranging from **3.97 to 12.12** percentage points in likelihood to call police for the various nonviolent scenarios, and an increase by **2.59** percentage points in the violent armed robbery scenario. This result remains stable across the political spectrum, indicating a bipartisan support for police alternatives.

Contexts and Interventions

In the experiment, participants were asked to watch a short video providing information regarding community-based police alternatives. We split the participants into a control group and a treatment group as described below.

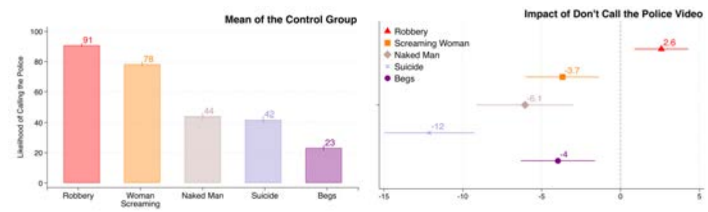
Control group	Only received information about the existence of governmental police alternatives (Government hotlines: 988, 311 and 211): here
Don't Call The Police (DCTP) group	Provided control group information and additional information about a rich set of community-based alternatives to the police: here

We then assessed participants' propensity to call the police in five scenarios, four of which mirrored actual incidents in the Mapping Police Violence (MPV) database that resulted in civilian fatalities, and an additional fifth hypothetical scenario.

The scenarios were:

1. **Robbery:** Two men attempt an armed robbery of a jewelry store.
2. **Woman Screaming:** A woman screams and cries while a man makes threats.
3. **Naked Man:** A naked man walks down the street near a music festival.
4. **Suicide:** A neighbor seems really upset and says they are thinking about "ending things."
5. **Begging:** A man begs in front of a restaurant and curses at people who ignore him.

Figure 1



Note: These figures present the impact of information about DCTP on the demand for police in each scenario. The dependent variable indicates the likelihood of calling the police in each proposed situation on a 0-100 scale.The left-hand side presents the mean of the dependent variable for the control group composed of individuals receiving information only about governmental police alternatives (988, 311 and 211). The right-hand side presents the effect of additional information from the DCTP group. We report the 95% confidence intervals using robust standard errors

Policy Implications

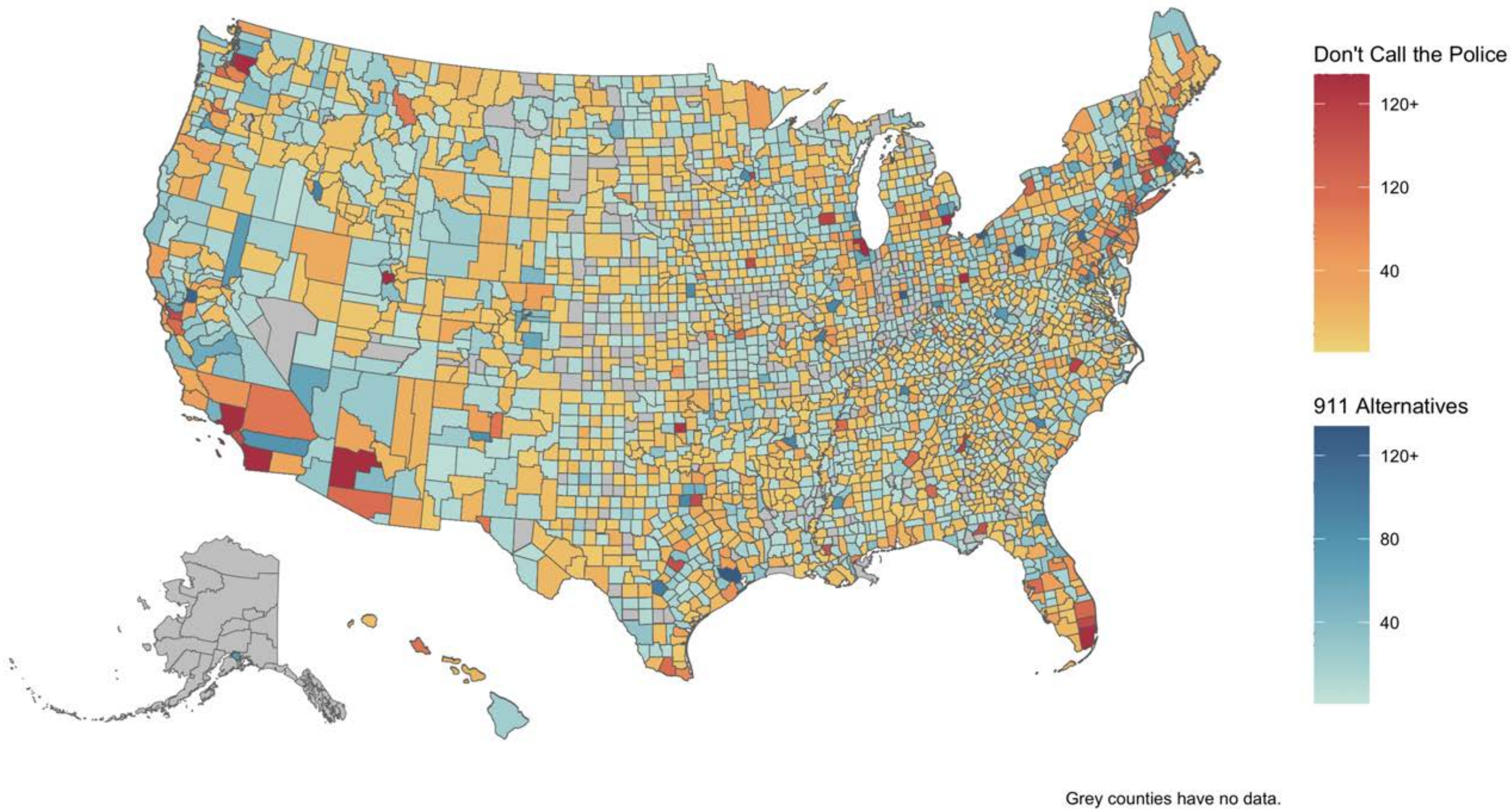
This study showed that people are likely to use non-police resources for non-violent resources if they have information about it. It provides a market opportunity to address non-violent issues through both community-based and governmental alternatives.

This leads to a natural first order policy that would **expand access and popularity of these alternatives**. This could look like a joint police and local-government campaign around what alternatives to use and when they are applicable. We see this as a bipartisan effort to reduce both the current work demanded from police and the potential violence resulting from police involvement.

Second order policy implications include **increasing availability and specialization of local police alternatives** that are trained to handle particular non-violent scenarios (ex. homelessness, mental health and suicide).

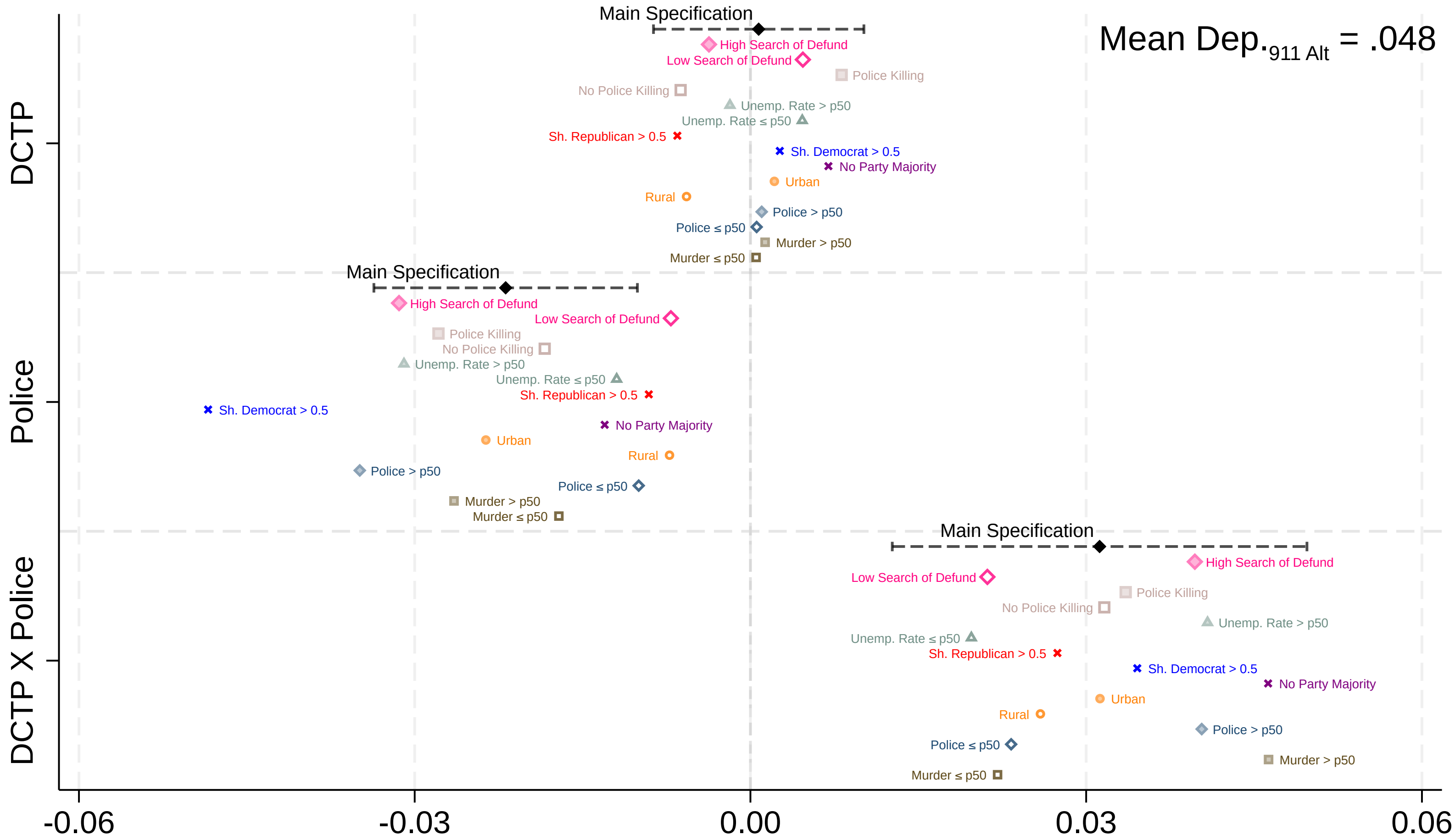
To contact us regarding this study, email us at **informing.policy.research@duke.edu.**

Figure 6: Geographical Distribution of Email Recipients by Treatment Status



Notes: This map presents the geographic distribution of email recipients in our field experiment, color-coded by their randomly assigned treatment status at the county level. Gray areas indicate counties for which we have no data.

Figure 7: Stakeholders' Willingness to Learn About Police Alternatives by County Characteristics



Notes: This figure presents the impact of being assigned to group receiving the email with the *DCTP* subject line on the willingness to receive information about support for police alternatives, broken down by county characteristics. The dependent variable , "Send Information," equals one if the respondent wanted to receive information about the study and zero otherwise. The county subsamples are: Google search intensity for "Defund the Police" (high/low search intensity), unemployment rate (above/below median), majority Republican, majority Democrat, no majority, urban/rural, murder rate (above/below median), police per capita (above/below median), and any police killing in 2022 (yes/no). We report the mean of the dependent variable for the omitted category, i.e., the control group, which includes respondents assigned to the *911 alternatives* subject line who are not police in the main specification. We report the estimates with controls in the regressions. We report 95% confidence intervals using standard errors clustered at the county level.

Figure 8: Words Associated by Stakeholders with Each Treatment Arm

(a) 911 Alternatives

(b) Don't Call the Police

Notes: These two word clouds show the words that interview participants identified in response to the question: "Name three words that you associate with [*911 Alternatives/DCTP*]." Participants were asked for their response to both framings, starting with the one in the subject line of the email that they received. Participants identified a total of 316 words/phrases, as not every respondent offered three. We standardized the words by collapsing synonyms to their root words (e.g. "mental health professional" and "mental health services" were coded as "mental health"), yielding a total of 271 words. Larger words were identified more often. Words are colored by stakeholder group: Blue words were identified by police and nonpolice participants, red words by police stakeholders only, and black words by nonpolice stakeholders only.

Table 1: Definitions of Outcomes

	Outcome	Type	Survey	Category j	Outcome	Scale
1	Likelihood of calling the police for scenario j	Main	Baseline, Week 1	Robbery; Screaming Woman; Naked Man; Suicidal Ideation; Disruptive Begging	y_j	0 to 100
2	Confidence in previous response for scenario j	Secondary	Baseline, Week 1	Robbery; Screaming Woman; Naked Man; Suicidal Ideation; Disruptive Begging	y_j	0 to 100
3	Police index			All scenarios		
4	Violent index	Main	Baseline, Week 1	Robbery; Screaming Woman	$(1/J)\sum_{j=1}^{J}(y_j - \mu_j^y)/\sigma_j^y$	z-score
5	Nonviolent index			Naked Man; Suicidal Ideation; Disruptive Begging		
6	Category j should respond	Secondary	Baseline, Week 1	Police; Social Worker; No one	$Responder_j$	0 = no, 1 = yes
7	Interest in website j	Secondary	Baseline, Week 1	Dontcallthepolice.com; 911alternatives.com; Not Interested	$Website_j$	0 = no, 1 = yes
8	Dial j for sucidal ideation	Main	Follow-up, Week 2	988; 911	$Call j$	0 = no, 1 = yes

Notes: This table defines the outcomes used in the analysis. The police demand, violent scenario, and nonviolent scenario indices are KLK indices, computed by subtracting the control group's mean, μ_j^y, and dividing by its standard deviation, σ_j^y.

Table 2: Summary Statistics by Treatment Arm

	(1) All	(2) Control	(3) Government	(4) DCTP	(5) p-value
Age	47.86	47.77	46.60	49.17	0.704
Black	0.19	0.18	0.20	0.19	0.592
Hispanic	0.06	0.07	0.05	0.06	0.274
Other Race	0.14	0.16	0.13	0.13	0.127
Male	0.45	0.45	0.43	0.47	0.447
High School or Less	0.14	0.15	0.14	0.12	0.043
Some College	0.22	0.22	0.21	0.22	0.940
Graduate Degree	0.20	0.21	0.18	0.22	0.621
No Party	0.21	0.21	0.20	0.21	0.922
Democratic	0.44	0.43	0.46	0.43	0.941
High Income	0.20	0.21	0.18	0.20	0.898
Low Income	0.13	0.13	0.14	0.13	0.768
Single	0.33	0.32	0.35	0.33	0.653
Baseline Police Demand Index	0.00	0.00	-0.01	0.01	0.829
Observations	2745	916	907	922	2745

Notes: The table presents the descriptive statistics by treatment arm. Column (1) provides the mean level of available variables from the 2022 American Community Survey census data (for population 18 and older). Column (2) provides the mean level of each variable for the full sample. Columns (3) to (5) report the mean level of each variable by treatment arm. Column (6) reports the p-value from a test of the hypothesis of equal means across the experimental conditions.

Table 3: Impact of Information Treatments on Demand

	(1) Police Index	(2) Violent Index	(3) Nonviolent Index	(4) Robbery	(5) Screaming Woman	(6) Naked Man	(7) Suicidal Ideation	(8) Disruptive Begging
DCTP	-0.178***	-0.0789**	-0.244***	1.124	-5.490***	-6.818***	-17.01***	-2.602**
	(0.0254)	(0.0343)	(0.0303)	(0.759)	(1.186)	(1.640)	(1.535)	(1.255)
Government	0.0414	0.0504	0.0355	0.537	1.799*	1.124	-1.084	3.051**
	(0.0255)	(0.0345)	(0.0306)	(0.798)	(1.090)	(1.682)	(1.569)	(1.321)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	0.00	0.00	0.00	93.35	80.66	50.42	51.77	24.67
p-value:DCTP=Government	0.00	0.00	0.00	0.43	0.00	0.00	0.00	0.00
Observations	2745	2745	2745	2745	2745	2745	2745	2745

Notes: This table presents the impact of the *Government* and *DCTP* information treatments on the demand for police in each situation. The dependent variable in columns (1) to (3) is a KLK index, i.e., a z-score computed by subtracting the control group's mean and dividing by its standard deviation. A higher score indicates greater demand for police. The dependent variable in columns (4) to (8) indicates the likelihood of calling the police in the proposed situation (0–100). We report robust standard errors in parentheses. We report the mean of the dependent variable of the omitted category, i.e., the control group, which is composed of individuals receiving information about different types of unemployment. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Impact of Information Treatments on Preference for First Responders in Crises

	(1) Robbery	(2) Screaming Woman	(3) Naked Man	(4) Suicidal Ideation	(5) Disruptive Begging
A) Police					
DCTP	0.00421	-0.0661***	-0.120***	-0.0475***	-0.113***
	(0.00612)	(0.0171)	(0.0220)	(0.0174)	(0.0192)
Government	0.00582	0.0159	-0.0159	-0.00632	-0.00627
	(0.00595)	(0.0153)	(0.0222)	(0.0180)	(0.0207)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	0.98	0.87	0.56	0.21	0.29
p-value:DCTP=Government	0.77	0.00	0.00	0.02	0.00
Observations	2745	2745	2745	2745	2745
B) Social Worker					
DCTP	0.00309	0.0671***	0.114***	0.0471**	0.146***
	(0.00362)	(0.0156)	(0.0204)	(0.0187)	(0.0228)
Government	0.000251	-0.00616	-0.00110	-0.00480	0.0417*
	(0.00301)	(0.0137)	(0.0194)	(0.0195)	(0.0230)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	0.00	0.10	0.23	0.76	0.44
p-value:DCTP=Government	0.41	0.00	0.00	0.01	0.00
Observations	2745	2745	2745	2745	2745
C) No Responder					
DCTP	-0.00404	-0.00204	0.00337	-0.000691	-0.0297
	(0.00462)	(0.00830)	(0.0189)	(0.00870)	(0.0202)
Government	-0.00262	-0.00976	0.0171	0.0111	-0.0321
	(0.00477)	(0.00777)	(0.0191)	(0.00936)	(0.0203)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	0.01	0.03	0.21	0.04	0.27
p-value:DCTP=Government	0.73	0.31	0.47	0.21	0.91
Observations	2745	2745	2745	2745	2745

Notes: This table presents the impact of the *Government* and *DCTP* information treatments on the type of first responder preferred for each situation: police, a social worker, or no one. The dependent variable is a binary indicator equal to 1 if the respondent prefers the indicated type of first responder and 0 otherwise. We report robust standard errors in parentheses. We report the mean of the dependent variable of the omitted category, i.e., the control group, which is composed of individuals receiving information about different types of unemployment. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: Impact of Information Treatments on Demand for Police by Partisanship

	(1) Police Index Democrat	(2) Police Index Republican	(3) Police Index No Party	(4) Violent Index Democrat	(5) Violent Index Republican	(6) Violent Index No Party	(7) Nonviolent Index Democrat	(8) Nonviolent Index Republican	(9) Nonviolent Index No Party
DCTP	-0.199***	-0.180***	-0.173***	-0.0442	-0.0712	-0.200**	-0.303***	-0.252***	-0.156**
	(0.0366)	(0.0425)	(0.0607)	(0.0529)	(0.0512)	(0.0861)	(0.0429)	(0.0540)	(0.0670)
Government	0.0441	0.0351	0.0335	0.0588	0.0557	0.00861	0.0343	0.0214	0.0500
	(0.0359)	(0.0434)	(0.0640)	(0.0496)	(0.0541)	(0.0918)	(0.0435)	(0.0554)	(0.0686)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value:DCTP=Government	0.00	0.00	0.00	0.03	0.02	0.02	0.00	0.00	0.00
Observations	1206	968	571	1206	968	571	1206	968	571

Notes: This table presents the impact of the *DCTP* and *Government* information treatments on the demand for police by partisan affiliation. Each column shows the results for a different subsample. The dependent variable is a KLK index, i.e., a z-score computed by subtracting the control group's mean and dividing by its standard deviation. A higher score indicates greater demand for police. The index captures the demand for police for the five scenarios, the violent scenarios ("armed robbery" and "screaming woman"), and the nonviolent scenarios ("naked man," "suicidal ideation," and "disruptive begging"). The dependent variable indicates the likelihood of calling the police in the proposed situation. We report robust standard errors in parentheses. We report the mean of the dependent variable of the omitted category, i.e., individuals receiving information about different types of unemployment. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Impact of Information Treatments on Interest in Website Detailing Police Alternatives, by Partisanship

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Interest in DCTP Website Democrat	Interest in DCTP Website Republican	Interest in DCTP Website No Party	Interest in 911 Website Democrat	Interest in 911 Website Republican	Interest in 911 Website No Party	No Interest Website Democrat	No Interest Website Republican	No Interest Website No Party
DCTP	0.451***	0.422***	0.468***	-0.421***	-0.320***	-0.358***	-0.0307*	-0.102***	-0.110***
	(0.0310)	(0.0323)	(0.0435)	(0.0322)	(0.0371)	(0.0474)	(0.0161)	(0.0296)	(0.0354)
Government	0.000928	-0.0108	-0.0727*	0.00485	0.0209	0.0266	-0.00578	-0.0101	0.0461
	(0.0278)	(0.0236)	(0.0373)	(0.0307)	(0.0371)	(0.0495)	(0.0171)	(0.0327)	(0.0430)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	0.20	0.10	0.19	0.73	0.67	0.61	0.07	0.23	0.21
p-value:DCTP=Government	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.00
Observations	1206	968	571	1206	968	571	1206	968	571

Notes: This table presents the impact of the *DCTP* and *Goverment* information treatments on website interest. Interest in alternative resources is gauged by engagement (or lack thereof) with the dontcallthepolice.com and 911alternatives.com websites. Note that although the websites have different names, their content is identical. We report robust standard errors in parentheses. We report the mean of the dependent variable of the omitted category, i.e., individuals receiving information about different types of unemployment. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: Summary Statistics by Treatment Arm

	(1) All	(2) 911 Alternatives	(3) Don't Call the Police	(4) p-value
Share Black	0.11	0.11	0.11	0.37
Share Hispanic	0.13	0.12	0.14	0.22
Share Other Race	0.08	0.07	0.08	0.15
Unemployment Rate	0.05	0.05	0.05	0.21
Share Republican	0.45	0.46	0.45	0.30
Urban	0.84	0.83	0.85	0.29
Murders per 100K	5.27	5.56	5.01	0.32
Violent Crimes per 1,000	3.01	3.18	2.87	0.31
Property Crimes per 1,000	15.22	15.35	15.11	0.80
Police per 1,000	2.25	2.29	2.21	0.72
Police Killings per 100K	0.33	0.35	0.31	0.24
High Search of Defund	0.58	0.58	0.57	0.67
Police	0.24	0.23	0.24	0.42
F-test	-	-	-	0.23
Observations	11623	5457	6166	11623

Notes: The table presents descriptive statistics by treatment arm for respondents who opened the email. Column (1) provides the mean level of each variable for the full sample. Columns (2) to (3) report the mean level of each variable by treatment arm. Column (4) reports the *p*-value from a test of the hypothesis of equal means across the experimental conditions. We cluster the standard errors at county level to test the differences in means.

Table 8: Impact of *DCTP* on Stakeholders' Willingness to Learn About Police Alternatives

	(1) Send Information	(2) Send Information	(3) Send Information	(4) Send Information
DCTP	0.00919**	0.00195	0.00815**	0.000736
	(0.00422)	(0.00497)	(0.00409)	(0.00479)
Police	-0.00486	-0.0213***	-0.00504	-0.0219***
	(0.00488)	(0.00578)	(0.00496)	(0.00600)
DCTP X Police		0.0305***		0.0312***
		(0.00939)		(0.00945)
Controls	No	No	Yes	Yes
Mean of 911 Alternatives	0.05	0.05	0.05	0.05
Observations	11623	11623	11623	11623

Notes: This table presents the impact of being assigned to the *DCTP* subject line on the likelihood of responding and the willingness to receive information about public openness to police alternatives, broken down by police status. The dependent variable, "Send Information," equals one if the respondent wanted to receive information about the study and zero otherwise. We report the mean of the dependent variable for the omitted category, i.e., the control group, which includes respondents assigned to the *911 alternatives* subject line who are not police. We report standard errors clustered at the county level in parentheses. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9: Distribution of Words that Interview Participants Associated with "DCTP" and "911 Alternatives"

	DCTP			911 Alt.			Overall		
	Supportive	Skeptical	Total Words	Supportive	Skeptical	Total Words	Supportive	Skeptical	Total Words
Police	43%	63%	40	95%	7%	42	70%	34%	82
Nonpolice	64%	42%	111	94%	11%	123	80%	26%	234
Sheriff & Other Law Enforcement	59%	55%	29	94%	22%	32	77%	38%	61
Local Officials	67%	38%	24	100%	3%	33	86%	18%	57
DOJ Grantees	66%	38%	58	91%	10%	58	78%	24%	116

Notes: This table characterizes the words that interview respondents stated in response to the question: "Name three words that you associate with [Don't Call the Police/911 Alternatives]." Interview respondents were asked for their responses to both framings beginning with the one to which they were assigned in the field experiment. Not every respondent offered three words. Respondents were also asked to explain the connection with each word. Two coders (a coauthor and a research assistant) coded each word alongside its explanation to determine whether the word expressed support or skepticism, with 93% intercoder reliability. Columns may not add up to the total because words and explanations could have expressed both skepticism and support or neither.

Contents

Supplementary Materials

A Conceptual Framework

Setup Consider a model where a bystander is randomly matched with a situation that requires her to choose an action, denoted by a. Her options are to either call the police, $a = P$, or not to call them, $a = A$. Nature determines the state of the world first, s, which can be either a situation that necessitates the involvement of the police with no substitutes, $s = V$, or one where a substitute for the police exists or their involvement is not required, $s = M$. The probability of the state $s = V$ is π, and the probability of the state $s = M$ is $1 - \pi$. Hence, we define the utility function of the bystander as $u(a, s)$.

The bystander's payoff depends on her decision to call the police in instances devoid of alternatives, thereby potentially minimizing superfluous police engagement and liberating law enforcement resources for scenarios where their presence is most warranted. Specifically, we define the utility function $u(a, s)$ where the bystander chose $a = P$, i.e., calling the police, when there is no alternative, $a = V$, for utility $u(P, V) = 1$, and if it is the state where there is an alternative, $u(P, M) = -\theta$, where $\theta > 0$. The value $-\theta$ corresponds to the loss from calling the police when there is a better alternative. If the bystander does not call the police A, the utility is 0 regardless of the state, i.e., $u(A, V) = u(A, M) = 0$.

We assume that the bystander incurs a cost related to the effort required to remember not to automatically rely on police in an incident. The effort, denoted $e \in [0, 1]$, affects the probability r of choosing the nonpolice action (A), represented by the function $f(e) = r$. Additionally, $c(e)$ denotes the cost associated with this effort. Both $f(\cdot)$ and $c(\cdot)$ are assumed to be increasing in e.

Optimization Problem The expected payoff for the bystander is determined by her action, the state of the situation, and her likelihood of recalling that alternatives to police intervention are available where applicable. Therefore, the expected payoff is given by:

$$\begin{aligned} V(r, \theta, \pi) &= \pi \cdot u(P, V) + (1 - \pi)[r \cdot u(A, M) + (1 - r) \cdot u(P, M)] \\ &= \pi \cdot 1 + (1 - \pi)\big[r \cdot 0 + (1 - r)(-\theta)\big] \\ &= \pi + (1 - \pi)(1 - r)(-\theta) \end{aligned}$$

Overall, the bystander chooses the level of effort, e, that maximize the following value function:

$$\begin{aligned} max_e\{V(r, \theta, \pi) - c(e)\} &= max_e\{V(f(e), \theta, \pi) - c(e)\} \\ &= max_e\{\pi + (1 - \pi) \cdot (1 - f(e)) \cdot (-\theta) - c(e)\} \end{aligned} \tag{3}$$

We impose the functional forms assumption for the effort function such that $f(e) = e$ and $c(e) = \frac{1}{2}e^2$. Hence, the first-order condition leads to the optimal effort level, given by

$$(1-\pi) \cdot \theta \cdot f'(e) = c'(e) \Rightarrow e^* = (1-\pi) \cdot \theta \tag{4}$$

The optimal effort e^* is derived from the first-order condition, balancing the marginal cost of additional effort against the marginal benefit of reduced mistakes (calling the police when it is unnecessary). This condition equates the derivative of the cost function with the derivative of the benefit function from remembering the alternatives, simplified due to the linear form of $f(e)$. Here, e^* adjusts based on the likelihood of being in a scenario in which police are unnecessary $(1-\pi)$ and the severity of the mistake θ.

Role of Information Equation 4 shows the optimal behavior of individuals in deciding when to engage police, balancing cognitive effort against the potential for making judgment errors under varying informational conditions. We assume that π is fixed. Our survey experiment manipulates the level of information provided within each treatment, potentially impacting θ, which in turn influences the decision to call the police or opt for alternatives.

In our experimental design, respondents are assigned to one of several treatment arms: the *Government* treatment, which presents information on the emergency services numbers $\{988, 211, 311\}$, and the *DCTP* treatment arm. Each treatment corresponds to a distinct θ value, representing the perceived severity of erroneously calling the police when alternatives are available: θ_N, θ_G, and θ_D for the control group (no information), the *Government* group, and the *DCTP* group, respectively.

B Qualitative Study: Data and Methods

This appendix details the methods used in the qualitative portion of this study.

B.1 Sampling and Recruitment

In the first email sent to stakeholders, we invited them to click on a link to receive a summary report of the original study and to provide feedback. Those who expressed interest in receiving additional information were then emailed (a) the summary report, (b) a study information sheet detailing the interview protocol, and (c) a survey for them to express interest in an interview by inputting their email address (see Supplementary Materials B).

Table A.14 shows the response rates for the qualitative interviews across different stages. We conducted interviews with a total of 60 stakeholders out of the 150 who expressed interest (40%). We sent two follow-up emails to those who expressed interest in participating in an interview but had not responded to our invitation to set up a time. A team of four research assistants attended a four-hour training led by a coauthor on best practices for conducting interviews in general and how to implement the specific interview guide for this study. The interview guide focused on asking participants to walk us through what they recalled about the original study, words they associated with *DCTP* and *911 alternatives*, and their reactions to the findings for each scenario contained within the original survey. The interviewers wrote an internal memo following each interview summarizing their main takeaways and anything surprising that they learned, facilitating an abductive analysis in subsequent stages (Timmermans and Tavory, 2012). The research team conducted the interviews via Zoom between April and June 2024, with the interviews lasting an average of 47 minutes each. Participants from each stakeholder group were relatively well represented, with the exception of sheriff and detention facilities, which had only one participant. Thus, we merged these with the other law enforcement category to preserve confidentiality.

DeLuca (2023) emphasizes that empirically sound qualitative research must justify and be transparent about how systematic the sampling strategies are. An important element is to consistently ask "who did I not talk to" and to reflect on whether the exclusion of those nonparticipants could systematically bias the study findings (Duneier, 2011). We received emails from individuals who were invited to participate in the study but declined (n = 34). While these emailers are still a selected sample, they nonetheless shed light into why some did not participate. On the one hand, 53% of the emails stated at least one "practical" reason: additional questions about study logistics and the safety of clicking links (32%), a perception that they would be unhelpful to the study (21%), or an explanation that the survey link had expired because the study period had ended (3%). In contrast, 62% offered more substantive comments in lieu of formal participation: They were against police alternatives (29%), they were supportive but cautious of police alternatives (26%), or they claimed our study was biased (9%). Only one email distinguished between *911 alternatives* and *DCTP*, warning about the negative message signaled by the latter framing. It may be the case that those least supportive of police alternatives were also least likely to engage with an academic study in any way. Nonetheless, we are confident that the interview participants shared many of the views expressed in these emails.

B.2 Analytic Approach

Each interview was conducted virtually, audio-recorded, and transcribed using Zoom's transcription function. A graduate research assistant cleaned each transcript and checked it against the audio file. Guided by best practices in qualitative coding (Charmaz, 2006; Saldaña, 2013), we used NVivo and Microsoft Excel to code the transcripts in the following steps. First, we conducted structural coding: We created a code for each question (and the related probes that interviewers used) and tagged the corresponding answers within the transcripts. We reviewed the structural codes, along with the internal memos that interviewers wrote after each interview, to develop a sense of the responses and variation across them. In an iterative process, we discussed emerging themes (Charmaz, 2006; Glaser and Strauss, 1967) and potentially surprising patterns (Timmermans and Tavory, 2012), which informed the next stage. Second, we completed focused coding: We settled on targeted codes to analyze the transcripts and help evaluate the frequency, significance, and logic of the emerging patterns that we identified (Deterding and Waters, 2021). These focused codes, which are similar to analytic or axial codes, were applied to each transcript and covered four main areas: (a) motivations for study participation; (b) sentiments toward *911 alternatives*; (c) sentiments toward *DCTP*; and (d) engagement with police alternatives in reacting to the scenarios from the original survey. Each of these parent codes contained subcodes, which formed the basis of the qualitative findings reported in the paper. For instance, in coding the motivations for study participation, we identified multiple reasons (e.g., learning about the evidence base, informing best practices) that we could then trace back to stakeholder groups and compare across them.

We took formal steps to verify the reliability of our codes. For instance, for the word association exercise, a coauthor and a research assistant coded each word for whether it expressed support or skepticism toward *DCTP* or *911 alternatives*. We established intercoder reliability in two stages. First, we each independently coded each word and found 84% agreement. We then identified the words for which our codes diverged, discussed why we had coded them as we did, and then independently recoded them. We achieved 93% agreement, and the coauthor made the final determination on the remainder.

The coauthor then coded the words and explanations for their content. As seen in Table A.15, these codes attempt to capture the justifications, logic, or general reactions that participants invoked toward *911 alternatives* and *DCTP*. The explanations were important because two participants may have used the same word but meant it in opposing ways. For instance, two stakeholders both identified "scared" as a word that they associate with "DCTP." Their explanations, however, suggested that they attached different meanings. One explained, "Your person of color in America for the last—like, since the police has been formed—you don't necessarily feel as their job may be to protect and serve due to different police brutalities." While this stakeholder cited the racialized violence of policing, another stakeholder also used the term "scared" but suggested that the fear of calling police stemmed from social undesirability: "People are scared, you know. Call the cops because either you're doing something wrong [or] somebody else is doing something wrong. You don't want to call the cops [because] you think you're gonna get nailed on something." The former expressed support toward, or at least understanding of, decisions not to call the police among African Americans, whereas the latter envisioned wrongdoers seeking to avoid arrest and, therefore, indicated skepticism toward the appropriateness of not calling the police. Thus while both used the term "scared," we coded the former as expressing support and the latter as expressing skepticism toward police alternatives. These codes collectively provided insights into how, even within the selective group of interview participants, variation emerged across stakeholders in their perceptions, understanding, and support of *911 alternatives* and *DCTP*.

C Video Transcripts

C.1 Control

Link to the video: *Control* Video

- **Narrator:** Let's talk about unemployment. It's a term we hear a lot, but what does it really mean?
- **Narrator:** Unemployment is a measure of the number of people who are willing and able to work but cannot find employment. Its expressed as a percentage of the total labor force. In order to understand unemployment, then, we must first consider who is part of the labor force.
- **Narrator:** First, we have the employed. These are individuals who have jobs, whether they are working full-time, part-time or are self-employed. They are actively contributing to the economy by providing goods and services.
- **Narrator:** The labor force also includes the unemployed: those who are willing and able to work but currently don't have jobs.
- **Narrator:** They are actively seeking employment and are available for work. Note, importantly, that this means the unemployment rate does not include those who are of working age and don't have jobs and are not actively seeking employment.
- **Narrator:** Now let's discuss the various types of unemployment. Frictional unemployment is when someone is in between jobs. It's a temporary type of unemployment. Cyclical unemployment is when there is a downturn in the economy. This type of unemployment is more long term. Then, there is structural unemployment, when there is a mismatch between the skills of jobseekers and the available jobs.
- **Narrator:** Unemployment varies over time depending on the health of the US economy. This graph from the US BLS [Bureau of Labor Statistics] displays the unemployment rate in the US from 2004 to 2024. Peaks of unemployment rates occur during economic recessions. During the recent COVID pandemic, the unemployment rate peaked at 14.8% but has since decreased to around 4% as the economy recovered.
- **Narrator:** Now let's talk about unemployment benefits. These are financial benefits provided to those who are unemployed. The purpose is to provide temporary financial assistance for those who are actively seeking work. Applying for unemployment benefits is a process that differs from state to state. In general, you will need to file paperwork, including personal identifying information, previous place and duration of employment, and provide evidence

that you are actively seeking employment. More information specific to each state can be found on government resources online.

- **Narrator:** So if you are experiencing frictional, cyclical or structural unemployment, there are resources to help you during this time!

C.2 Government

Link to the video: *Government Alternatives* Video

- **Narrator:** Let's take a moment to understand the purpose and significance of three important hotlines: 988, 211, and 311.
- **Narrator:** 988—the Suicide Prevention Hotline. 988 is a lifeline for those facing mental health challenges. By dialing 988, individuals can connect with compassionate professionals who provide immediate support and guidance, helping navigate the complexities of mental health crises.
- **Narrator:** 211—the Community Assistance Hotline. 211 is a gateway to vital resources. Dialing 211 connects you with trained experts who offer guidance, referrals, and information on a range of community-based services such as housing, food assistance, employment, and mental health support.
- **Narrator:** 311—the City Services Hotline. 311 is your link to local assistance. When you dial 311, knowledgeable representatives provide information and support regarding city services, regulations, and resources. They can address concerns related to public works, sanitation, transportation, and more.
- **Narrator:** These hotlines are crucial government resources which can be utilized whenever needed.
- Video title appears on screen: "988, 211, 311: hotlines for support and assistance."
- Commercial clips

C.3 Don't Call the Police

Link to the video: *Don't Call the Police* Video

- **Narrator:** In the United States, police are generally used as the default response to emergencies and community issues. But did you know that only 10% of calls to the police involve violent crimes? In fact, for most situations, there are better ways to address the issue at hand.

- **Narrator:** For example, the website, "Don't Call the Police dot com," is a database of community-based resources that can be used as alternatives to calling the police or 911 when faced with a situation that requires de-escalation, intervention, or community support and can best be managed by an unarmed crisis response provider.
- **Narrator:** Don't Call the Police dot com's resources are organized by city and focus on organizations that provide emergency or crisis services related to housing, mental health, LGBTQ+ issues, domestic violence, youth, elders, substance abuse, and crime victim services. Every resource on the site is vetted for its policies related to police involvement in order to minimize law enforcement interaction. Calling these resources allows people in crisis to connect with trained volunteers, social workers, and people trained in nonviolent crisis intervention. By redirecting your calls to these specialized organizations whenever possible, you can help make your community safer and healthier without the risk of violence or unnecessary law enforcement interaction.
- **Narrator:** In addition to Don't Call the Police dot com, the government provides alternatives to police that can be useful in nonviolent situations.
- **Narrator:** Let's take a moment to understand the purpose and significance of three important hotlines: 988, 211, and 311.
- **Narrator:** 988—the Suicide Prevention Hotline. 988 is a lifeline for those facing mental health challenges. By dialing 988, individuals can connect with compassionate professionals who provide immediate support and guidance, helping navigate the complexities of mental health crises.
- **Narrator:** 211—the Community Assistance Hotline. 211 is a gateway to vital resources. Dialing 211 connects you with trained experts who offer guidance, referrals, and information on a range of community-based services, such as housing, food assistance, employment, and mental health support.
- **Narrator:** 311—the City Services Hotline. 311 is your link to local assistance. When you dial 311, knowledgeable representatives provide information and support regarding city services, regulations, and resources. They can address concerns related to public works, sanitation, transportation, and more.
- **Narrator:** These hotlines are crucial government resources which can be utilized whenever needed.
- Video title appears on screen: "988, 211, 311: hotlines for support and assistance."

We also refer to the *Government* treatment group as an active control group; this design guarantees that all participants received pertinent information, though the specifics vary. This contrasts with a pure control setup and allows us to detect a diverse range of belief changes, not only among those with initial misconceptions but also among individuals with initially accurate beliefs, thereby facilitating determination of the average causal impact of beliefs across a wider demographic (Bottan and Perez-Truglia, 2022; Roth et al., 2022; Haaland et al., 2023).

D Scenarios

Crime. Original story from Mapping Police Violence: *"Officers responded to a report of an armed robbery at a jewelry store. The incident was reported about 12:15 p.m. Officers found a woman in a waiting vehicle and took her into custody. A search began for two men. Police shot and killed Vondarrow Dewayne Fisher when he failed to follow orders. Details as to what precipitated the killing were withheld by police."*

- **Robbery:** *"Two men attempt an armed robbery of a jewelry store."*

Domestic Violence. Original story from Mapping Police Violence: *"Around 10:38 p.m. someone inside a home called 911. On the call, a woman was heard screaming and crying, while a man was heard 'making threats.' Officers heard screaming when they arrived at the home and forced their way into the home to stop what they said was an immediate threat to the woman's safety. As the officers entered through the front door, a woman ran out of the home, and a man appeared in a hallway with the air pistol and reportedly fired at the officers. Four officers shot and killed Cruz."*

- **Screaming Woman:** *"A woman screams and cries while a man makes threats."*

Mental Health (Erratic Behavior). Original story from Mapping Police Violence: *"Police got a call around 10 p.m. about a naked man walking down the near a music festival at Atlanta Motor Speedway. Officers said when they approached Fernando Rodriguez, he would not cooperate with their demands. Police said that Rodriquez became combative. At least three officers shocked him with stun guns—some reports said simultaneously—killing him."*

- **Naked Man:** *"A naked man walks down the street near a music festival."*

Mental Health (Suicidal Ideation). Original story from Mapping Police Violence: *"A neighbor concerned that Sullivan was suicidal called police to an apartment complex around 8:30 p.m. Sullivan was inside his locked apartment when officers, firefighters and medics arrived. He refused to open the door, but police broke in, and Sullivan confronted them with a knife, and police ordered him to drop the knife and then shot and killed him."*

- **Suicide:** *"A neighbor seems really upset and says he is 'thinking about ending things.'"*

Homelessness. Fictional story

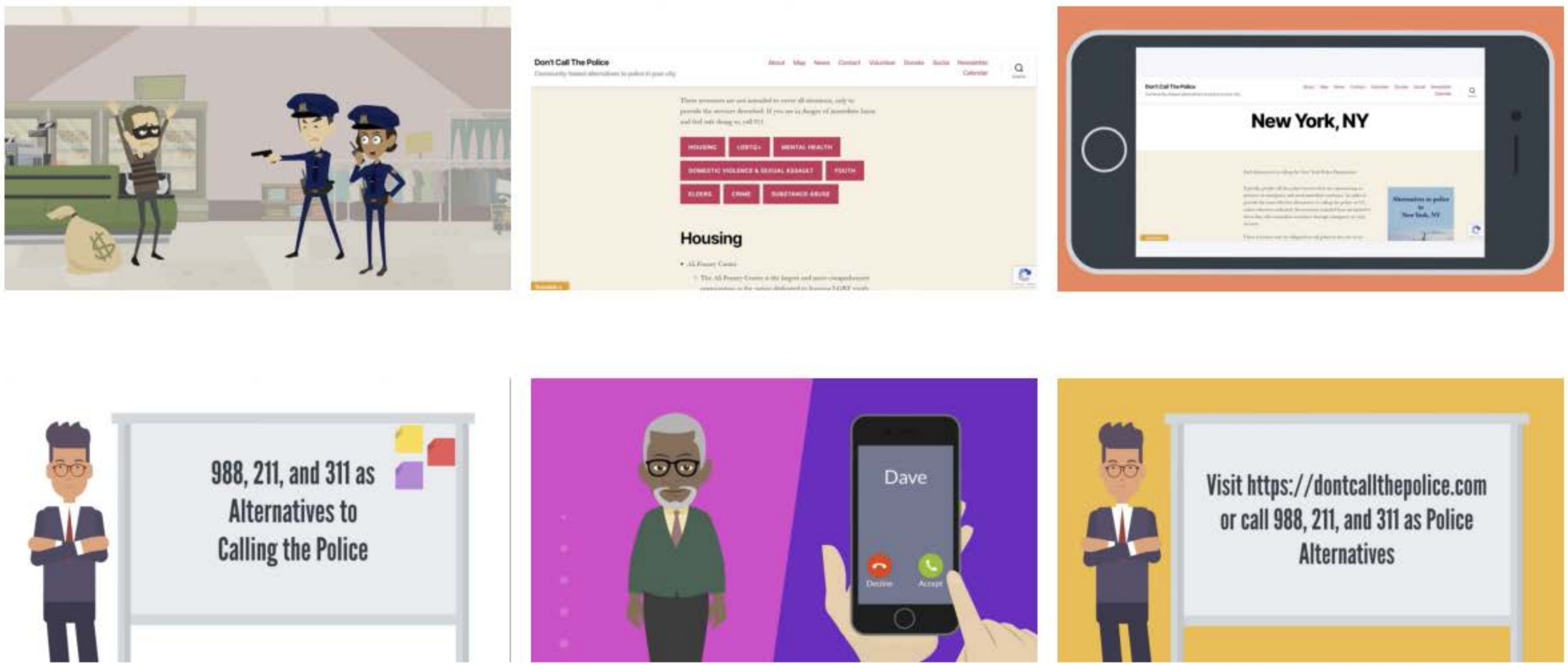
- **Disruptive Begging:** *"A man begs in front of a restaurant and curses at people who ignore him."*

E Additional Figures and Tables

Figure A.1: Screenshots from the *Control* Video

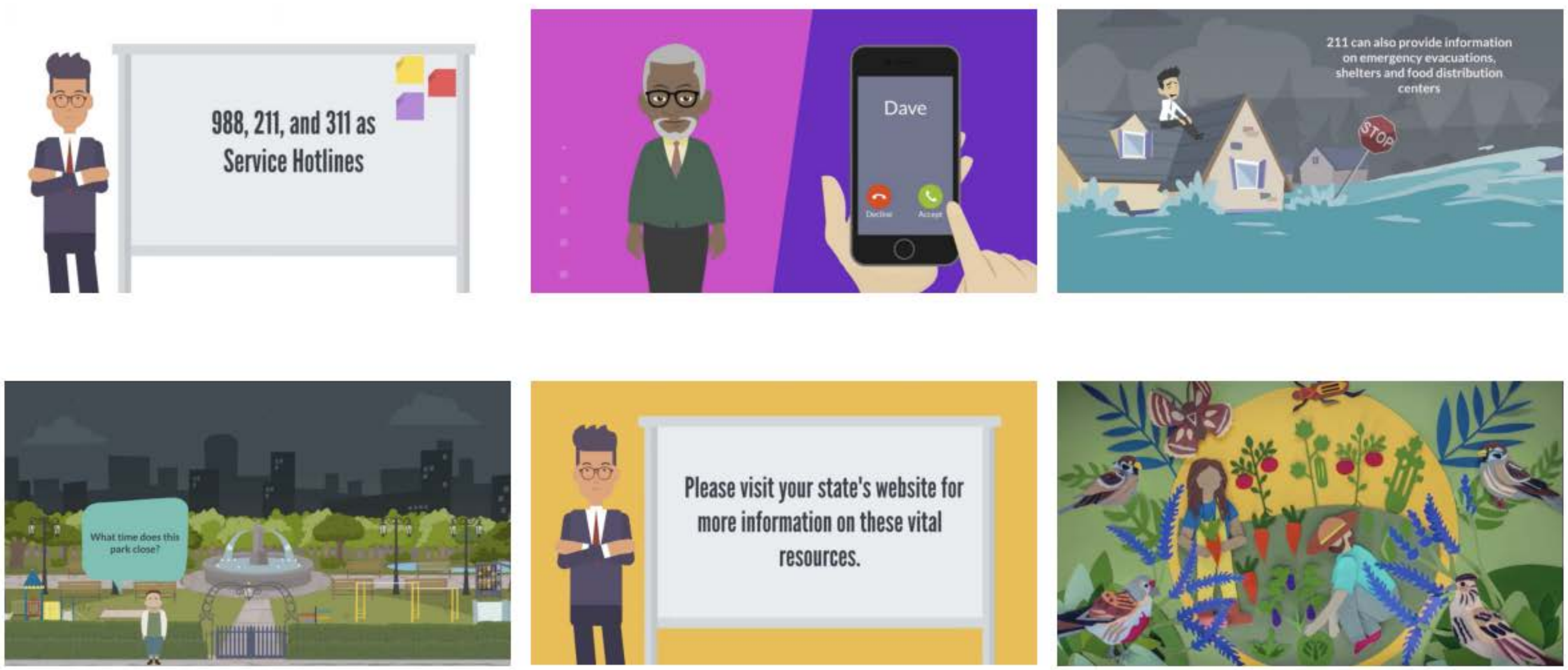
Notes: This figure presents screenshots from the *Control* video.

Figure A.2: Screenshots from the *Don't Call the Police* Video



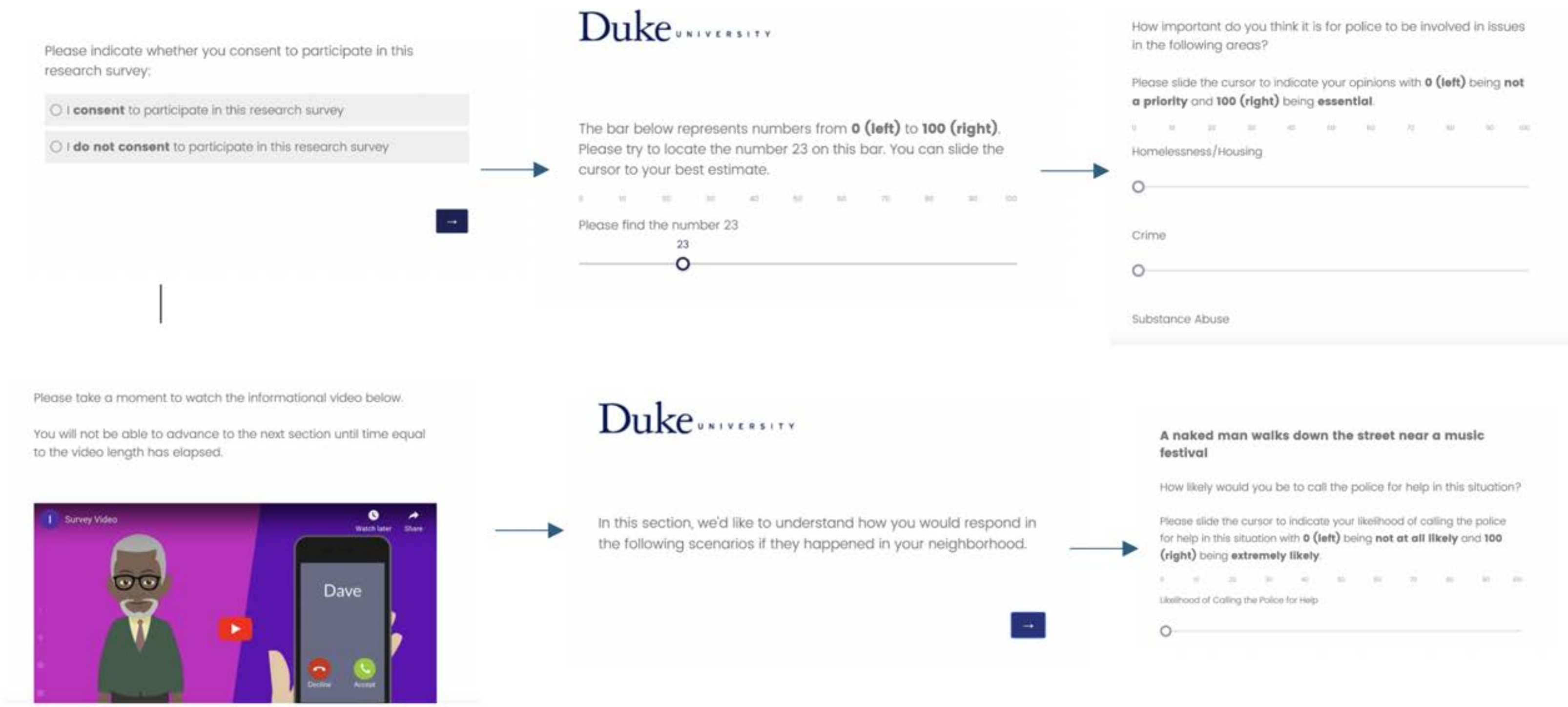
Notes: This figure presents screenshots from the *Don't Call the Police* video.

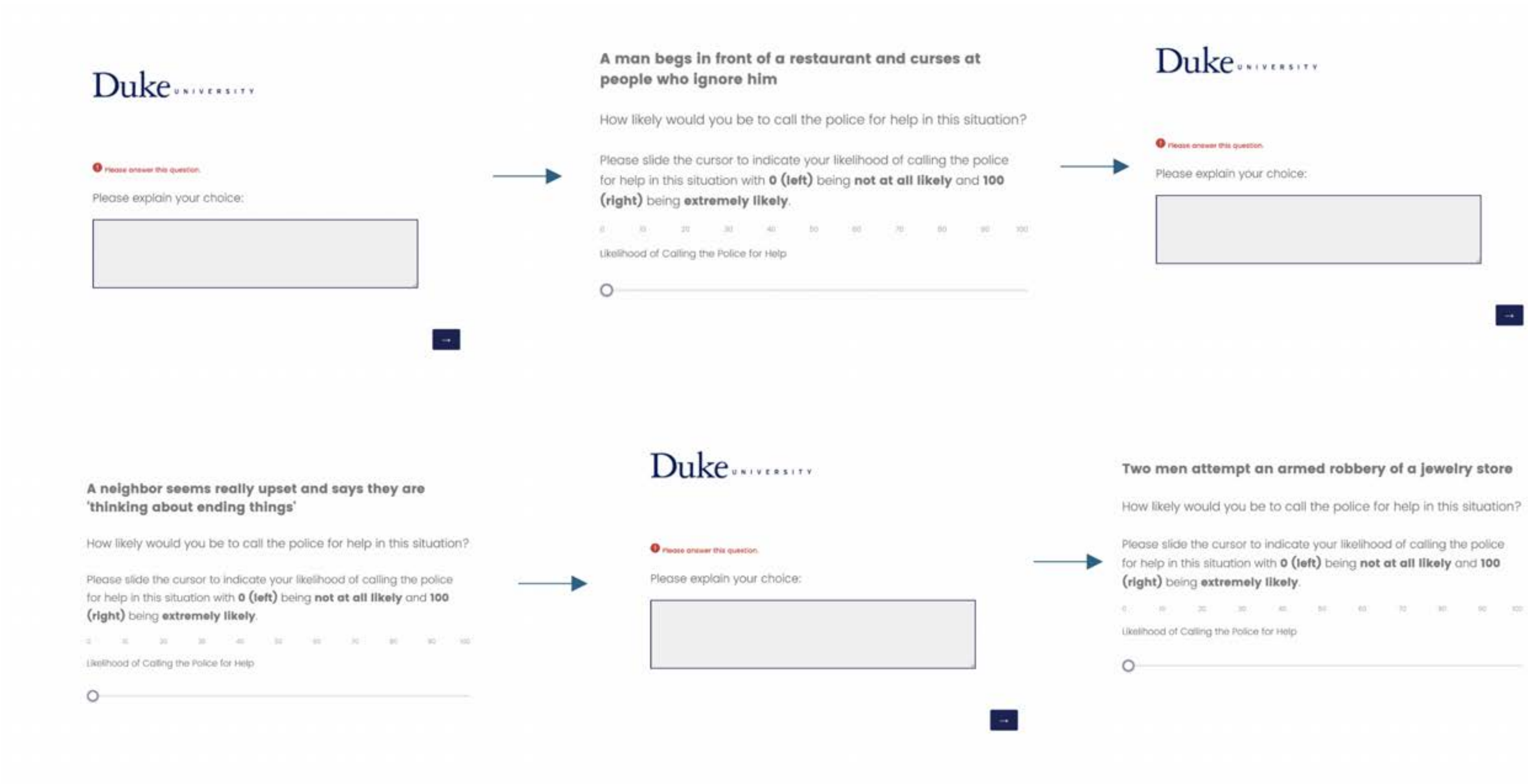
Figure A.3: Screenshots from the *Government Alternatives* Video



Notes: This figure presents screenshots from the *Government Alternatives* video.

Figure A.4: Screenshots from the Main Prolific Survey

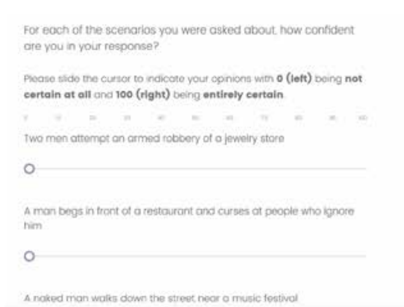



Duke UNIVERSITY
Please answer this question.
Please explain your choice:
A man begs in front of a restaurant and curses at people who ignore him
How likely would you be to call the police for help in this situation?
Please slide the cursor to indicate your likelihood of calling the police for help in this situation with 0 (left) being not at all likely and 100 (right) being extremely likely.
Likelihood of Calling the Police for Help
Duke UNIVERSITY
Please answer this question.
Please explain your choice:
A neighbor seems really upset and says they are 'thinking about ending things'
How likely would you be to call the police for help in this situation?
Please slide the cursor to indicate your likelihood of calling the police for help in this situation with 0 (left) being not at all likely and 100 (right) being extremely likely.
Likelihood of Calling the Police for Help
Duke UNIVERSITY
Please answer this question.
Please explain your choice:
Two men attempt an armed robbery of a jewelry store
How likely would you be to call the police for help in this situation?
Please slide the cursor to indicate your likelihood of calling the police for help in this situation with 0 (left) being not at all likely and 100 (right) being extremely likely.
Likelihood of Calling the Police for Help


Duke UNIVERSITY
Please explain your choice:
→


A woman screams and cries, while a man makes threats
How likely would you be to call the police for help in this situation?
Please slide the cursor to indicate your likelihood of calling the police for help in this situation with 0 (left) being not at all likely and 100 (right) being extremely likely
Likelihood of Calling the Police for Help


Duke UNIVERSITY
Please explain your choice:
→


For each of the scenarios you were asked about, how confident are you in your response?
Please slide the cursor to indicate your opinions with 0 (left) being not certain at all and 100 (right) being entirely certain
Two men attempt an armed robbery of a jewelry store
A man begs in front of a restaurant and curses at people who ignore him
A naked man walks down the street near a music festival


Who do you think should be sent to help in each of these cases?
Social Worker
Police Officer
No One
Two men attempt an armed robbery of a jewelry store
A naked man walks down the street near a music festival
A neighbor seems really upset and says they are thinking about


People are very busy these days, and many do not have time to follow what goes on in the government. We are testing whether people read survey questions. To show that you've read this much, please answer both "extremely interested" and "very interested."
Extremely interested
Very interested
Moderately interested
Slightly interested
Not interested at all

If you were going to a site to learn about alternatives to police, which site name is most appealing to you?

- ○ 911alternatives.com
- ○ I'm not interested in learning about police alternatives
- ○ dontcallthepolice.com

→

What year were you born?
(yyyy)

→

What is your gender?

- ○ Female
- ○ Male
- ○ Other (specify)

What racial or ethnic group best describes you?

- ○ American Indian or Alaska Native
- ○ Asian
- ○ Black or African American
- ○ Hispanic or Latino
- ○ Native Hawaiian or Pacific Islander
- ○ White
- ○ Other (specify)

What is your marital status?

- ○ Single, never married
- ○ Married or domestic partnership
- ○ Widowed
- ○ Divorced
- ○ Separated

→

What is the highest level of schooling you've completed?

- ○ Less than a high school diploma
- ○ High school diploma or GED
- ○ Some college but no degree
- ○ College degree (for example: AA, BA)
- ○ Graduate degree (for example: MA, MBA, JD, PhD)

→

What was your income in 2022, before taxes?

- ○ I did not earn income in 2022
- ○ $1 to $19,999
- ○ $20,000 to $39,999
- ○ $40,000 to $59,999
- ○ $60,000 to $79,999
- ○ $80,000 to $99,999
- ○ $100,000 to $149,999
- ○ $150,000 or more

Do you generally think of yourself as closer to the Democratic Party or Republican Party?

- ○ Republican Party (President Trump and President Bush are Republicans)
- ○ Neither
- ○ Democratic Party (President Biden and President Obama are Democrats)

→

Figure A.8: Screenshots from the Follow-Up Prolific Survey

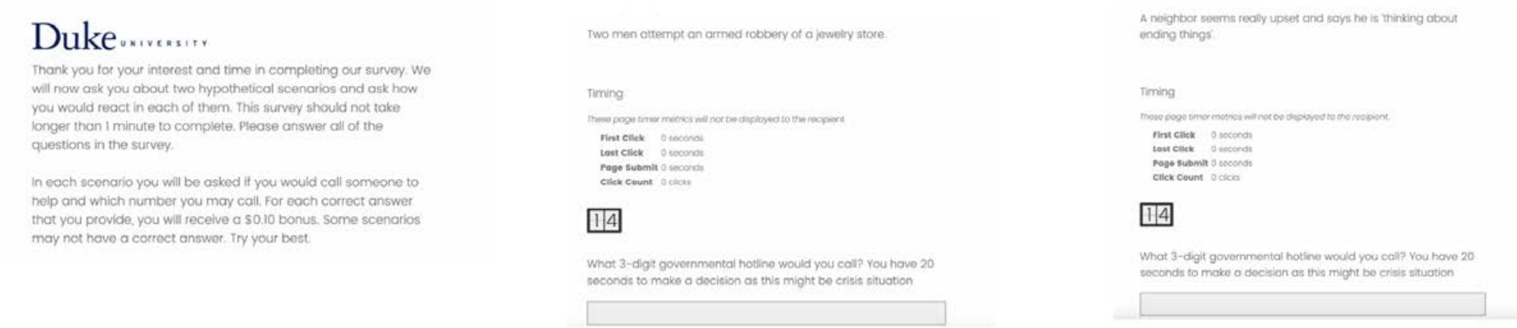
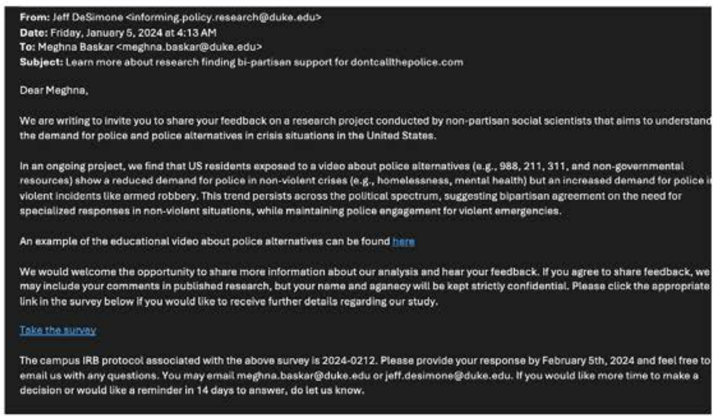


Figure A.9: Screenshots from the Field Experiment Emails



From: Jeff DeSimone <informing.policy.research@duke.edu>
Date: Friday, January 5, 2024 at 4:13 AM
To: Meghna Baskar <meghna.baskar@duke.edu>
Subject: Learn more about research finding bi-partisan support for dontcallthepolice.com

Dear Meghna,

We are writing to invite you to share your feedback on a research project conducted by non-partisan social scientists that aims to understand the demand for police and police alternatives in crisis situations in the United States.

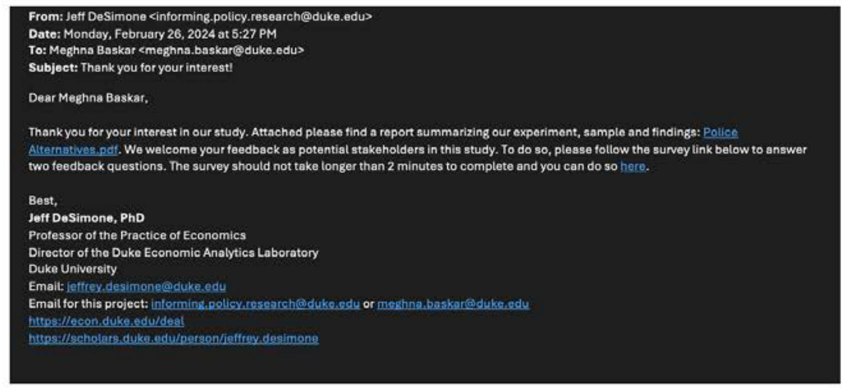
In an ongoing project, we find that US residents exposed to a video about police alternatives (e.g., 988, 211, 311, and non-governmental resources) show a reduced demand for police in non-violent crises (e.g., homelessness, mental health) but an increased demand for police i violent incidents like armed robbery. This trend persists across the political spectrum, suggesting bipartisan agreement on the need for specialized responses in non-violent situations, while maintaining police engagement for violent emergencies.

An example of the educational video about police alternatives can be found here

We would welcome the opportunity to share more information about our analysis and hear your feedback. If you agree to share feedback, we may include your comments in published research, but your name and aganecy will be kept strictly confidential. Please click the appropriate link in the survey below if you would like to receive further details regarding our study.

Take the survey

The campus IRB protocol associated with the above survey is 2024-0212. Please provide your response by February 5th, 2024 and feel free to email us with any questions. You may email meghna.baskar@duke.edu or jeff.desimone@duke.edu. If you would like more time to make a decision or would like a reminder in 14 days to answer, do let us know.



From: Jeff DeSimone <informing.policy.research@duke.edu>
Date: Monday, February 26, 2024 at 5:27 PM
To: Meghna Baskar <meghna.baskar@duke.edu>
Subject: Thank you for your interest!

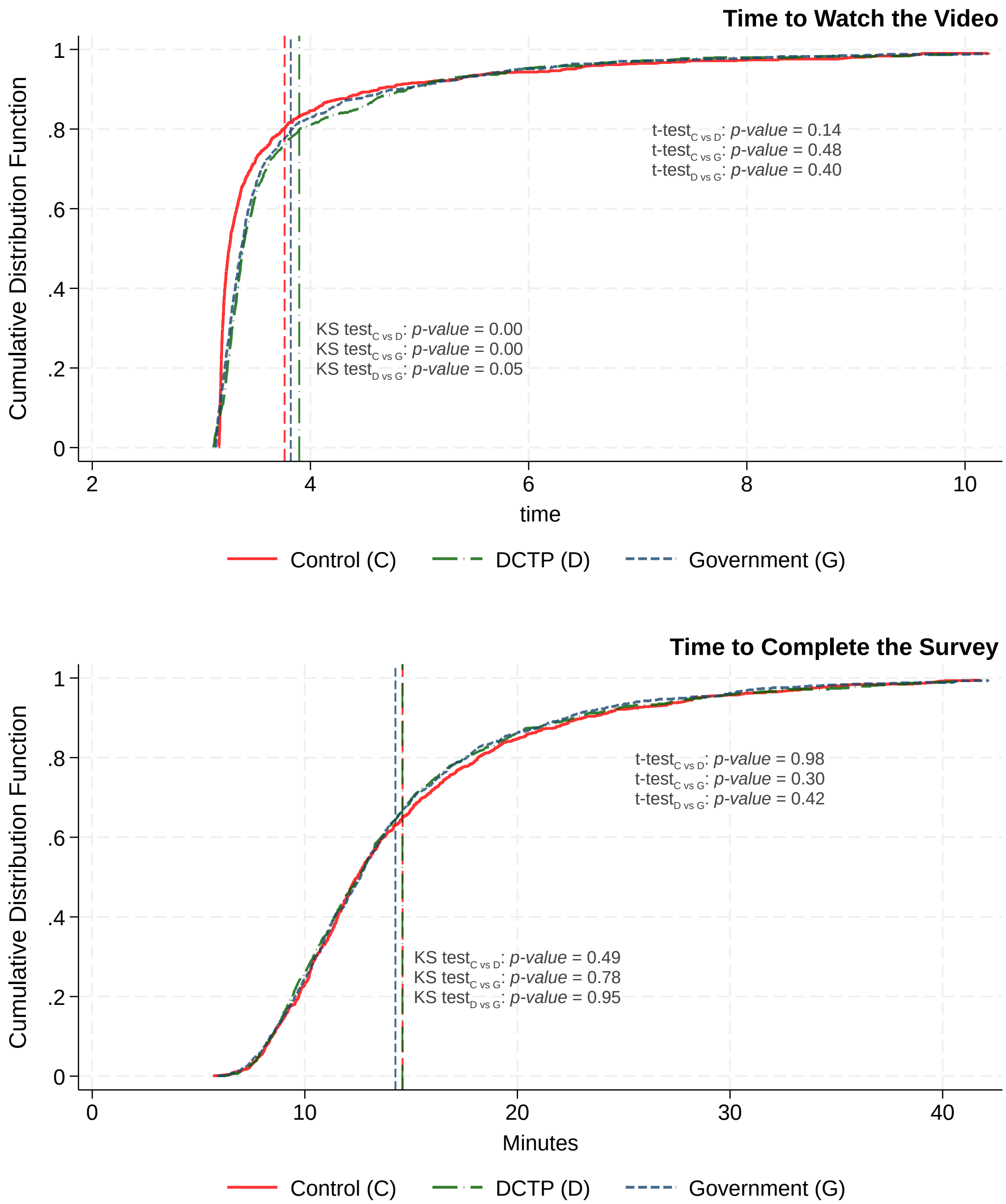
Dear Meghna Baskar,

Thank you for your interest in our study. Attached please find a report summarizing our experiment, sample and findings: Police Alternatives.pdf. We welcome your feedback as potential stakeholders in this study. To do so, please follow the survey link below to answer two feedback questions. The survey should not take longer than 2 minutes to complete and you can do so here.

Best,
Jeff DeSimone, PhD
Professor of the Practice of Economics
Director of the Duke Economic Analytics Laboratory
Duke University
Email: jeffrey.desimone@duke.edu
Email for this project: informing.policy.research@duke.edu or meghna.baskar@duke.edu
https://econ.duke.edu/deal
https://scholars.duke.edu/person/jeffrey.desimone

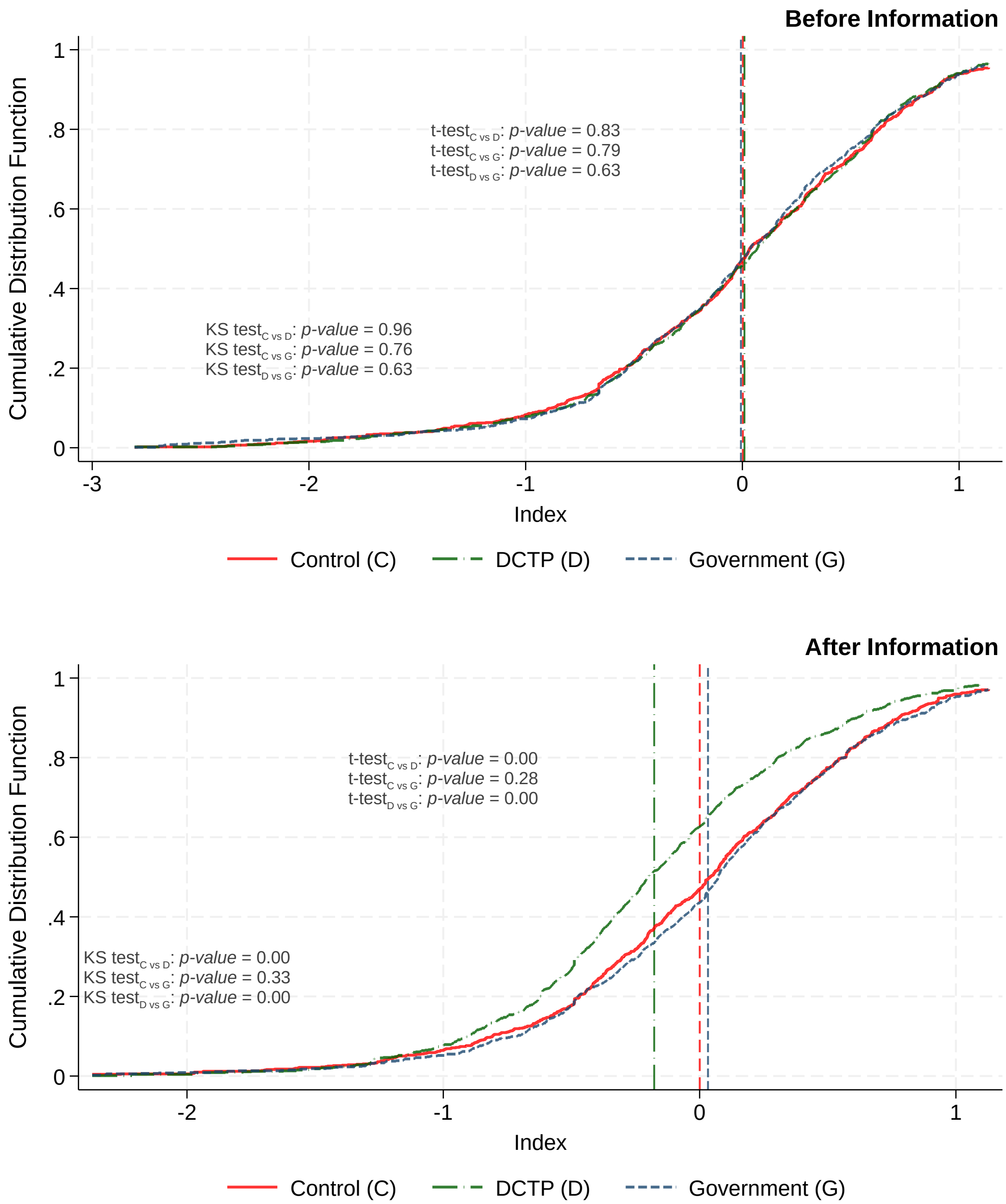
Notes: This figure presents screenshots from the emails sent out as a part of the field experiment. The Duke DEAL Lab, run by Professor Jeffrey DeSimone was used to centralize the tracking and distribution.

Figure A.10: CDFs of Time to Watch the Informational Video and Complete the Survey, by Treatment Arm



Notes: Empirical cumulative distribution functions of the time to watch the informational video and to complete the survey by treatment arm. The vertical lines indicate the means of each distribution. We report the p-value for a test of equality of means between each treatment arm and the p-value from a KS test to assess the equality of distributions between pairs of treatments: *Control* (C), *DCTP* (D), and *Government* (G).

Figure A.11: CDFs of Police Demand Index by Treatment Arm Before and After Information Exposure



Notes: Empirical cumulative distribution functions of the index capturing the demand for police by treatment arm before and after information treatment. The dependent variable is a KLK index, i.e., a z-score computed by subtracting the control group's mean and dividing by its standard deviation. A higher score indicates greater demand for police. The vertical lines indicate the means of each distribution. We report the p-value for a test of equality of means between each treatment arm and the p-value from a KS test to assess the equality of distributions between pairs of treatments: *Control* (C), *DCTP* (D), and *Government* (G).

Table A.1: Sample Characteristics: US Population vs Prolific

	U.S. Population	Prolific Sample
Age	45	47.86
Black	0.12	0.19
Hispanic	0.16	0.06
Other Race	0.07	0.14
Male	0.49	0.45
High School or Less	0.24	0.14
Some College	0.20	0.22
Graduate Degree	0.14	0.20
No Party	0.29	0.21
Democratic	0.31	0.44
High Income	0.22	0.20
Low Income	0.14	0.13
Single	0.34	0.33
Observations	–	2745

Notes: This table displays demographic statistics for the overall U.S. population and compares it to the characteristics of the survey respondents. National statistics on age, race, gender, education, political affiliation and socioeconomic status come from ACS 2022 and the IPUMS CPS dataset for 2022.

Table A.2: Impact of Information Treatments on Demand for Police Using Within Variation

	(1) Diff. Robbery	(2) Diff. Screaming Woman	(3) Diff. Naked Man	(4) Diff. Suicidal Ideation	(5) Diff. Disruptive Begging
DCTP	1.588*	-5.779***	-7.744***	-17.98***	-4.069**
	(0.886)	(1.311)	(1.942)	(1.783)	(1.635)
Government	0.504	1.857	2.066	-0.200	1.717
	(0.902)	(1.212)	(1.966)	(1.790)	(1.695)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	-0.68	-8.16	8.39	9.74	-15.45
Observations	2745	2745	2745	2745	2745

Notes: This table presents the impact of the *Government* and *DCTP* information treatments on the demand for police across various scenarios, utilizing pre/post treatment variation. The dependent variable measures the change in the likelihood of calling the police in each situation before and after the treatment. For each scenario, we adjust for baseline demand by matching the scenario with its respective category: "Robbery" with crime, "Screaming Woman" with domestic violence, "Naked Man" and "Suicidal Ideation" with mental health, and "Disruptive Begging" with homelessness/housing. The baseline demand for police was initially assessed by asking respondents to rate the importance of police involvement in issues such as domestic violence, substance abuse, mental health, sexual assault, and homelessness/housing. Robust standard errors are reported in parentheses. The mean of the dependent variable for the control group (individuals receiving information about different types of unemployment who are Republicans) is also provided. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.3: Confidence in Reported Likelihood of Calling the Police

	(1) Armed Robbery	(2) Screaming Woman	(3) Naked Man	(4) Suicidal Ideation	(5) Disruptive Begging
DCTP	0.262	-2.665***	-4.480***	-0.0356	-1.099
	(0.575)	(0.975)	(1.232)	(1.197)	(1.259)
Government	0.140	1.912**	-1.335	1.557	-2.757**
	(0.570)	(0.910)	(1.223)	(1.164)	(1.286)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	95.70	85.92	80.22	79.07	79.41
p-value:DCTP=Government	0.82	0.00	0.01	0.18	0.20
Observations	2745	2745	2745	2745	2745

Notes: This table presents the impact of the *Government* and *DCTP* information treatments on the confidence in the reported likelihood of calling the police. The dependent variable is the respondent's level of confidence in the reported likelihood of calling the police in the proposed situation (0–100). We report robust standard errors in parentheses. We report the mean of the dependent variable of the omitted category, i.e., the control group, which is composed of individuals receiving information about different types of unemployment. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.4: Heterogeneity Analysis: Demand for Police by Baseline Propensity to Call Police

	(1) Armed Robbery	(2) Screaming Woman	(3) Naked Man	(4) Suicidal Ideation	(5) Disruptive Begging
A) Low					
DCTP	1.600	-3.319	-5.346*	-10.04***	-0.260
	(2.232)	(2.644)	(3.041)	(2.879)	(2.007)
Government	1.402	0.187	0.523	0.763	4.718**
	(2.214)	(2.593)	(3.172)	(3.104)	(2.144)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	86.21	70.98	31.97	31.78	12.85
p-value:DCTP=Government	0.93	0.18	0.06	0.00	0.02
Observations	686	686	686	686	686
B) Mid					
DCTP	0.661	-6.390***	-7.690***	-20.28***	-3.023*
	(0.911)	(1.720)	(2.397)	(2.170)	(1.734)
Government	-0.541	2.851*	-0.0130	-3.682*	1.679
	(1.018)	(1.544)	(2.445)	(2.221)	(1.761)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	95.13	81.36	51.11	53.39	24.07
p-value:DCTP=Government	0.20	0.00	0.00	0.00	0.01
Observations	1375	1375	1375	1375	1375
C) High					
DCTP	1.454	-5.622***	-7.705**	-18.11***	-4.808
	(0.944)	(1.966)	(3.295)	(3.268)	(3.081)
Government	1.370	0.495	3.645	2.049	4.047
	(1.042)	(1.825)	(3.362)	(3.129)	(3.304)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	96.90	88.79	67.23	68.25	37.45
p-value:DCTP=Government	0.91	0.00	0.00	0.00	0.01
Observations	684	684	684	684	684

Notes: This table presents the impact of the *DCTP* and *Governement* information treatments on the demand for police in each situation by baseline propensity to call the police. Respondents with low (Panel A) and high (Panel C) propensity to call the police are those in the bottom and top quartiles of the baseline police demand index, respectively. Individuals in the second and third quartiles are categorized as having a moderate propensity to call the police (Panel C). The dependent variable indicates the likelihood of calling the police in the proposed situation (0–100). We report robust standard errors in parentheses. We report the mean of the dependent variable of the omitted category, i.e., the control group, which is composed of individuals receiving information about different types of unemployment. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.5: Heterogeneity Analysis: Impact of Information Treatments on Demand for Police

	(1) Main sample	(2) Female	(3) Male	(4) White	(5) Black	(6) Hispanic	(7) 39 yo or less	(8) 40 yo or more	(9) Less than college	(10) More than college
DCTP	-0.178***	-0.248***	-0.109***	-0.186***	-0.270***	-0.0582	-0.133***	-0.213***	-0.167***	-0.186***
	(0.0254)	(0.0329)	(0.0396)	(0.0295)	(0.0688)	(0.0971)	(0.0418)	(0.0318)	(0.0448)	(0.0306)
Government	0.0414	0.0385	0.0387	0.0231	0.0446	0.134	0.0491	0.0355	0.0549	0.0350
	(0.0255)	(0.0315)	(0.0415)	(0.0293)	(0.0698)	(0.107)	(0.0411)	(0.0321)	(0.0452)	(0.0309)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value:DCTP=Government	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00
Observations	2745	1514	1231	1851	515	158	1134	1611	976	1769

Notes: This table presents the impact of the *DCTP* and *Police Violence* information treatments on the demand for police. Each column shows the results for a different subsample across various characteristics (main sample, gender, race, age, and education). The dependent variable is a KLK index, i.e., a z-score computed by subtracting the control group's mean and dividing by its standard deviation. A higher score indicates greater demand for police. The index captures the demand for police for all scenarios. The dependent variable indicates the likelihood of calling the police in the proposed situation. We report robust standard errors in parentheses. We report the mean of the dependent variable of the omitted category, i.e., the control group, which is composed of individuals receiving information about different types of unemployment.. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.6: Heterogeneity Analysis: Impact of Information Treatments on Demand for Police for Violent Scenarios

	(1) Main Sample	(2) Female	(3) Male	(4) White	(5) Black	(6) Hispanics	(7) 39yo or less	(8) 40yo or more	(9) Less than college	(10) More than college
DCTP	-0.0789**	-0.0948**	-0.0693	-0.0962**	-0.169*	0.231	-0.0961	-0.0650	-0.0661	-0.0901**
	(0.0343)	(0.0433)	(0.0557)	(0.0379)	(0.0956)	(0.155)	(0.0614)	(0.0400)	(0.0625)	(0.0403)
Government	0.0504	0.0670	0.0280	0.0289	0.0411	0.255	0.0314	0.0716*	0.0789	0.0364
	(0.0345)	(0.0407)	(0.0591)	(0.0384)	(0.0976)	(0.159)	(0.0611)	(0.0392)	(0.0633)	(0.0410)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value:DCTP=Government	0.00	0.00	0.09	0.00	0.02	0.86	0.03	0.00	0.02	0.00
Observations	2745	1514	1231	1851	515	158	1134	1611	976	1769

Notes: This table presents the impact of the *DCTP* and *Government* information treatments on the demand for police in violent situations. Each column shows the results for a different subsample across various characteristics (main sample, gender, race, age, and education). The dependent variable is the KLK score, i.e., a z-score computed by subtracting the control group's mean and dividing by its standard deviation. A higher score indicates greater demand for police. The index captures the demand for police for the violent scenarios, i.e., "armed robbery" and "screaming woman." The dependent variable indicates the likelihood of calling the police in the proposed situation. We report robust standard errors in parentheses. We report the mean of the dependent variable of the omitted category, i.e., the control group, which is composed of individuals receiving information about different types of unemployment. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.7: Heterogeneity Analysis: Impact of Information Treatments on Demand for Police for Nonviolent Scenarios

	(1) Main sample	(2) Female	(3) Male	(4) White	(5) Black	(6) Hispanic	(7) 39 yo or less	(8) 40 yo or more	(9) Less than college	(10) More than college
DCTP	-0.244***	-0.350***	-0.135***	-0.246***	-0.337***	-0.251**	-0.157***	-0.312***	-0.235***	-0.250***
	(0.0303)	(0.0395)	(0.0467)	(0.0365)	(0.0778)	(0.102)	(0.0459)	(0.0398)	(0.0505)	(0.0378)
Government	0.0355	0.0196	0.0458	0.0193	0.0470	0.0527	0.0610	0.0114	0.0390	0.0341
	(0.0306)	(0.0392)	(0.0480)	(0.0363)	(0.0794)	(0.121)	(0.0456)	(0.0408)	(0.0512)	(0.0384)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value:DCTP=Government	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
Observations	2745	1514	1231	1851	515	158	1134	1611	976	1769

Notes: This table presents the impact of the *DCTP* and *Government* information treatments on the demand for police for nonviolent situations. Each column shows the results for a different subsample across various characteristics (main sample, gender, race, age, and education). The dependent variable is a KLK index, i.e., a z-score computed by subtracting the control group's mean and dividing by its standard deviation. A higher score indicates greater demand for police. The index captures the demand for police for the nonviolent scenarios, i.e., "naked man," "suicidal ideation," and "disruptive begging." The dependent variable indicates the likelihood of calling the police in the proposed situation. We report robust standard errors in parentheses. We report the mean of the dependent variable of the omitted category, i.e., the control group, which is composed of individuals receiving information about different types of unemployment.. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.8: Impact of Information Treatments on Demand for Police by Partisanship

	(1) Police Index	(2) Violent Index	(3) Nonviolent Index	(4) Robbery	(5) Screaming Woman	(6) Naked Man	(7) Suicidal Ideation	(8) Disruptive Begging
DCTP	-0.174***	-0.0654	-0.247***	0.784	-4.350**	-7.105**	-17.99***	-1.842
	(0.0428)	(0.0509)	(0.0544)	(0.940)	(2.013)	(2.837)	(2.722)	(2.318)
Government	0.0411	0.0679	0.0233	0.0970	3.277*	-2.459	-2.207	5.494**
	(0.0431)	(0.0541)	(0.0552)	(1.155)	(1.848)	(2.904)	(2.765)	(2.478)
DCTP X Democrat	-0.0203	0.0243	-0.0500	0.992	-0.131	-1.527	-1.605	-1.896
	(0.0563)	(0.0730)	(0.0693)	(1.486)	(2.672)	(3.719)	(3.506)	(2.886)
Government X Democrat	0.00305	-0.00788	0.0103	0.417	-0.964	5.264	0.469	-3.318
	(0.0560)	(0.0729)	(0.0703)	(1.616)	(2.418)	(3.804)	(3.570)	(3.058)
DCTP X No Party	0.0157	-0.104	0.0955	0.0934	-5.350	4.004	7.141*	-0.343
	(0.0737)	(0.0999)	(0.0854)	(2.389)	(3.323)	(4.581)	(4.285)	(3.606)
Government X No Party	-0.00544	-0.0461	0.0217	1.826	-4.801	5.584	3.684	-5.091
	(0.0759)	(0.106)	(0.0866)	(2.561)	(3.141)	(4.730)	(4.451)	(3.797)
Democrat	-0.110***	0.122**	-0.265***	1.137	4.603**	-14.66***	-8.188***	-5.557***
	(0.0410)	(0.0521)	(0.0507)	(1.138)	(1.791)	(2.771)	(2.554)	(2.114)
No Party	-0.138**	-0.0173	-0.218***	-3.099*	3.345	-10.09***	-10.37***	-3.187
	(0.0537)	(0.0726)	(0.0612)	(1.811)	(2.213)	(3.304)	(3.121)	(2.568)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	-0.10	0.00	-0.16	93.37	80.74	41.92	46.96	20.54
Observations	2745	2745	2745	2745	2745	2745	2745	2745

Notes: This table presents the impact of the *Government* and *DCTP* information treatments on the demand for police in each situation by partisanship status. The dependent variable in columns (1) to (3) is a Kling–Liebman–Katz index, i.e., a z-score computed by subtracting the control group's mean and dividing by its standard deviation. A higher score indicates greater demand for police. The dependent variable in columns (4) to (8) indicates the likelihood of calling the police in the proposed situation (0–100). We report robust standard errors in parentheses. We report the mean of the dependent variable of the omitted category, i.e., the control group, which is composed of individuals receiving information about different types of unemployment who are republican. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.9: Impact of Information Treatments on Interest in Website Detailing Police Alternatives, by Partisanship

	(1) Interest in DCTP Website Democrat	(2) Interest in 911 Website Democrat	(3) No Interest Website Democrat
DCTP	0.415***	-0.312***	-0.103***
	(0.0326)	(0.0372)	(0.0296)
Government	-0.0167	0.0297	-0.0130
	(0.0236)	(0.0370)	(0.0326)
DCTP X Democrat	0.0346	-0.106**	0.0712**
	(0.0449)	(0.0490)	(0.0338)
Government X Democrat	0.0210	-0.0261	0.00505
	(0.0363)	(0.0481)	(0.0369)
DCTP X No Party	0.0480	-0.0264	-0.0216
	(0.0542)	(0.0598)	(0.0453)
Government X No Party	-0.0651	0.0190	0.0461
	(0.0436)	(0.0619)	(0.0536)
Democrat	0.0636**	0.0856**	-0.149***
	(0.0263)	(0.0345)	(0.0267)
No Party	0.0631*	-0.0293	-0.0338
	(0.0326)	(0.0441)	(0.0373)
Controls	Yes	Yes	Yes
Mean of Dep.	0.20	0.73	0.07
Observations	2745	2745	2745

Notes: This table presents the impact of the *DCTP* and *Goverment* information treatments on website interest. Interest in alternative resources is gauged by engagement (or lack thereof) with the dontcallthepolice.com and 911alternatives.com websites by partisanship. Note that although the websites have different names, their content is identical. We report robust standard errors in parentheses. We report the mean of the dependent variable of the omitted category, i.e., individuals receiving information about different types of unemployment. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.10: Summary Statistics by Treatment Arm for the Whole Sample

	(1) All	(2) 911 Alternatives	(3) Don't Call the Police	(4) p-value
Share Black	0.10	0.11	0.10	0.61
Share Hispanic	0.13	0.12	0.13	0.23
Share Other Race	0.08	0.07	0.08	0.06
Unemployment Rate	0.05	0.05	0.05	0.38
Share Republican	0.47	0.48	0.46	0.19
Urban	0.80	0.80	0.81	0.53
Murders per 1,000	5.14	5.36	4.94	0.39
Violent Crimes per 1,000	2.97	3.12	2.83	0.30
Property Crimes per 1,000	14.87	14.97	14.77	0.83
Police per 1,000	2.23	2.27	2.19	0.68
Police Killings per 100K	0.33	0.36	0.30	0.13
High Search of Defund	0.58	0.58	0.57	0.59
Police	0.22	0.21	0.22	0.76
F-test	-	-	-	0.13
Observations	44162	21099	23063	44162

Notes: The table presents the descriptive statistics by treatment arm for respondents for the whole sample, not restricted to those who opened the email. Column (1) provides the mean level of each variable for the full sample. Columns (2) to (3) report the mean level of each variable by treatment arm. Column (4) reports the *p*-value from a test of the hypothesis of equal means across the experimental conditions. We cluster the standard errors at the county level to test the differences in means.

Table A.11: Who Opened the Email?

	(1) Open Email	(2) Open Email	(3) Open Email	(4) Open Email
DCTP	0.00871	0.00572	0.00700	0.00356
	(0.00548)	(0.00607)	(0.00535)	(0.00607)
Police	0.0353***	0.0280***	0.0352***	0.0269***
	(0.00616)	(0.00817)	(0.00611)	(0.00806)
DCTP X Police		0.0139		0.0159
		(0.0122)		(0.0120)
Share Black			0.0409	0.0411
			(0.0263)	(0.0263)
Share Hispanic			0.00770	0.00773
			(0.0160)	(0.0160)
Share Other Race			0.00617	0.00661
			(0.0355)	(0.0354)
Unemployment Rate			-0.105	-0.107
			(0.147)	(0.147)
Share Republican			-0.0363**	-0.0363**
			(0.0152)	(0.0152)
Urban			0.0501***	0.0502***
			(0.00654)	(0.00654)
High Search of Defund			-0.00663	-0.00672
			(0.00579)	(0.00580)
Murders per 1,000			0.00179	0.00255
			(0.0435)	(0.0436)
Violent Crimes per 1,000			-0.00198	-0.00203
			(0.00164)	(0.00163)
Property Crimes per 1,000			0.000292	0.000299
			(0.000417)	(0.000416)
Police per 1,000			0.000315	0.000314
			(0.00176)	(0.00176)
Police Killings per 100K			-0.000190	-0.000197
			(0.00253)	(0.00253)
Controls	No	No	Yes	Yes
Mean of 911 Alternatives	0.26	0.26	0.26	0.26
Observations	44162	44162	44162	44162

Notes: This table presents the factors impacting the likelihood of opening the email. The dependent variable equals one if the respondent opened the email and zero otherwise. We report the mean of the dependent variable for the omitted category, i.e., the control group, which includes respondents assigned to the *911 alternatives* subject line who are not police. We report standard errors clustered at the county level in parentheses. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.12: Impact of DCTP on Opinion on Police Alternatives and Willingness to Be Interviewed

	(1) Police Alt. Useful	(2) Police Alt. Useful	(3) Police Alt. Useful	(4) Police Alt. Useful	(5) Agree to Interview	(6) Agree to Interview	(7) Agree to Interview	(8) Agree to Interview
DCTP	-0.0187	-0.0290	-0.0120	-0.0282	0.101	0.171**	0.106	0.172**
	(0.0296)	(0.0337)	(0.0309)	(0.0348)	(0.0630)	(0.0713)	(0.0668)	(0.0777)
Police	0.0202	-0.0116	0.0307	-0.0171	0.0980	0.317***	0.0944	0.289***
	(0.0337)	(0.0584)	(0.0290)	(0.0533)	(0.0819)	(0.104)	(0.0832)	(0.109)
DCTP X Police		0.0523		0.0790		-0.359**		-0.321**
		(0.0712)		(0.0697)		(0.152)		(0.155)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Mean of 911 Alternatives	0.93	0.93	0.93	0.93	0.69	0.69	0.69	0.69
Observations	236	236	236	236	236	236	236	236

Notes: This table presents the impact of being assigned to the *DCTP* subject line on respondents' opinions about police alternatives and their willingness to be interviewed, categorized by police status. The dependent variable, "Police Alt. Useful," in columns (1)–(4), equals one if the respondent finds police alternatives useful and zero otherwise. The dependent variable in columns (5)–(8), "Agree for Interview," equals one if the respondent agreed to a one-hour interview to share her opinion and zero otherwise. We report the mean of the dependent variable for the omitted category, i.e., the control group, which includes respondents assigned to the *911 alternatives* subject line who are not police. We report standard errors clustered at the county level in parentheses. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.13: Impact of *DCTP* on Stakeholders' Willingness to Learn About Police Alternatives for the Whole Sample

	(1) Send Information	(2) Send Information	(3) Send Information	(4) Send Information
DCTP	0.00282**	0.000780	0.00248**	0.000380
	(0.00113)	(0.00129)	(0.00109)	(0.00125)
Police	0.000355	-0.00463***	0.000652	-0.00445***
	(0.00140)	(0.00156)	(0.00142)	(0.00161)
DCTP X Police		0.00950***		0.00972***
		(0.00271)		(0.00272)
Controls	No	No	Yes	Yes
Mean of 911 Alternatives	0.01	0.01	0.01	0.01
Observations	44162	44162	44162	44162

Notes: This table presents the impact of being assigned to the *DCTP* subject line on the likelihood of responding and the willingness to receive information about support for police alternatives, broken down by police status. The dependent variable, "Send Information," equals one if the respondent wanted to receive information about the study and zero otherwise. We report the mean of the dependent variable for the omitted category, i.e., the control group, which includes respondents assigned to the *911 alternatives* subject line who are not police. We report standard errors clustered at the county level in parentheses. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.14: Qualitative Interviews Response Rates

	(1) Send Information	(2) Interested in Interview	(3) Participated in Interview	(4) Participation | Information	(5) Participation | Interested
Police	123	36	15	12%	42%
Nonpolice	436	114	45	10%	39%
Sheriff & Other Law Enforcement	136	39	12	9%	31%
Local Officials	140	28	12	9%	43%
DOJ Grantees	160	47	21	13%	45%
Total	559	150	60	11%	40%

Notes: This table presents the response rates of police and nonpolice stakeholders for the qualitative interviews. Column (4) shows response rates as the number of interview participants divided by those who requested additional study information. Column (5) shows response rates as the number of interview participants divided by those who expressed interest in participating. Interviews were conducted between April and June 2024.

Table A.15: Code Definition & Frequency for Explanations of Word Associations

		Police		Nonpolice	
		911 Alt	DCTP	911 Alt	DCTP
Code	Definition	N = 42	N = 40	N = 123	N = 111
Model/Domain	Identifies specific model or domain of intervention	50%	30%	50%	20%
Training/Equipment	Refers to responders best trained & best equipped to manage incident	40%	28%	37%	23%
Resources/Efficiency	Focuses on resource allocation and budget impact	48%	23%	17%	14%
Trust/Fear	Refers to lack of trust or fear of police	5%	23%	3%	26%
Minoritized Groups	Describes perspective or treatment of minoritized groups, especially African Americans and immigrants	2%	28%	2%	14%
Compassion/Community	Focuses on need for greater compassion and stronger community	10%	8%	14%	8%
Education	Describes need for more education, e.g., about appropriate occasions for dialing 911	10%	10%	10%	15%
Noncriminal Issues	Refers to the frequency of noncriminal, nonemergency, or noncrisis issues	7%	15%	15%	10%
Safer/Less Police Violence	Describes potential for increased safety due to less police violence	7%	5%	14%	13%

Note: This table summarizes definition and frequencies of codes for the explanations that interview participants provided for the words they associated with *911 Alternatives*(911 Alt) and *Don't Call the Police* (DCTP). A co-author coded these explanations after establishing inter-coder reliability on whether the words expressed support or skepticism toward the two conditions. Explanations could include multiple issues. Codes that were less salient across stakeholders that are not shown were immediate response times, legislation, and increased police violence.