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UNDERSTANDING DEMAND FOR POLICE ALTERNATIVES

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ABSTRACT

While police brutality has sparked demands to scale back policing, public constituencies still have limited knowledge about policing alternatives. In survey experiments, we provide information about *dontcallthepolice.com*—a database of police alternatives—and police violence statistics and evaluate their impact on respondents' stated likelihood of calling the police. We find information about police alternatives increases the likelihood of relying on police in violent scenarios but significantly reduces it in scenarios for which police alternatives exist. These findings hold across political affiliations, suggesting broad support for limiting police involvement to violent crises and investing in police alternatives for nonviolent situations. In a follow-up survey six months later, individuals informed about police alternatives were 12 percentage points more likely to recall that the newly available 988 government hotline is available for suicidal crises, a result highlighting the enduring effectiveness of targeted educational interventions. Our study shows that providing information on existing 911 alternatives results in increased demand for these police substitutes in non-violent situations both in the short and long run.

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"Unfortunately, the police department has been made the catchall for everything. All the problems," said Anderson, a 30-year veteran of the Metropolitan Police Department. [...] "You know, psychiatric centers can't hold the patients. So we put them on the street. Call the police to deal with it," Anderson explained, as a couple of officers in the chain of men beside him nodded their helmet-heads in agreement. "There's a drug issue . . . police are called to assist with that drug issue. The community has allowed that. The community is not saying, 'Wait a minute, we can't put all this on police.'"

Washington Post, June 2020

1 Introduction

In the wake of George Floyd's death at the hands of police in 2020, calls to explore alternatives to traditional policing surged to the forefront of public discourse (Kaba et al., 2021; Akbar, 2020). Longstanding calls to shift from what some constituencies have characterized as an overreliance on police to meet a broad range of social needs toward community-based and public health–focused mechanisms for providing public safety gained new momentum in this period (Dee and Pyne, 2022; Hendricks, 2021). At the same time, (Ba et al., 2023a,b) show that these social movements have not succeeded in reducing the scale of policing. In this paper, we investigate whether the subdued efficacy of social movements is due to a lack of demand for police alternatives or a lack of information about such alternatives. We show strong evidence for the latter, with large bipartisan shifts away from calling the police in non-violent situations once individuals become aware of police alternatives.

Using online survey experiments, we examine the impact of providing information about alternatives to police and police violence statistics on people's willingness to call the police in response to crises. We find that while exposure to information about police alternatives lessens respondents' reported likelihood of relying on law enforcement to attend to nonviolent matters such as mental health–related incidents, it conversely heightens their likelihood of turning to the police in violent situations such as armed robberies. This result is most pronounced among those initially less likely to call the police. In cases of domestic violence and nonviolent crises, demand for police services significantly decreases among individuals moderately to highly reliant on police when they are informed about dontcallthepolice.com (DCTP), a website offering information on police alternatives, and the extent of police violence. The consistency of these findings across respondent political affiliations suggests potentially broad grassroots support for limiting police involvement in public safety matters to pressing, violent crises and reallocating resources to alternative mechanisms for responding to nonviolent situations. Six months after our intervention, a follow-up survey showed that individuals informed about police alternatives were more likely to remember the availability of the 988 government hotline for suicidal crises, underscoring the lasting impact of targeted educational efforts.

Developing an empirical understanding of different constituencies' views of police alternatives presents many challenges. The introduction of police alternatives and reallocation of resources from police in some jurisdictions have led to a polarizing debate that has complicated attempts to evaluate both the functioning of and residents' sentiment toward alternative public safety mechanisms (Bursztyn et al., 2023). Furthermore, different subpopulations, including infrequent to frequent users of emergency services, are likely to have heterogeneous perceptions of police alternatives, and identifying the mechanisms driving this heterogeneity is crucial.

We address these challenges in several steps. First, we design a survey to evaluate how likely participants are to turn to law enforcement as first responders in a range of crisis scenarios. The survey reports scenarios featuring four real-life incidents that led to likely preventable civilian deaths at the hands of police, and one fictional situation. The scenarios feature civilian encounters with police as first responders in cases ranging from violent incidents such as armed robbery and domestic violence to nonviolent situations involving people with potential mental health vulnerabilities or individuals experiencing homelessness. This methodology offers insights into respondents' attitudes on policing and police alternatives and allows us to isolate patterns in public perceptions across diverse and realistic contexts. Note that the presentation of all the scenarios is phrased such that the respondent is cast as a witness or bystander to the incident, so the survey measures the propensity to call the police as a *witness* rather than as a victim.

Second, we partner with dontcallthepolice.com, a website that provides a directory of specialized, community-based crisis intervention services as alternatives to law enforcement, and we randomly assign one of three animated educational videos (Alesina et al., 2018; Bernstein et al., 2023) across more than 2,900 respondents to implement nondeceptive experimental variation. Each video offers accurate details on government services that can serve as police alternatives (211, 311, and 988). The *DCTP* treatment also highlights vetted nongovernmental options focusing on minimizing police involvement. We also implement a *Police Violence* treatment featuring statistics about police violence in the U.S. We then assess respondents' reported inclination to call the police for assistance across the scenarios, and we collect information on their demand for police alternatives, their policy preferences, and the reasoning behind their decisions on how to handle the different scenarios.

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 notably reduces overall demand for police services by 0.129σ ($p < 0.01$), with a more pronounced decrease in nonviolent situations (0.207σ, $p < 0.01$). Similarly, the *Police Violence* treatment leads to a general reduction in demand for police, especially in nonviolent scenarios, although the effects are smaller. Therefore, providing information regarding police alternatives appears to be a more effective strategy to reduce reliance on police as first responders than exclusively presenting constituents with statistics concerning police violence, aligning with observations from various contexts that emphasize the power of narratives and stories over statistics alone (Graeber et al., 2022). Notably, neither treatment significantly alters the demand for police in violent scenarios.

The analysis of each scenario reveals key heterogeneities in the impact of the educational videos. The *DCTP* treatment significantly increases respondents' likelihood of indicating that they would call the police in an armed robbery scenario by 2.5 pp ($SE = 0.871$). At the same time, it markedly reduces their likelihood of indicating that they would call the police in nonviolent situations, such as encountering a naked man on the street, learning that a friend is contemplating suicide, and dealing with someone engaged in aggressive begging. This variation underscores an element of discernment in constituents' perspectives on police involvement, where their preferences for first responders are tailored to the specific nature of the crisis. The *Police Violence* treatment has a smaller, yet still significant, effect in reducing demand for police in the nonviolent scenarios but increases it, albeit to a less pronounced extent than the *DCTP* treatment, in the "armed robbery" case. These insights demonstrate that neither the *DCTP* nor the *Police Violence* treatment discourage the public from seeking police assistance in high-stakes, violent situations, suggesting an understanding of the crucial role that police play in emergencies requiring specialized intervention.

We also evaluate the impact of each treatment on participant preferences for different names of websites presenting information on police alternatives. Considering two domain names, dontcallthepolice.com and 911alternatives.com, which both host identical content, we assess how the treatments influence participant preferences for each website name. The results indicate that receiving information about DCTP significantly increases participants' interest in the DCTP website while receiving information about police violence does not alter their interest in either site.

Individuals' propensity to contact law enforcement varies significantly. Capturing this spectrum of police reliance, we uncover that individuals' baseline tendencies to call the police, ranging from inherent hesitancy to routine dependence, significantly shape their response to the information treatments. This differential reliance at baseline can manifest among different constituencies as a reticence to access police services, misaligned incentives (e.g., regarding the reporting of crimes), or inaccurate beliefs, ultimately moderating the impact of policy measures intended to support vulnerable populations. In particular, among those with moderate to high baseline reliance, the *DCTP* treatment increases demand for police in the "armed robbery" scenario but markedly decreases it for nonviolent incidents. In essence, providing additional information can influence individuals at each level of baseline reliance in their decision to seek police intervention. Nonetheless, the effect varies across reliance levels depending on the (violent or nonviolent) character of the scenario.

In surveys and discussions about policing, partisanship is consistently found to strongly predict perspectives (Sances, 2023c,b,a). In notable contrast to this typical finding, we find that both Democrat and Republican respondents show decreased demand for police in nonviolent scenarios after learning about DCTP, while their responses to the police violence information are more muted. This suggests a widespread openness at the grassroots level to community-based police alternatives. Additionally, we examine whether political affiliation affects interest in websites about police alternatives such as dontcallthepolice.com. Interestingly, both Democrats and Republicans demonstrate a heightened interest in DCTP after exposure to information about it, in contrast to the intuition that such a website name might alienate conservatives, who are consistently found in surveys and research to be more strongly pro-police and opposed to efforts to reduce or reform the role of police than less conservative constituents.

Our analysis primarily uses an active control group to assess the impact of providing information about police alternatives on emergency response decisions. Additionally, we add a pure control group consisting of respondents uninformed about alternative resources, which serves to clarify the effects of information about police alternatives. We find that while the awareness of alternatives does not affect decisions in high-stakes scenarios such as the "armed robbery" case, it significantly decreases the likelihood of calling the police in nonviolent situations such as the "naked man" and "suicidal ideation" incidents. This reduction in police contact is particularly driven by exposure to resources such as dontcallthepolice.com, which underscores the strong public preference for nonpolicing solutions in less critical circumstances. These findings highlight the potential of community-based and preventative approaches in reshaping public safety strategies.

In the final section, we explore the persistence of the impact of our educational intervention regarding the recently launched 988 helpline, a vital new emergency resource for suicide prevention that relies on public recognition and proper use yet suffers from low awareness (PEW (2023)). We present the results of a follow-up survey evaluating the long-term effect of our three-minute educational video about the 988 helpline, originally shown six months prior. This survey, assessing information retention in high-pressure, timed scenarios, shows that individuals informed about police alternatives significantly preferred using the 988 helpline over calling the police during suicidal ideation–related crises (Graeber et al., 2022). Specifically, those educated about this alternative showed an increase of over 12 pp ($p < 0.01$) in their likelihood of choosing 988, in stark contrast to the base rate of just 2% among those without this prior exposure. Furthermore, the results highlight a pronounced increase in the likelihood of dialing 988, of approximately 20 pp ($p < 0.01$), for those exposed to the *DCTP* treatment. This underscores the significant, lasting influence of targeted information interventions and of the DCTP website name on emergency response decision-making.

Related Literature Our study intersects with diverse strands of research. First, it contributes to literature examining the impact of information treatments on support for policies affecting underrepresented groups across fields such as policy analysis (Haaland and Roth, 2021; Alesina et al., 2018), finance (D'Acunto et al., 2020), healthcare (Alsan et al., 2023), and law enforcement (Bursztyn et al., 2023; Ba et al., 2023a). Second, informed by the discourse on police abolition (Gilmore, 2007; Akbar, 2020; Davis, 2011; Kaba et al., 2021; Davies et al., 2021)—which calls for a reduction in the societal reliance on police presence to provide public safety—we employ survey experiments to delve into constituents' public safety preferences and the cognitive frameworks informing their choices (Bordalo et al., 2020; Andre et al., 2021, 2022; Stantcheva, 2023).

Next, our work contributes to economics of crime research, underscoring the dynamics and risks of police involvement with vulnerable and at-risk groups, such as young men of color and economically disadvantaged individuals (Fuller et al., 2015), LGBTQ+ individuals (Satuluri and Nadal, 2018),[1] individuals experiencing gender-based violence (Miller and Segal, 2019; Cunnigham and Shah, 2018; Adams-Prassl et al., 2022) such as domestic violence (Aizer and Dal Bo, 2009; Leslie and Wilson, 2020; Adams-Prassl et al., 2023), individuals experiencing homelessness (Evans et al., 2016, 2021), and individuals struggling with mental health vulnerabilities or substance abuse (Dee and Pyne, 2022). By delving into the determinants of police–civilian encounters (Ang et al., 2021; Rivera and Ba, 2023), our work can inform policies aimed at mitigating the risks inherent in these critical interactions.[2]

Additionally, our study contributes to a broader discussion on the distributional impacts of policies—an area that has seen significant attention in recent economic research (Heckman et al., 1997; Bitler et al., 2006, 2017). We delve into the societal trade-offs present in police interactions and analyze how disseminating information on alternatives to a traditional police response can reshape demand for police services across various community segments. In addition to the intricate dynamics of police engagement with vulnerable groups, our study highlights concerns prevalent in the healthcare and welfare literatures about the cognitive and psychological factors influencing uptake of welfare programs (Moffitt, 1983; Finkelstein and Notowidigdo, 2019).[3] This differential baseline reliance on public services—which could manifest as or foster access barriers, misaligned incentives, or inaccurate beliefs, among others—can seriously hinder the effectiveness of policy interventions designed to aid those in greatest need, challenging policymakers to consider these factors in the development and implementation of supportive measures for vulnerable populations.

Finally, 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 actions and decisions of individuals in the political sphere, 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 tend to shape beliefs (Ang and Tebes, 2023) and behavior (Grosjean et al., 2022; Ba et al., 2023; Goncalves and Tuttle, 2022) in these areas similarly to those in the domain of policing, our research shines a spotlight on a context characterized by limited evidence of polarization: specifically, we find a surprising consensus regarding reliance on police alternatives in nonviolent crises.

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

[2] More specifically, using insights from the literature on statistical treatment rules, which aid in crafting targeted interventions (Manski, 2004), we focus on delineating heterogeneity in constituents' response to information about police alternatives (Jácome, 2022; Goncalves et al., 2023; Golestani, 2023), which is crucial for understanding their willingness to engage with law enforcement (Ba, 2018; Hendricks, 2021; Graef et al., 2023).

[3] These concerns extend to immigrant communities, whose apprehensions about interacting with the state can further complicate their access to essential services such as work safety programs (Grittner and Johnson, 2021), welfare (Alsan and Yang, 2022), public safety services (Goncalves et al., 2023), and healthcare (Sabety et al., 2023).

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 the experimental design and empirical specification for our study. Section 4 presents our analysis and findings. Section 5 discusses our findings by respondents' initial propensity to rely on police. Section 6 investigates the role of partisanship in our findings. Section 7 presents the impact of public awareness on demand for police alternatives and the long-term impact on the demand for the 988 Suicide & Crisis Lifeline. Section 8 concludes.

2 Background on Police Alternatives

Governmental Resources The United States has established several government-administered hotlines as integral components of its public service infrastructure; these resources can serve as potential alternatives to traditional policing 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 dedicated services are applicable.

Nongovernmental Resources In this study, we collaborate with the platform dontcallthepolice.com to evaluate the efficacy of 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, and 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. A notable traffic spike on dontcallthepolice.com occurred around the conviction of Derek Chauvin—the police officer responsible for George Floyd's death—in contrast to the steady traffic on communityresourcehub.com and the varying visits to defundthepolice.com. This surge 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; Devi and Fryer, 2020), civilian responses (Ang et al., 2021), or both (Rivera and Ba, 2023). We provide more information about DCTP in Section A.1 of the appendix.

3 Experimental Design

3.1 Research Design

Overview and Logistics We surveyed an online sample of 2,910 U.S. adults to gauge preferences for police involvement in specific scenarios. Participants, recruited via Prolific on October 17, 2023, were randomized into treatments in which they viewed educational videos on police alternatives or U.S. police violence statistics. Our research protocol was preregistered with the AEA registry (ID: AEARCTR-0011938). 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 11 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) *Police Violence*, and (3) *Don't Call the Police*. 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 witness or bystander to the incident. Hence, the survey measures the propensity to call the police for assistance as a witness rather than as a victim. Participants were also asked whom they thought should be sent to help in each situation among three available options—(1) a police officer, (2) a social worker, or (3) no one—and were asked to rank their preferences for which type of expert they would like to receive advice from about how to handle the situation among five available options—(1) an academic, (2) a community organizer, (3) a lawyer, (4) a police officer, or (5) no one.

Next, as another way to assess preferences for the status quo, reform, or a shift toward police alternatives, we asked participants which nonprofit organization they would choose to donate to from among three available options: (1) an organization that aims to improve officer safety and health and wellness in police, (2) an organization involved in training police officers to improve their empathy and understanding of mental illness through crisis intervention training, and (3) an organization that provides information on mental health crisis resources that do not involve the police.

We then presented another attention check to ensure that participants were still reading and answering carefully. Any respondents failing the attention check were screened out at this stage. Next, to assess how messaging might affect receptivity, 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 employed animated videos similar to those used in the studies of Alesina et al. (2018), Alesina et al. (2018), and Bernstein et al. (2023). All of these videos present truthful information about alternative governmental services—211, 311, and 988. The two treatment (noncontrol) conditions also conveyed statistics about police violence in the U.S. and information about vetted nongovernmental options prioritizing minimizing police involvement, respectively.

We maintained consistency by ensuring that each video was of similar duration, such that respondents across treatment arms performed tasks of similar length. Complete video transcripts are provided in Appendix D, and screenshots from the videos are displayed in Appendix Figures A.1, A.2, and A.3. The conditions are as follows:

- **Control Group Video:** The video for this experimental arm provides information on government resources that can serve as viable alternatives to a police response, such as 988 for 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.[4]

- **Police Violence Video:** The video for this experimental arm highlights the disproportionate use of police as responders to nonviolent emergencies in the U.S., emphasizing the risk of escalation to violence, particularly among people of color and vulnerable groups. The video uses statistics about police violence in the U.S. and comparative data on police fatalities in the

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

U.S. and other countries derived from peer-reviewed publications and white papers. The end of the video also presents the *Control* video information on the government hotlines (988, 211, and 311).[5]

- **Don't Call the Police Video:** The video for this experimental arm emphasizes that police are often the default responders to emergencies in the U.S. even though most calls do not involve violent crimes. It then introduces dontcallthepolice.com and presents 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 *Control* video information on the government hotlines (988, 211, and 311).[6]

Scenarios Our primary outcome measure is respondents' reported propensity to contact law enforcement in response to crisis situations. We evaluate their reactions to four scenarios, each mirroring actual incidents that resulted in civilian fatalities during police encounters as cataloged in the Mapping Police Violence database (see Appendix E for details). While we mention that these scenarios mirror incidents that led to civilian deaths, they also routinely occur without any casualties. [7] These four scenarios serve as grounded, real-world examples, while a fifth, fictional scenario extends the inquiry into the realm of the hypothetical. These scenarios identify respondents' beliefs about the appropriateness of relying on police as first responders across various plausible real-life situations. A similar approach 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 s cenarios 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:

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

[6] The link to the *DCTP* video can be found here.

[7] More specifically, the following news articles report examples of incidents mirroring our scenarios that did not lead to a civilian death armed robbery, screaming woman, naked man, and suicidal ideation.

$$y_i = \alpha + \beta_D DCTP_i + \beta_P PoliceViolence_i + X_i'\gamma + \epsilon_i \quad (1)$$

where outcome y_i of respondent i is a function of each treatment condition. The variable $DCTP_i$ is a binary variable that equals one if the respondent received the *DCTP* treatment and zero otherwise. The variable $PoliceViolence_i$ is a binary variable that equals one if the respondent received the *Police Violence* treatment and zero otherwise. The omitted group corresponds to the control group. In addition, in X_i, we control for individual covariates. We use robust standard errors, as we randomized at the individual level.

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. We compute the z-score by subtracting the control group's mean and dividing by its standard deviation. Additionally, preferences for responders (police, social workers, or none) are captured as binary choices for specific scenarios and cumulatively on a scale from 0 to 5. Rankings of preferred sources for expert advice and binary support for organizations affiliated with police well-being, police reform, and community-based resources that do not involve the police are also included. 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.

3.2 Validation of Design

Balance Tests Table 2 shows demographic distributions for the overall sample and the subdivisions of the *Control*, *Police Violence*, and *DCTP* experimental conditions. The demographic consistency across these groups—with no significant differences ($p > 0.1$) by age, race, gender, education level, political affiliation, marital status, and baseline value on our index of policing demand—indicates that the randomization was successful.

We also compare the demographic composition of our sample with data from the 2022 iteration of the American Community Survey to demonstrate its national representativeness. When we compare columns (1) and (2) of this table, we observe that the sample mean across all variables generally aligns closely with that in the ACS data, suggesting that the sample is fairly representative, with slight variations in demographic characteristics such as age, education, and income levels.

Our sample is more than two-thirds White, with smaller proportions of Black respondents and respondents of other races. Nearly half of the sample is male, and younger than 40 years old.

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.

Time to Watch Video and Complete Survey Figure A.4 displays the cumulative distribution functions (CDFs) for the time that participants spent watching the informational video and completing the survey, categorized by treatment arm. The survey's design compelled respondents to engage fully: audio was required, and respondents could not advance in the survey until the full video time had elapsed. Participants had to choose responses for each query actively, and for questions necessitating numeric responses, only numerical entries were permitted. The left graph, which accounts for the time to watch the video, demonstrates statistically significant variations across the treatment groups. The *Control* group took the least time to watch the video, while the *Police Violence* group took the longest. However, these differences are minor in economic terms, i.e., of 5 to 10 seconds, and are likely attributable to mechanical effects given the slight variations in the video durations. The right graph, which tracks the time to complete the survey, shows negligible differences in completion times across the different treatment arms, suggesting that the video lengths did not have a meaningful impact on survey completion time by treatment arm.

Preliminary Evidence Figure 2 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 in demand for police across groups, with both treatment groups' CDFs shifting leftward, with a change in mean of approximately 0.1σ to 0.16σ ($p < 0.01$) for the groups shown the information on police alternatives. This signals lower postintervention demand for police among respondents receiving additional information about police violence and police alternatives. Thus, these preliminary results indicate that information provision may influence public preferences concerning police involvement.

4 Impact of Information on Demand for Police and Alternatives

4.1 Response to Scenarios

Demand for Police by Scenarios' Level of Violence Table 3 presents our main results using equation 1 to assess the effect of the educational videos on our indices of demand for police. Respondents exposed to the *DCTP* video show a decrease in their overall demand for police of 0.129 standard deviations (σ) ($SE = 0.024$); this effect is more substantial for the nonviolent scenarios, with a reduction of 0.207σ ($SE = 0.029$). Information about police violence also leads to a causal reduction in demand for police of 0.091σ ($SE = 0.024$) overall, with a specific decrease of 0.165σ ($SE = 0.029$) for the nonviolent incidents. For neither treatment arm do we find a significant effect on demand for police in the violent scenarios overall.[8] Finally, the p-values at the bottom of the table indicate no significant difference between the effects of the *DCTP* and *Police Violence* treatments on respondents' demand for police involvement as measured by these indices. These results suggest that such informational interventions can effectively shift public demand away from a preference for police involvement, particularly for nonviolent situations.

Demand for Police by Specific Scenario Table 4 assesses the impact of the *DCTP* and *Police Violence* treatments on demand for police across scenarios to determine whether the treatment effects are heterogeneous by situation. The *DCTP* treatment leads to a 2.5 pp ($SE = 0.871$) increase in the reported likelihood of calling the police in the "armed robbery" case, despite the implication of the treatment name, revealing respondents' prioritization of police intervention in high-stakes situations. Conversely, the *DCTP* treatment significantly reduces police demand in the nonviolent scenarios: "naked man" by 5.9 pp ($SE = 1.562$), "suicidal ideation" by 11.9 pp ($SE = 1.456$), and "disruptive begging" by 3.9 pp ($SE = 1.200$). In the violent scenarios, the contrasting decrease of 3.7 pp ($SE = 1.186$) for the "screaming woman" scenario suggests nuanced public perspectives on the necessity of police response by context, consistent with prior findings that individuals are reluctant to call the police in domestic violence scenarios (Iyengar, 2009).

The *Police Violence* treatment also elevates demand for police in the "armed robbery" case, albeit less so than the *DCTP* treatment. It significantly lowers police demand in the "naked man," "suicidal ideation," and "disruptive begging" scenarios, possibly reflecting increased concern about police violence in situations where the risks inherent in a police response seem to outweigh the risk of the situation itself. The p-values reveal no significant differences in effect between the *DCTP* and *Police Violence* treatments in the "armed robbery," "naked man" or "disruptive begging" scenarios, but there is a significant difference for the "screaming woman" and "suicidal ideation" scenarios. In addition, they indicate a stronger impact of the *DCTP* treatment in decreasing demand for police

[8] Demand in the "armed robbery" scenario increases, while demand in the "domestic violence" scenario decreases, leading to a null effect when the violent scenarios are evaluated together.

in the “screaming woman,” “naked man,” “suicidal ideation” and “disruptive begging” cases but a stronger impact in *increasing* demand for police in the “armed robbery” scenario. These findings suggest that *DCTP* information is more effective (in terms of effect magnitude) than the *Police Violence* information for both high- and low-stakes scenarios.

Who Should Respond? Table 5 investigates the impact of the information treatments on preferences for who should respond in each scenario: the police, a social worker, or no one. The *DCTP* treatment significantly reduces the preference for a police response by 0.17 ($SE = 0.041$) relative to the control mean of 2.6. Simultaneously, the preference for a social worker response increases by 0.17 ($SE = 0.0433$) relative to the control mean of 1.7, indicating a shift toward favoring community-based support options.

The *Police Violence* treatment also leads to a decrease of 0.10 ($SE = 0.0405$) in the preference for police intervention, suggesting a shift away from police as preferred crisis responders that is similar to, but slightly less pronounced than, that in the *DCTP* treatment. For social worker response, the increase is 0.11 ($SE = 0.0427$), reinforcing the trend toward a preference for nonpolice alternatives. 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, particularly a social worker, respond. This shift in preference implies that constituents may recognize the importance of responding to crises but may value responses other than a traditional police reponse, with a growing inclination toward specialized, nonpolice interventions.

Preferred Responder by Scenario Figure 4 supplements Table 5 by illustrating the effects of the information on preferences for first responders across the different crisis scenarios. The left side of the figure displays the control group’s baseline preferences, revealing a strong inclination toward police intervention, particularly in the “armed robbery” and “screaming woman” scenarios. Conversely, exposure to the *DCTP* information tends to reduce the preference for police involvement, notably in the “screaming woman” scenario by approximately 5 pp, while concurrently increasing the preference for social worker engagement. A social worker response is already favored by the control group in the “suicidal ideation” scenario, a tendency that exposure to the *DCTP* information strengthens for both this and the “naked man” scenarios. While the general inclination toward preferring no response at all is low, it trends upward when respondents are exposed to information, with the “naked man” and “disruptive begging” scenarios showing the most noticeable rise, although the respective estimates are less precise.

4.2 Policy Endorsements

Support for Policy Table 6 examines the effect of the *DCTP* and *Police Violence* information on participants’ support for organizations focusing on nonpolice crisis resources, police reform, or police well-being. The results show no significant changes in participants' preferences for organizations promoting nonpolice crisis resources or police well-being following exposure to either type of information. However, the *DCTP* information slightly reduces support for the organization advocating police reform, although not statistically significantly. The table suggests that the *DCTP* and *Police Violence* treatments may not have a strong influence on public support for these particular police-related causes.

Interest in dontcallthepolice.com Table 7 illustrates the impact of the *DCTP* and *Police Violence* information treatments on participants' inclination to explore websites describing alternatives to 911. Within the control group, nearly 60% express interest in 911alternatives.com, while 21% lean toward *DCTP* or remain uninterested in such resources. The *Police Violence* treatment does not significantly alter these responses relative to those in the control group. In contrast, the *DCTP* treatment notably increases interest in the DCTP website by 30.4 pp ($SE = 0.0205$). This coincides with a marked decline in interest for the 911 alternatives website of 24.1 pp ($SE = 0.0219$) and a decrease in the proportion of participants uninterested in either website of 6.29 pp ($SE = 0.0169$).

These findings underscore the significant influence of naming and branding on user behavior and perceptions even when the information presented by the two websites remains identical. Without additional information, respondents strongly prefer the "911 alternatives" messaging to the "don't call the police" messaging. While the *Police Violence* treatment does not significantly alter preferences, the *DCTP* treatment distinctly steers participants toward the DCTP website. This suggests that effectively communicated educational content about nongovernmental police alternatives can substantially shift public preferences even when the website content remains unchanged. These findings also imply that the website name does not necessarily deter individuals from looking for information on police alternatives.

4.3 Additional Analyses

Experimenter Demand Effect The possibility of respondents' altering their answers to align with their perceived expectations of the experiment is a concern.[9] While this could influence respondents in the *DCTP* or *Police Violence* groups to reduce their reported likelihood of calling the police, the findings for the "armed robbery" scenario suggest otherwise. After viewing the *DCTP* or *Police Violence* video, respondents were *more* 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.[10]

[9]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).

[10]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).

Heterogeneity Analysis Tables A.1, A.2, and A.3 present the heterogeneity in our findings across various respondent characteristics and indices. 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 the violent scenarios, the patterns are mixed, with White 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. Interestingly, respondents of "other races," which include Hispanic respondents, exposed to the *DCTP* information are 0.233σ ($p < 0.01$) more likely to call the police for the violent scenarios, 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.

Demand for Expertise Table A.4 analyzes the influence of the *DCTP* and *Police Violence* treatments on constituents' preference for receiving advice from various expert groups about how to handle the scenarios. We find that exposure to the *DCTP* video significantly increases respondents' reported likelihood of seeking advice from academics by 0.13 ($SE = 0.0571$) and significantly decreases the likelihood of their being uninterested in receiving any advice by 0.13 ($SE = 0.0571$). Similarly, the *Police Violence* treatment significantly reduces the estimate for the "uninterested" category by 0.10 ($SE = 0.0562$), suggesting that some respondents become more open to receiving advice. The effects on preferences for advice from police, community organizers, and lawyers are smaller and too noisy to allow us to draw any conclusions. These results suggest that information interventions can subtly increase public demand for expert advice about appropriate responses to crisis scenarios, particularly from academic experts.

Multiple Hypothesis Testing Table A.5 presents our main results with family-wise error-adjusted p-values assessing statistical significance and controls for multiple hypotheses. We define two mutually exclusive hypothesis families, following Jones et al. (2019). Equation 1 tests multiple hypotheses, and we calculate the family-wise adjusted p-values using 10,000 bootstraps of the free step-down procedure from Westfall and Young (1993).

For the Kling–Liebman–Katz index, the *DCTP* treatment significantly reduces demand for police overall and police demand in the nonviolent scenarios, with robust p-values even after family-wise error adjustment. The *Police Violence* treatment also significantly lowers police demand in general and in the nonviolent scenarios, with the estimates maintaining their significance postadjustment. However, neither treatment significantly alters the demand index for the violent scenarios. Regarding the likelihood of calling the police, the *DCTP* treatment increases demand for police in the "armed robbery" scenario but reduces it for the "screaming woman," "naked man," "suicidal ideation," and "disruptive begging" scenarios, with statistical significance before and after family-wise error rate adjustment. The *Police Violence* treatment has a less pronounced but still significant effect by reducing demand for police in the "naked man," "suicidal ideation," and "disruptive begging" scenarios, with no significant impact on the "armed robbery" and "screaming woman" scenarios before or after multiple hypotheses adjustment.

Information Processing As a complementary analysis, we also present respondents' reasoning associated with their demand for police involvement in Section B. Perceived danger significantly influences both the demand for police services and officer use of force (Fryer, 2019; Ang et al., 2021). We analyze the impact of this factor in our context by combining human annotation and AI classification of responses from open-ended questions about the various crisis scenarios, achieving over 90% intercoder reliability (Stantcheva, 2023; Andre et al., 2021, 2022). Our findings highlight that scenarios such as "armed robbery" and "woman screaming" are perceived as more dangerous than "naked man" and "disruptive begging." Using a mediation analysis approach (Heckman et al., 2013; Heckman and Pinto, 2015), we find that exposure to information on police alternatives affects decisions variably across the scenarios, with perceived danger crucially mediating the responses in the violent situations, significantly altering preferences for police intervention (Goncalves et al., 2023). In contrast, we observe a more direct impact of information for nonviolent situations, suggesting that decisions are less dependent on perceived danger in such cases. This complexity underscores the importance of tailoring information campaigns to optimize public safety resource allocation and enhance community trust in crisis response systems.

5 Who Responds to the Information?

Our study begins by considering individuals' *average* propensity to contact law enforcement, recognizing that actual behavior spans a broad spectrum. On one end, certain individuals may rarely initiate contact with police, perhaps because of past negative experiences (Graef et al., 2023), cultural barriers, or concerns specific to immigrants (Jácome, 2022; Goncalves et al., 2023). On the other end are individuals who regularly rely on police intervention across various contexts, often without consideration of the seriousness of the situation (Golestani, 2023). This section delves into different constituencies' propensities to engage with law enforcement, aiming to clarify the factors driving the differing responses.

Results by Initial Propensity to Call the Police We investigate the influence of the *DCTP* and *Police Violence* treatments on the propensity to call the police in Table 8, segmented 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.

Column (1) in Panels A to C displays the effects of the *DCTP* treatment on the likelihood of calling the police for the "armed robbery" incident by baseline calling tendency. The *DCTP* treatment notably increases low-propensity callers' likelihood of contacting the police by 6.7 pp ($p < 0.01$)

against a control mean of 78.10%. This increment is subdued for moderate- and high-propensity callers, who show increases of 1.3 pp and 0.85 pp, respectively, from the control means of 94.1% and 95.9%. In comparison, the *Police Violence* treatment's impact is less pronounced, with a notable increase of 5.0 pp ($p < 0.1$) for low-propensity callers, indicating that while both treatments affect decision-making, the *DCTP* treatment's impact is more substantial.

Conversely, the moderate- and high-propensity groups show heightened responsiveness to the treatments for the nonviolent contexts. The *DCTP* treatment leads to a significant decrease in the likelihood of recurring to the police in nonviolent scenarios such as the "suicidal ideation" and "disruptive begging" cases for these groups. The *Police Violence* treatment similarly prompts a reduction in demand for police, albeit less consistently. Notably, high-propensity callers exhibit a significant decline in their reported likelihood of calling the police for the "screaming woman" and "suicidal ideation" scenarios.

Quantile Regressions To capture the varying propensities to contact law enforcement across individuals, we also compute quantile treatment effects in Figures 5 and 6 rather than averages (Bitler et al., 2006, 2017) and account for baseline reliance on police following Bitler et al. (2017). This method offers a detailed view of the treatment's impact on different population segments, a perspective not revealed by the average responses alone.[11]

Learning about alternatives to police intervention increases the propensity to contact law enforcement in the "armed robbery" case among individuals initially less inclined to do so, notably within the lower quantiles. However, for those with a higher propensity—represented in the upper quantiles—such information appears to have no significant impact. In contrast, the *DCTP* treatment reduces demand for police involvement in the "screaming woman" scenario within the lower quantiles, particularly among those who typically have a high dependence on police. This suggests that individual demand responses for the different violent situations vary based on respondents' initial likelihood of seeking police assistance.

For the nonviolent crises, the impact of both the *DCTP* and *Police Violence* treatments is more pronounced, with a significant reduction in demand for police among individuals with moderate to high police reliance. The decrease is especially notable for the "suicidal ideation" scenario, reflecting a robust shift in public preference toward alternative, nonpolice crisis intervention.

These insights suggest that strategic dissemination of information about police alternatives could realign public safety preferences, directing individuals away from recurring to the police by default in nonviolent situations. Policymakers could leverage these findings to optimize public safety strategies, reducing the unnecessary use of police resources in nonviolent contexts and focusing them on critical, violent emergencies where police officers' skills are indispensable.

[11] Section A.3 provides additional analysis and explores whether the treatment effects vary by quantile for each scenario.

6 Does Partisanship Matter?

Much existing research finds that partisanship significantly influences attitudes toward police alternatives and the reallocation of police budgets (Bursztyn et al., 2023; Sances, 2023c,b,a), as political stances shape both beliefs about the role of law enforcement in society (Ang and Tebes, 2023) and officer behavior (Grosjean et al., 2022; Ba et al., 2023; Goncalves and Tuttle, 2022). In particular, surveys and existing research generally demonstrate that Republicans are more likely than Democrats to strongly support police, to oppose reform and accountability measures, and to oppose movements such as "Defund the Police" and "Black Lives Matter."[12] Given these findings, we might expect Republicans to be less receptive or responsive to information about police alternatives. This section evaluates this hypothesis to help us more thoroughly understand how our results vary by respondent partisanship.

Demand for Police Table 9 provides insights into the impact of the *DCTP* and *Police Violence* information treatments on demand for police, segmented by partisanship. The data reveal that both Democrats and Republicans experience a statistically significant decrease in their demand for police intervention across the nonviolent scenarios when exposed to the *DCTP* information, with Democrats showing a decrease of 0.201σ ($SE = 0.0365$) and Republicans a decrease of 0.198σ ($SE = 0.0645$). However, the effect is not as pronounced or statistically significant with respect to the violent scenarios for either group.

The response to the *Police Violence* treatment is varied: Neither Democrats nor Republicans show a significant change in demand for police across the violent scenarios. For the nonviolent scenarios, Democrats exhibit a statistically significant decrease of 0.17σ ($SE = 0.0360$), while Republicans show a lesser yet still statistically significant decrease of 0.144σ ($SE = 0.0636$), indicating a bipartisan response to the information treatments.

Our analysis indicates that the *DCTP* and *Police Violence* information treatments do not lead to significantly different impacts on demand for police between Republicans and Democrats. Interestingly, while both groups show a reduction in demand for police in the nonviolent scenarios under the *DCTP* information treatment, Republicans exhibit a notably large decrease. This suggests that when presented with alternative options, Republicans may be as receptive as Democrats, if not more so, to reducing their reliance on traditional policing methods. The results underscore a shared responsiveness to new information on alternatives to police across party lines without significant partisan divergence.

[12] For example, our analysis in Section A.2.2 utilizes a nationally representative survey to illustrate that Democrats residing in regions with heightened Google search interest in "defund the police" are more inclined to express increased support for reducing police funding. In contrast, Republicans in these same areas do not exhibit a similar impact on their stance regarding police funding.

Interest in dontcallthepolice.com Intuitively, the domain name dontcallthepolice.com might resonate more with liberals who advocate police reform or reduction, while it might deter conservatives who support traditional law enforcement models. With respect to such a political divide, Figure 7 shows that the interest in the dontcallthepolice.com website among the Republicans in the *DCTP* treatment is unexpectedly higher (38.1%) than that of the Democrats in the control group (23.7%). The Democrats under the *DCTP* treatment show the most significant interest (58.3%), the highest among all categories. In contrast, the *Police Violence* treatment increases interest among Democrats but does so less than the *DCTP* treatment and prompts a decrease in interest among Republicans.

Transitioning to Table 10, we delve into regression analyses that dissect the influence of partisanship on relative engagement with the two websites offering information on alternatives to police involvement. This comparison specifically highlights the differential impacts of disseminating information about the DCTP website versus the (identical) website outlining 911 alternatives.

Democrats show a notable uptick in interest in the DCTP website following the information exposure, with an increase of 33.6 pp ($SE = 0.0278$), while Republicans also demonstrate a significant rise of 26.8 pp ($SE = 0.0397$). Notably, Republicans exhibit a substantial interest in DCTP once informed about it, in contrast to our initial expectations. Similarly, independents show a significant increase in interest in DCTP. On the other hand, the propensity to explore the 911 alternatives website diminishes across all political categories, with the most pronounced decline among Democrats, ranging from 15.6 to 28.6 pp. The *Police Violence* information treatment, however, does not significantly shift levels of interest in the websites across the different political affiliations, with negligible coefficient values that suggest a uniform response irrespective of party affiliation.

These findings reveal that information interventions on police alternatives can have effects that bridge political divides, directing individuals toward alternative policing resources and underscoring the influential role of branding even when the substantive content is held constant.

7 Public Awareness of Police Alternatives and its Long-Term Impacts

This section addresses two critical questions with policy ramifications: the effect of awareness about police alternatives on traditional police service demand, and the horizon over which the effects of information campaigns persist. We initially assess how informing individuals about police alternatives impacts those with no previous knowledge of them. Our focus then shifts to the long-term efficacy of our informational outreach in maintaining knowledge of the 988 service, a newly introduced resource for suicide prevention.

7.1 Impact of Learning about Police Alternatives on Demand for Police

Our research design in this exercise captures the prior beliefs of both the treatment and control groups (see Figure 2) and employs an active control group, which differs only in the content of the information it receives, helping us disentangle the effects of priming from those of genuine belief updating (Haaland et al., 2023). In addition, we complement our analysis with a pure control group to assess the impact of providing information about police alternatives on respondents' demand for police. A concurrent survey, conducted in January 2024 via Prolific, intentionally did not provide any information regarding alternative police resources to participants. The outcomes of this survey may thus serve as our de facto control results. Moreover, Table A.16 ensures that participants' demographic profiles are consistent across both the informed and uninformed groups, reinforcing the integrity of our analysis.

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

$$y_i = \alpha + Alternative_i \beta + X_i' \gamma + \epsilon_i \tag{2}$$

where outcome y_i of respondent i is s the likelihood of calling the police in the proposed situation (0–100) as a function of each treatment condition. The variable $Alternative_i$ is a dummy variable equals one if the respondent receive information about any police alternatives, i.e. the emergency service numbers from the active control group $\{988, 211, 311\}$ given to the active control group, as well as information from the *DCTP* and *Police Violence* treatments, and zero otherwise. The reference group is the pure control group, which did not receive any information on police alternatives. Additionally, we assess the effect of the different treatment conditions separately, including the emergency service numbers from the active control group, along with the *DCTP* and *Police Violence* treatments. Note that both the *DCTP* and the *Police Violence* treatment groups receive the emergency service numbers information provided to the active control group.

Results In Table 11, we evaluate the effect of informing participants about available police alternatives on their subsequent choices about police intervention in several hypothetical situations. For high-stakes situations such as robberies, knowledge of alternatives does not significantly sway the likelihood of calling the police. However, for scenarios where nonviolent alternatives are viable, we observe a pronounced reduction in the demand for police services. This is particularly evident in the context of the *DCTP* treatment, where knowledge of alternative options substantially decreases the propensity to call the police in nonthreatening incidents, with statistical significance marked by asterisks indicating p-values below conventional thresholds.

For instance, in the "naked man" and "suicidal ideation" situations, the informed group demonstrates a significant preference for alternatives to the traditional police response, with coefficients of -5.9 and -16.6 pp, respectively, both with $p < 0.01$. Similarly, there is a decreased tendency to involve the police in the "disruptive begging" scenario, with a coefficient of -5.8 pp under the *DCTP* treatment. These findings elucidate a clear public predilection for nonpolicing solutions in less critical situations for which alternatives exist and are known to potential callers. Our analysis suggests that providing the public with information about nonpolicing alternatives can significantly impact their reliance on traditional law enforcement, especially in scenarios where the use of police services may not be the most appropriate or necessary response. This underscores the potential for community-based and preventative approaches to play a larger role in public safety strategies, especially in contexts where the risk of escalation or violence is low.

Robustness Our analysis demonstrates that the demographics across both the experimental and pure control groups are consistent, as detailed in Table A.16, with minor variations that do not significantly affect the outcomes. In Figure A.5, we present the influence of awareness about police alternatives on the demand for police, comparing informed groups with uninformed ones, both with and without covariate adjustments. The findings confirm our primary conclusion: knowledge of police alternatives significantly diminishes the probability of engaging police in noncritical situations, a trend that persists irrespective of whether we include covariates. This consistency confirms the viability of strategies prioritizing police alternatives in nonviolent situations.

Conceptual Framework We complement our analysis with a simple model, detailed further in Section C of the Appendix. In this framework, a bystander is presented with a scenario that necessitates a decision to either call the police or choose an alternative, based on whether the situation requires police involvement. The probability of each type of situation is predetermined. The decision process incorporates the potential utility gained from making the correct choice -calling the police when necessary, and avoiding them when not- and a penalty for errors -calling the police when there is an alternative. 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 probability of choosing the alternative to calling the police. The bystander maximizes their expected payoff, balancing utility against effort cost, to find the optimal level of cognitive effort.

Our framework and empirical design are connected through the examination of how different levels of informational treatments influence decision-making. The model predicts that in nonviolent scenarios, the perceived severity of incorrectly calling the police increases progressively across the different treatments, corresponding to an increase in cognitive efforts and a greater likelihood of opting for non-police actions. This progression highlights that as the potential mistake becomes more severe, bystanders are more motivated to exert effort in remembering to use alternatives, which leads to a higher probability of choosing non-police options. Information from *DCTP* notably enhances this propensity, demonstrating how critical detailed and specific information is in guiding public decisions towards more appropriate emergency responses.

7.2 Long-Term Impact on Demand for the 988 Suicide & Crisis Lifeline

This section examines the enduring impact of our intervention on respondents' ability to remember the 988 Suicide & Crisis Lifeline—a crucial governmental resource. With the launch of the 988 Lifeline on July 16, 2022, the National Suicide Prevention Lifeline's 10-digit number switched to the more accessible three-digit 988 code. The 24/7 hotline provides free and confidential support to distressed individuals and their relatives. The efficacy of such a standardized number hinges on public awareness of its existence and appropriate usage. However, uptake has been modest, with a Pew study indicating that only 13% of the public is aware of the 988 number (Pew (2023)). This section delves into the influence of our educational intervention on recall of this information.

Incentivized Follow-Up Survey In April 2024, a follow-up survey registered as #170119 on aspredicted.org assessed the persistent effects of our intervention on awareness of the 988 helpline for emotional crises. This survey was designed to examine respondents' ability to recall the key messages from our nondeceptive educational videos—a three-minute intervention introduced six months prior.

We compared groups we had informed about police alternatives with their uninformed counterparts in the "suicidal ideation" and "armed robbery" scenarios. Each participant could earn $0.10 for correctly identifying the relevant government resources. The survey posed a question on which emergency hotline to call, providing only 20 seconds for the respondent to answer, simulating a real-life crisis situation. The scenarios were presented in random order to mitigate online search bias, which might prove particularly acute when the suicidal ideation scenario appeared first. Our objective was to examine whether sustained awareness of alternatives such as the 988 hotline could better channel emergency communications and increase the effectiveness of crisis response.

Empirical Specification We analyze the impact of the information treatments on the respondent's likelihood of dialing 988 for the "suicidal ideation" scenario using the following OLS specification:

$$Dial_i^{988} = \alpha + First_i\lambda + Alternative_i'\delta + First_i \times Alternative_i'\beta + X_i'\gamma + \epsilon_i \tag{3}$$

where the outcome $Dial_i^{988}$ of respondent i indicates whether the respondent would dial 988 with a value of one if "yes" and zero otherwise. The binary variable $First_i$ equals one if the "suicidal ideation" scenario was presented first to the respondent and zero otherwise. The variable $Alternative_i$ is a dummy variable representing the different treatment conditions, including the emergency service numbers from the active control group $\{988, 211, 311\}$ but also $DCTP$ and $PoliceViolence$. Both the *DCTP* treatment and the *Police Violence* treatment groups receive the emergency service numbers information that is provided to the active control group.

The constant term sets the reference point for participants who neither received information about alternative emergency numbers nor were presented with the "suicidal ideation" scenario first. The coefficient λ specifically isolates the influence of encountering the "suicidal ideation" scenario at the outset. Together, the constant and λ differentiate the intrinsic response from any potential internet search behavior triggered by the respondent's not anticipating the question sequence.

The coefficients of interest, β, measure the combined effect of exposure to information on police alternatives and presentation of the suicidal scenario first. As the order of the scenarios is randomized, the coefficients measure the persistent impact of our intervention on the inclination to choose 988 among participants who did not anticipate the forthcoming question and thus could not resort to online searches for the correct answer.

Deviating from our pre-analysis plan (PAP), we account for the sequence in which the suicidal scenario is presented. Initially, we did not consider the order and we employ an OLS specification with a constant and a dummy for the Police Alternatives treatment assignment, controlling for demographics such as age, race, gender, education, marital status, and the baseline index of policing demand. Thus, the pre-register specification did not account for the possibility that respondent would search online the correct answer.

Results Table 12 shows how prior knowledge about police alternatives can shape the decision to recur to the mental health crisis hotline 988 six months after the initial information exposure. Using the initial specification from the PAP, the immediate effects of the information exposure are relatively minor reported in columns (1) and (2). However, the interaction term $First \times PoliceAlternatives$ captures a persistent influence of our intervention, indicating a substantial rise—over 12 pp ($p < 0.01$)—in the choice to recur to 988 during episodes of suicidal ideation. This result is particularly notable considering that the base rate for dialing 988 under similar conditions, absent any prior exposure to information on police alternatives, hovers at a mere 2%. Moreover, the analyses in columns (5) and (6) bring to light that the $First \times DCTP$ interaction is crucial to our results, displaying an increase of approximately 20 pp ($p < 0.01$). This effect likely stems from the initial exposure to the *DCTP* treatment, which seems to enhance recall of the 988 number, perhaps because of the site's name and its connection to the various alternatives.

The implications of these findings are twofold. First, they affirm the significance of how and when information is conveyed, which profoundly influences the propensity to engage with the mental health crisis hotline 988 in contexts of suicidal ideation. In contrast, Figure 8 illustrates a starkly different dynamic for the "armed robbery" scenario; knowledge of police alternatives does not alter respondents' overwhelming likelihood of dialing 911. The persistent nature of these effects—which remain evident half a year after the initial exposure—signals that educating the public on specialized crisis services such as 988 and nongovernmental resources such as dontcallthepolice.com can foster a lasting behavioral shift toward utilizing these specialized services in the face of mental health crises while simultaneously ensuring that traditional emergency responders remain the go-to recourse for crime situations such as robberies.

8 Conclusion

This paper has investigated a set of information treatments on individuals' propensity to call the police in various violent and nonviolent scenarios. We show that exposure to nondeceptive educational videos on police alternatives in our *Police Violence* or *DCTP* treatments decreases demand for police involvement in nonviolent crisis scenarios and increases demand for police involvement in violent scenarios such as incidents of armed robbery, with the effect being largest for participants in the *DCTP* treatment condition. Importantly, these results cut across political lines and baseline levels of police reliance, revealing a shared belief in the need for tailored crisis responses. In addition, we highlight the sustained effectiveness of our educational video: six months post-exposure, respondents significantly recalled the 988 number as a recourse for responding to suicidal crises, despite the fact that public awareness of this new hotline is still limited. 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., 2021; 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. Furthermore, we take into account the perspectives of individuals who are hesitant or unwilling to rely on the police (see Figure A.6), which marks a significant step toward understanding and addressing the concerns of communities that have been reluctant to interact with state or government entities (Moffitt, 1983; Finkelstein and Notowidigdo, 2019; Alsan and Yang, 2022). This approach also allows us to consider the potential for selection in the sample of individuals who interact with police (Knox and Mummolo, 2020), which may disproportionately include individuals who are more willing to engage with law enforcement.

Second, the consensus among constituents across party affiliations on when police should and should not be involved in crisis response presents an opportunity for policymakers to collaborate across party lines on 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 surprising consensus across party lines when it comes to the website dontcallthepolice.com. This may indicate a broader, shared understanding of the need for 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. This unexpected alignment could pave the way for more nuanced discussions on public safety and resource allocation that transcend traditional partisan divides.

Next, the strong public receptiveness to nonpolice alternatives, especially for nonviolent scenarios, justifies increasing support for services such as mental health hotlines, social work interventions and community-based support networks (Dee and Pyne, 2022; Bhatt et al., 2024). Critically, our study leverages only existing resources, suggesting that significant changes in the public's behavior can be achieved rapidly by means of well-crafted information campaigns—even before or independently of any efforts to expand or create new resources. Public education campaigns could inform citizens about the resources available for different types of crises, guiding them to make more informed decisions when they seek help.

Finally, by reducing demand for police in nonviolent scenarios, law enforcement resources can be directed toward dealing with urgent, high-priority violent offenses, thus focusing attention on areas where police are most needed and cannot easily be substituted with another service provider. This would reduce unnecessary police–civilian encounters and the inherent risks associated with them and allow law enforcement to receive more targeted training relevant for the smaller range of scenarios that they would face more often.

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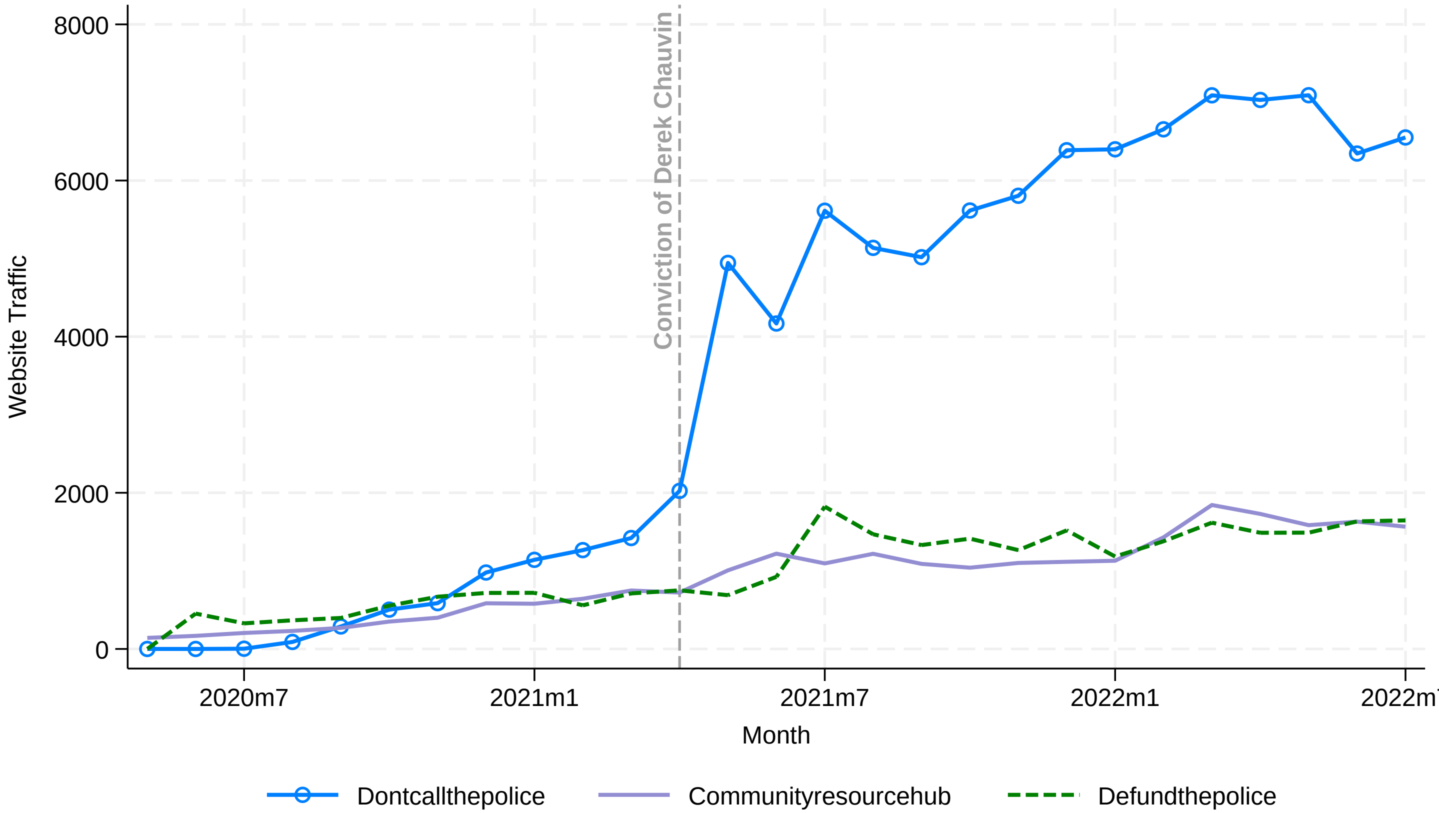
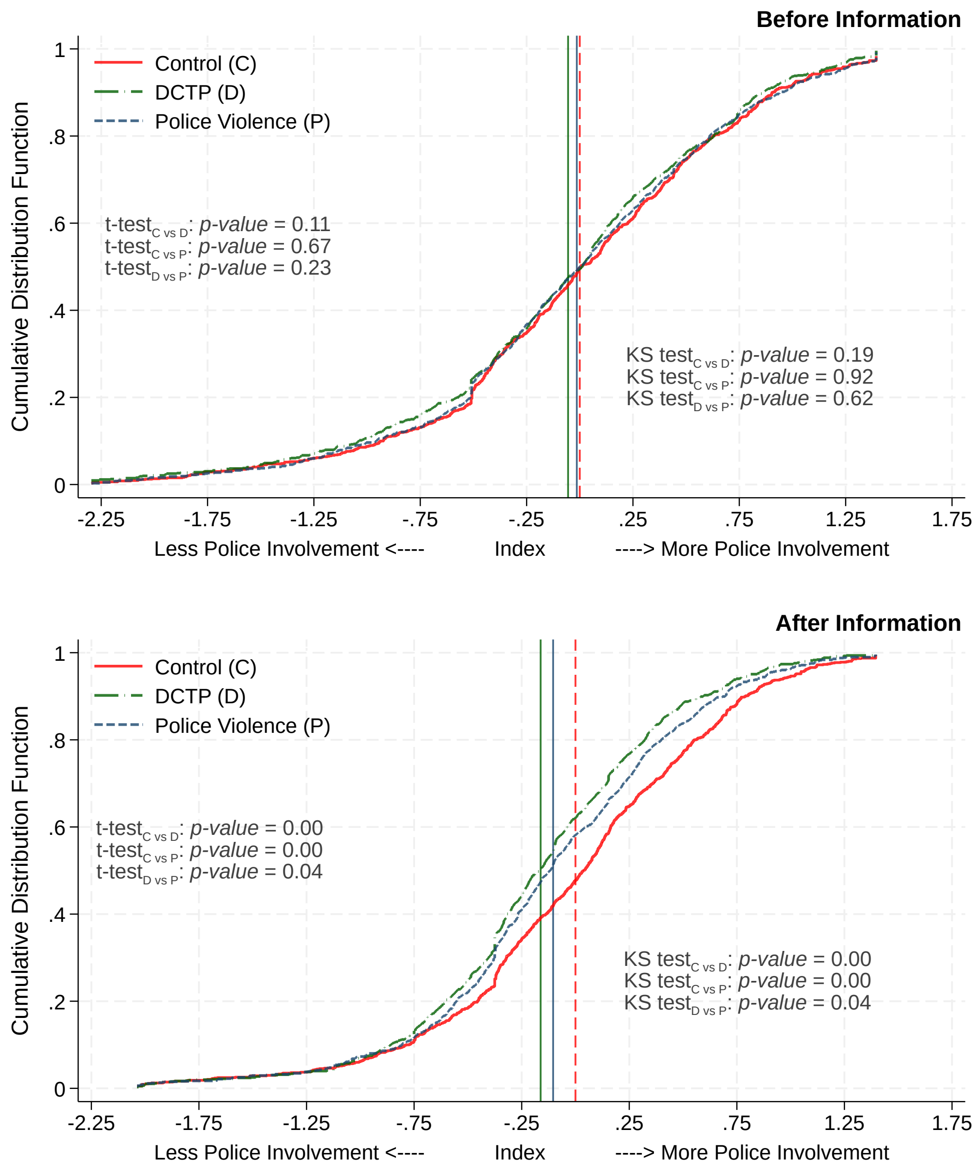
Figure 1: Website Traffic over Time



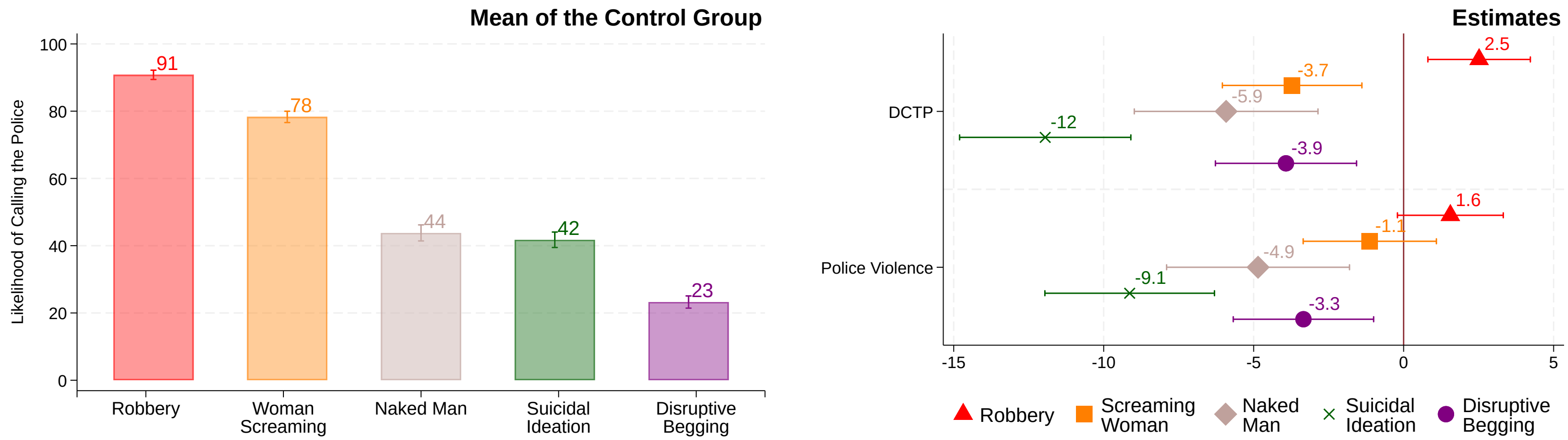
Notes: This figure presents website traffic trends for three different resources related to police and community services over time: (1) dontcallthepolice.com, a website offering alternatives to calling law enforcement in crisis situations; (2) communityresourcehub.com, a site providing a range of community 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 2: CDFs of Police Demand Index by Treatment Arm before and after Information Exposure



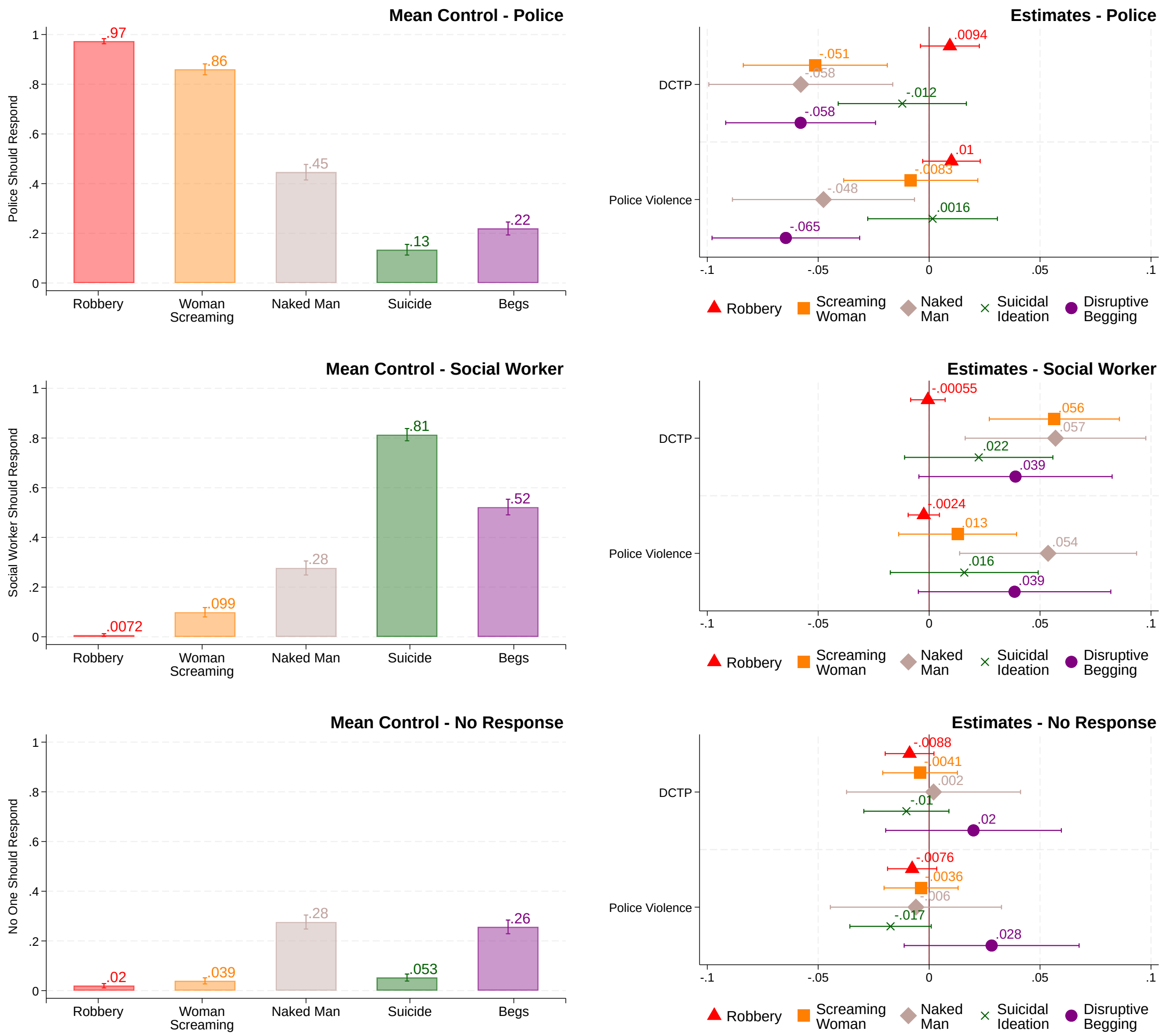
Notes: Empirical cumulative distribution functions of the index capturing the demand for police by treatment arm before and after information treatment. The dependent variable is a Kling–Liebman–Katz index, i.e., a z-score computed by subtracting the control group's mean and dividing by its standard deviation. A higher score indicates greater demand for police. We also report the *p*-value of a Kolmogorov–Smirnov (KS) test of equality for pairs of distributions among the *Control* (C), *Police Violence* (P), and *DCTP* (D) treatments.

Figure 3: Demand for Police by Scenario



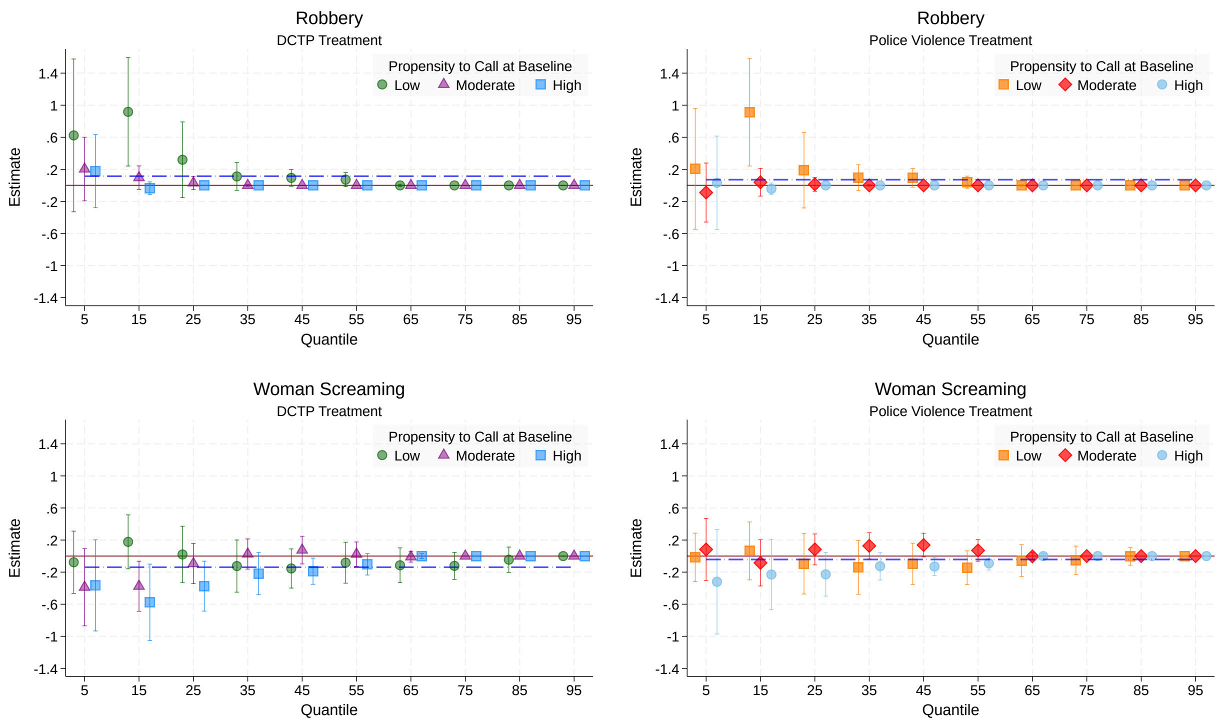
Notes: These figures present the impact of the *DCTP* and *Police Violence* information treatments on the demand for police in each scenario. The dependent variable indicates the likelihood of calling the police in the proposed situation (0–100). The left-hand side presents the mean of the dependent variable for the control group, which is composed of individuals receiving information about 988, 311, and 211 only. The right-hand side presents the effect of information based on equation 1. We report the 95% confidence intervals using robust standard errors.

Figure 4: Impact of Information Treatments on Preference for First Responders by Scenario



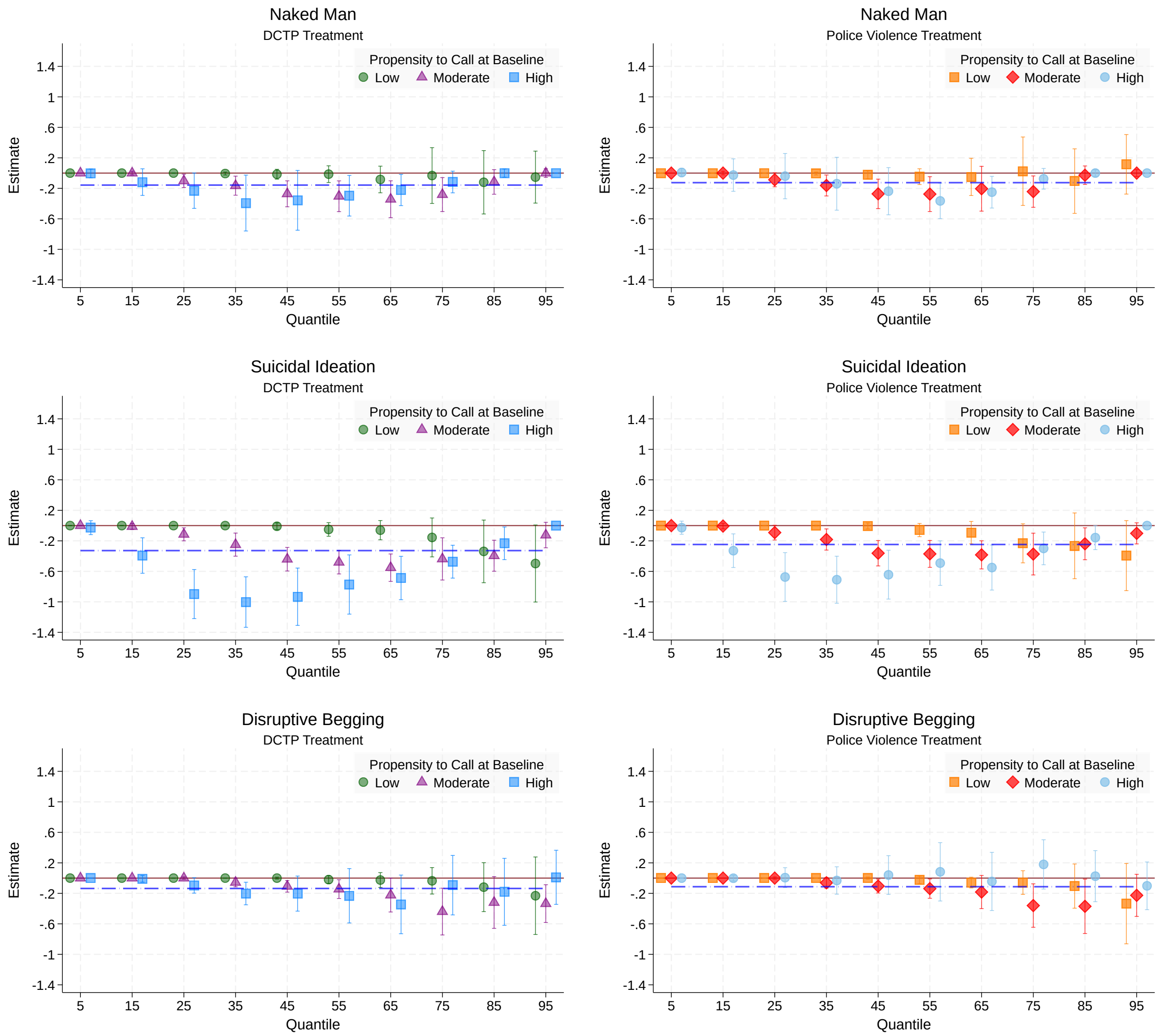
Notes: These figures present the impact of the *DCTP* and *Police Violence* information treatments on the preferred first responder in a crisis: police, a social worker, or no one. The dependent variable is a binary indicator equal to 1 if yes and 0 otherwise. The left-hand side presents the mean of the dependent variable for the control group, which is composed of individuals receiving information about 988, 311, and 211 only. The right-hand side presents the effect of information based on equation 1. We report the 95% confidence intervals using robust standard errors.

Figure 5: Quantile Regressions by Baseline Propensity to Call Police for Violent Scenarios



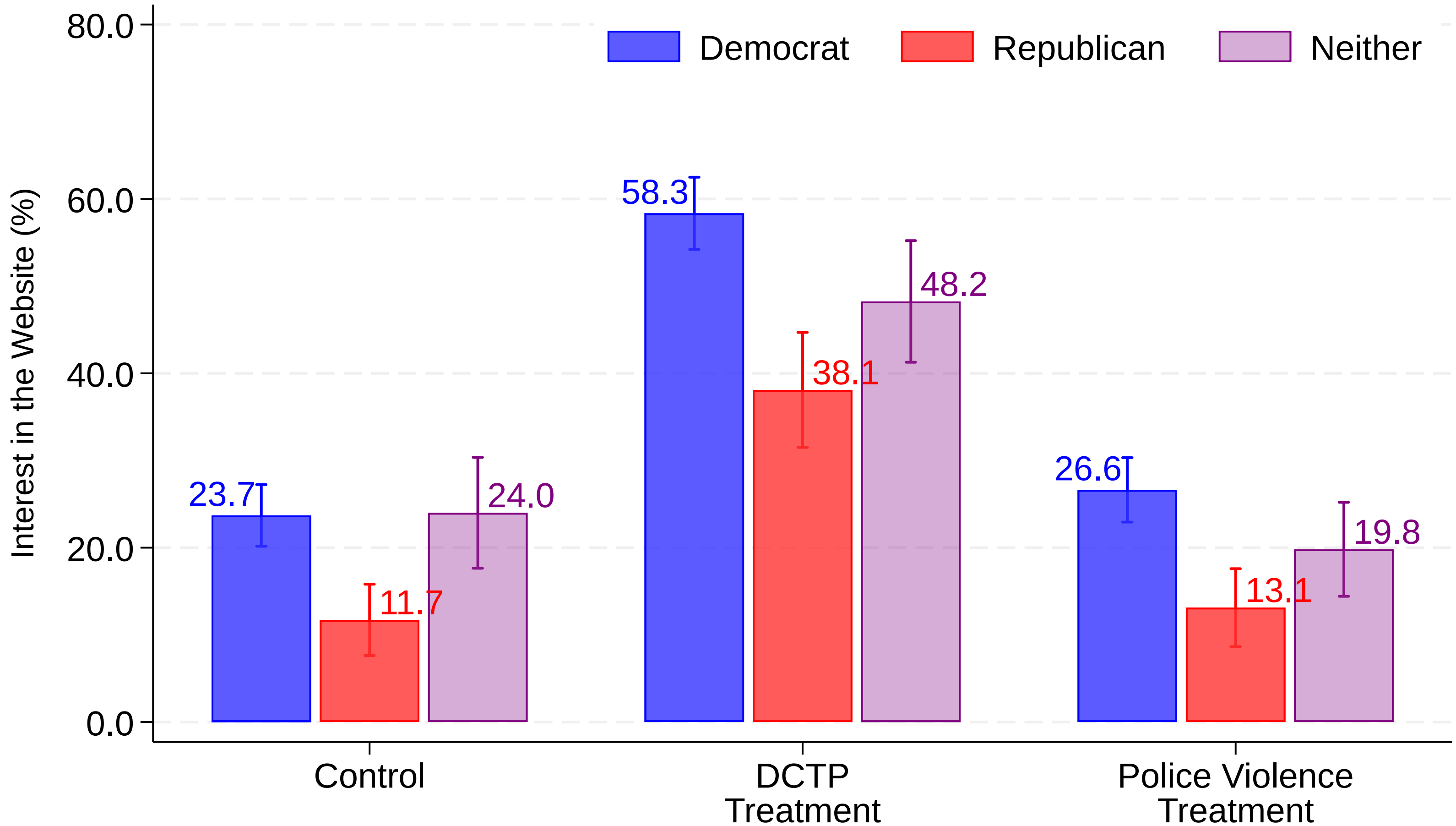
Notes: This figure reports the results of ordinary least squares and quantile regressions estimating the impact of the *DCTP* and *Police Violence* information treatments on the demand for police in each violent scenario by propensity to call the police at baseline. Respondents with low and high propensity 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. The dependent variable 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 dashed horizontal line represents the average treatment effects from the main specification. The omitted category, i.e., the control group, comprises individuals receiving information about 988, 311, and 211 only. We provide the estimates and their 95% confidence intervals using bootstrap standard errors with 100 replications.

Figure 6: Quantile Regressions by Baseline Propensity to Call Police for Nonviolent Scenarios



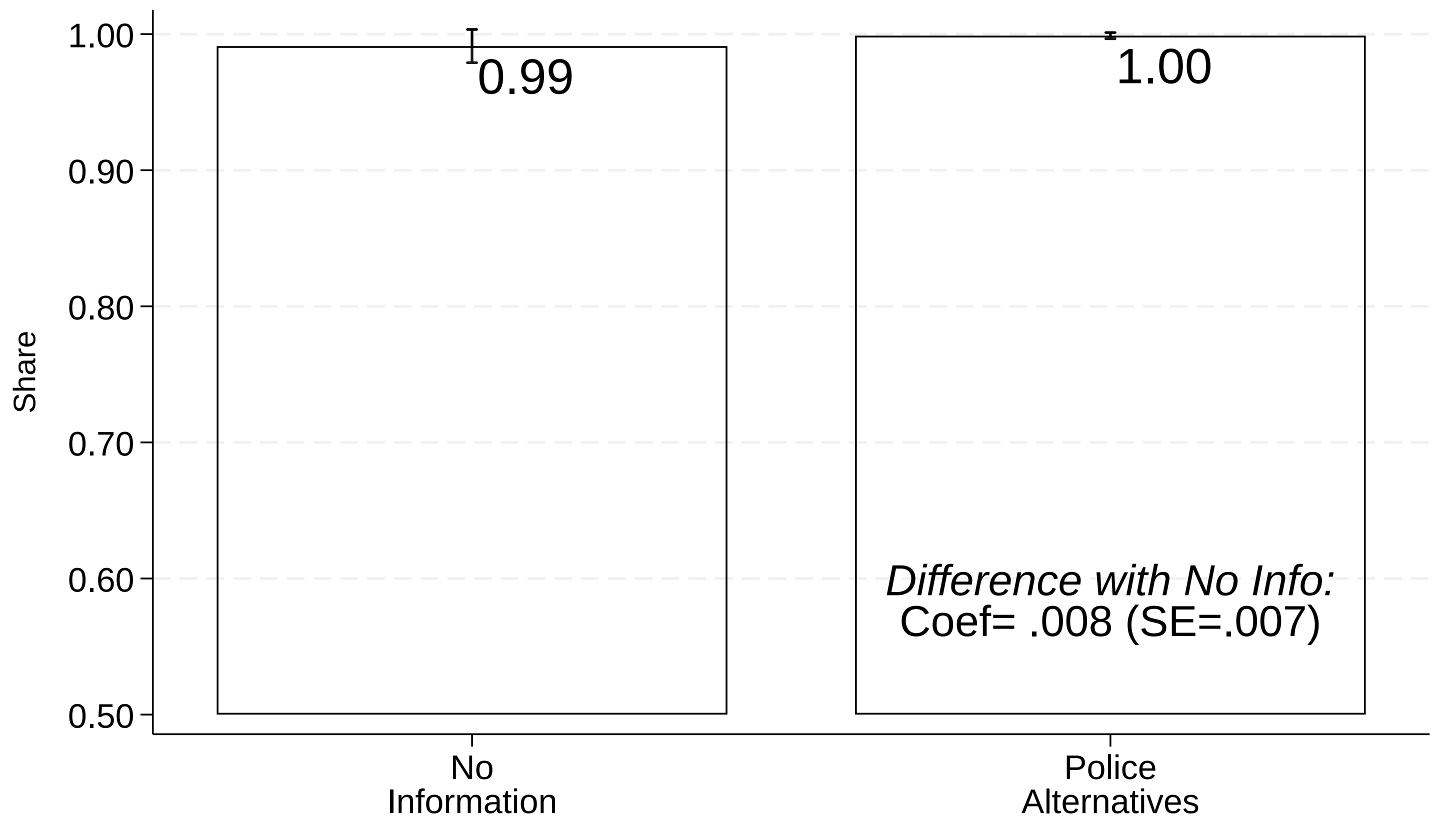
Notes: This figure reports the results of ordinary least squares and quantile regressions estimating the impact of the *DCTP* and *Police Violence* information treatments on the demand for police in each nonviolent scenario by propensity to call the police at baseline. Respondents with low and high propensity 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. The dependent variable 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 dashed horizontal line represents the average treatment effects from the main specification. The omitted category, i.e., the control group, comprises individuals receiving information about 988, 311, and 211 only. We provide the estimates and their 95% confidence intervals using bootstrap standard errors with 100 replications.

Figure 7: Interest in dontcallthepolice.com by Partisanship



Notes: This figure presents the mean interest in dontcallthepolice.com by treatment status and respondent's partisanship status. We report 95% confidence intervals.

Figure 8: Long-Term Impact of Information Treatment on 911 Demand for the Robbery Scenario



Notes: This figure presents the share of respondents' reported likelihood of using 911 services in the "armed robbery" scenario, differentiated by treatment arm (*No Information* and *Police Alternatives*). Participants in the *Police Alternatives* arm were surveyed six months after viewing the *Police Alternatives* informational video, in contrast to the *No Information* group, which was not exposed the 988 information. We present the difference between the treatment and control responses with 95% confidence intervals and robust standard errors.

Table 1: Definitions of Outcomes

	Outcome	Category j	Reoriented the Outcome	Outcome	Scale
1	Likelihood of calling the police for scenario j	Robbery, Woman Screaming, Naked Man, Suicidal Ideation, Disruptive Begging	No	y_j	0 to 100
2	Police demand index	All scenarios			
3	Violent scenarios index	Robbery, Woman Screaming	No	$(1/J)\sum_{j=1}^{J}(y_j - \mu_j^y)/\sigma_j^y$	z-score
4	Nonviolent scenarios index	Naked Man, Suicidal Ideation, Disruptive Begging			
5	Category j should respond	Police, Social Worker, No One	No	$Responder_j$	0 = no, 1 = yes
6	Respondent index for j		No	$\sum_{j=1}^{J} Responder_j$	0 to 5
7	Preference for expert j index	Academic, Community organizer, Lawyer, Police, No One	Yes	$Advice_j$	1 = bottom to 5 = top
8	Support for organization j	Reduce Police Involvement, Police Reform, Police Wellbeing	No	$Support_j$	0 = no, 1 = yes
9	Interest in website j	Dontcallthepolice.com, 911alternatives.com, Not Interested	No	$Website_j$	0 = no, 1 = yes

Notes: This table defines the outcomes used in the analysis. The police demand, violent scenario, and nonviolent scenario indices are Kling–Liebman–Katz 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) ACS (2022)	(3) Control	(4) Police Violence	(5) DCTP	(6) p-value
Age 18-29	0.20	0.18	0.19	0.20	0.21	0.477
Age 30-39	0.30	0.33	0.30	0.32	0.27	0.106
Age 60 or more	0.14	0.16	0.14	0.14	0.13	0.982
Black	0.13	0.12	0.12	0.13	0.14	0.368
Other Race	0.18	0.23	0.18	0.17	0.18	0.838
Male	0.49	0.50	0.50	0.49	0.49	0.903
High School or Less	0.14	0.37	0.14	0.13	0.14	0.983
Some College	0.22	0.20	0.23	0.21	0.23	0.542
Graduate Degree	0.15	0.13	0.13	0.16	0.15	0.226
No Party	0.20		0.18	0.21	0.22	0.114
Democratic	0.57		0.57	0.57	0.56	0.820
High Income	0.15	0.15	0.14	0.16	0.13	0.154
Low Income	0.18	0.15	0.18	0.19	0.18	0.819
Single	0.42	0.45	0.41	0.43	0.41	0.566
Baseline Police Demand Index	-0.02		-0.00	-0.06	-0.01	0.247
Observations	2910	258M	971	954	985	2910

Notes: The table presents the descriptive statistics by treatment arm. Column (1) provides the mean level of each variable for the full sample. Column (2) compares the mean of our sample to the American Community Survey 2022 census data. 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 for Police

	(1) Police Index	(2) Violent Index	(3) Nonviolent Index
DCTP	-0.129***	-0.0122	-0.207***
	(0.0240)	(0.0341)	(0.0287)
Police Violence	-0.0931***	0.0144	-0.165***
	(0.0240)	(0.0340)	(0.0285)
Controls	Yes	Yes	Yes
p-value:DCTP=Police Violence	0.13	0.43	0.13
Observations	2910	2910	2910

Notes: This table presents the impact of the *DCTP* and *Police Violence* information treatments on the demand for police. The dependent variable 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. We report robust standard errors in parentheses. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Impact of Information Treatments on Demand for Police by Scenario

	(1) Robbery	(2) Screaming Woman	(3) Naked Man	(4) Suicidal Ideation	(5) Disruptive Begging
DCTP	2.516***	-3.718***	-5.918***	-11.95***	-3.923***
	(0.871)	(1.186)	(1.562)	(1.456)	(1.200)
Police Violence	1.558*	-1.128	-4.854***	-9.134***	-3.340***
	(0.900)	(1.133)	(1.555)	(1.442)	(1.193)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	90.81	78.30	43.80	41.77	23.25
p-value:DCTP=Police Violence	0.26	0.03	0.49	0.04	0.61
Observations	2910	2910	2910	2910	2910

Notes: This table presents the impact of the *DCTP* and *Police Violence* information treatments on the demand for police in each situation. 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 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: Impact of Information Treatments on Preference for First Responders in Crises

	(1) Police	(2) Social Worker	(3) No Response
DCTP	-0.170***	0.174***	-0.00116
	(0.0410)	(0.0433)	(0.0359)
Police Violence	-0.109***	0.118***	-0.00643
	(0.0405)	(0.0427)	(0.0356)
Controls	Yes	Yes	Yes
Mean of Dep.	2.63	1.72	0.64
p-value:DCTP=Police Violence	0.13	0.20	0.88
Observations	2910	2910	2910

Notes: This table presents the impact of the *DCTP* and *Police Violence* information treatments on the preferred first responder in crises. The dependent variable is a score corresponding to the sum of all the scenarios. A higher score indicates a greater overall preference (0 = preferred in no scenario to 5 = preferred in all scenarios). 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 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Impact of Information Treatments on Issue Support

	(1) Reduce Police Involvement	(2) Advocate for Police Reform	(3) Advocate for Police Wellbeing
DCTP	0.0257	-0.0118	-0.0138
	(0.0211)	(0.0220)	(0.0152)
Police Violence	0.0264	-0.0307	0.00426
	(0.0207)	(0.0218)	(0.0155)
Controls	Yes	Yes	Yes
Mean of Dep.	0.38	0.47	0.15
p-value:DCTP=Police Violence	0.97	0.39	0.23
Observations	2910	2910	2910

Notes: This table presents the impact of the *DCTP* and *Police Violence* information treatments on support for organizations advocating various police-related causes. 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 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: Impact of Information Treatments on Interest in Websites Detailing Police Alternatives

	(1) Interest in DCTP Website	(2) Interest in 911 Website	(3) No Interest Website
DCTP	0.304***	-0.241***	-0.0629***
	(0.0205)	(0.0219)	(0.0169)
Police Violence	0.0102	-0.00165	-0.00858
	(0.0179)	(0.0219)	(0.0178)
Controls	Yes	Yes	Yes
Mean of Dep.	0.21	0.58	0.21
p-value:DCTP=Police Violence	0.00	0.00	0.00
Observations	2910	2910	2910

Notes: This table presents the impact of the *DCTP* and *Police Violence* 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 the mean of the dependent variable of the omitted category, i.e., the control group composed of individuals receiving information about 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Heterogeneity Analysis: Demand for Police by Baseline Propensity to Call Police

	(1) Robbery	(2) Screaming Woman	(3) Naked Man	(4) Suicidal Ideation	(5) Disruptive Begging
A) Low Propensity to Call					
DCTP	6.799***	-3.306	-1.791	-3.992	-1.113
	(2.571)	(2.680)	(2.757)	(2.475)	(1.917)
Police Violence	5.070*	-2.912	-0.432	-3.870	-3.346*
	(2.651)	(2.767)	(2.854)	(2.507)	(1.738)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	78.10	65.04	23.28	19.47	10.77
p-value:DCTP=Police Violence	0.47	0.88	0.62	0.96	0.18
Observations	728	728	728	728	728
B) Moderate Propensity to Call					
DCTP	1.367	-2.255	-7.633***	-11.90***	-5.519***
	(0.964)	(1.620)	(2.218)	(2.063)	(1.638)
Police Violence	0.177	1.204	-6.515***	-8.669***	-4.821***
	(1.026)	(1.489)	(2.235)	(2.062)	(1.655)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	94.18	79.74	44.37	41.75	23.82
p-value:DCTP=Police Violence	0.23	0.03	0.61	0.10	0.65
Observations	1455	1455	1455	1455	1455
C) High Propensity to Call					
DCTP	0.855	-6.756***	-7.240**	-20.79***	-5.016*
	(1.122)	(2.140)	(3.446)	(3.283)	(2.933)
Police Violence	0.426	-4.525**	-5.290	-15.28***	-0.640
	(1.208)	(2.004)	(3.282)	(3.146)	(2.892)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	95.90	87.74	61.70	62.48	33.70
p-value:DCTP=Police Violence	0.66	0.31	0.56	0.09	0.14
Observations	727	727	727	727	727

Notes: This table presents the impact of the *DCTP* and *Police Violence* information treatments on the demand for police in each situation by propensity to call the police at baseline. 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 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9: 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	-0.122***	-0.123**	-0.128**	-0.00335	-0.0110	-0.0108	-0.201***	-0.198***	-0.206***
	(0.0299)	(0.0509)	(0.0628)	(0.0443)	(0.0602)	(0.0932)	(0.0365)	(0.0651)	(0.0665)
Police Violence	-0.0873***	-0.106**	-0.0612	0.0360	-0.0491	0.0569	-0.170***	-0.144**	-0.140**
	(0.0297)	(0.0516)	(0.0608)	(0.0438)	(0.0630)	(0.0899)	(0.0360)	(0.0636)	(0.0658)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value:DCTP=Police Violence	0.22	0.75	0.25	0.36	0.56	0.44	0.37	0.42	0.28
Observations	1654	670	586	1654	670	586	1654	670	586

Notes: This table presents the impact of the *DCTP* and *Police Violence* information treatments on the demand for police by partisan affiliation. Each column shows the results for a different subsample. The dependent variable 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 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 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 10: Impact of Information Treatments on Interest in Website Detailing Police Alternatives, by Partisanship

	(1) Interest in DCTP Website Democrat	(2) Interest in DCTP Website Republican	(3) Interest in DCTP Website No Party	(4) Interest in 911 Website Democrat	(5) Interest in 911 Website Republican	(6) Interest in 911 Website No Party	(7) No Interest Website Democrat	(8) No Interest Website Republican	(9) No Interest Website No Party
DCTP	0.336***	0.268***	0.243***	-0.286***	-0.186***	-0.156***	-0.0491**	-0.0825**	-0.0864**
	(0.0278)	(0.0397)	(0.0470)	(0.0285)	(0.0469)	(0.0500)	(0.0197)	(0.0418)	(0.0424)
Police Violence	0.0246	0.0112	-0.0415	-0.00588	-0.0128	0.0377	-0.0187	0.00158	0.00385
	(0.0251)	(0.0307)	(0.0418)	(0.0283)	(0.0463)	(0.0505)	(0.0209)	(0.0430)	(0.0439)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	0.24	0.12	0.24	0.61	0.58	0.50	0.15	0.30	0.26
p-value:DCTP=Police Violence	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.05	0.02
Observations	1654	670	586	1654	670	586	1654	670	586

Notes: This table presents the impact of the *DCTP* and *Police Violence* 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 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 11: Knowledge about Police Alternatives on Demand for Police by Scenario

	(1) Robbery	(2) Robbery	(3) Screaming Woman	(4) Screaming Woman	(5) Naked Man	(6) Naked Man	(7) Suicidal Ideation	(8) Suicidal Ideation	(9) Disruptive Begging	(10) Disruptive Begging
Police Alternatives	0.807		-1.447		-3.812***		-12.74***		-3.434***	
	(0.787)		(0.968)		(1.402)		(1.317)		(1.049)	
Active Control Group		-0.491		0.332		-0.374		-5.883***		-1.307
		(0.990)		(1.179)		(1.722)		(1.618)		(1.311)
DCTP		2.248**		-3.427***		-6.024***		-17.50***		-4.934***
		(0.905)		(1.251)		(1.709)		(1.596)		(1.279)
Police Violence		0.704		-1.298		-5.082***		-14.92***		-4.092***
		(0.961)		(1.201)		(1.706)		(1.563)		(1.260)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	91.29	91.29	79.13	79.13	44.23	44.23	48.41	48.41	23.49	23.49
p-value:DCTP=Police Violence		0.09		0.10		0.58		0.09		0.50
Observations	3388	3388	3388	3388	3388	3388	3388	3388	3388	3388

Notes: This table presents the effect of being informed about police alternatives on the propensity to request police assistance across various scenarios, compared to individuals with no such information. The dependent variable indicates the likelihood of calling the police in the proposed situation (0–100). We report robust standard errors in parentheses. The treatment arm, *Police Alernatives* encompasses several distinct components: emergency service numbers in the active contol group *988,211,311*, *DCTP* and *Police Violence* treatment. Both the *DCTP* treatment and the *Police Violence* treatment groups receive the emergency service numbers information that is provided to the active control group. We report the mean of the dependent variable of the omitted category, i.e., individuals who have not been provided with any details regarding these alternatives. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 12: Long-Term Impact of Information Treatment on Probability of Calling 988 for Suicidal Ideation

	(1) Dial 988	(2) Dial 988	(3) Dial 988	(4) Dial 988	(5) Dial 988	(6) Dial 988
Police Alternatives	0.0257	0.0279	0.00182	0.00335		
	(0.0246)	(0.0250)	(0.0292)	(0.0294)		
First X Police Alternatives			0.121***	0.124***		
			(0.0460)	(0.0469)		
First X Active Control Group					0.0706	0.0736
					(0.0563)	(0.0570)
First X DCTP					0.197***	0.204***
					(0.0715)	(0.0719)
First X Police Violence					0.104	0.101
					(0.0641)	(0.0660)
Active Control Group					0.0133	0.0139
					(0.0352)	(0.0358)
DCTP					0.00114	0.00108
					(0.0343)	(0.0343)
Police Violence					-0.00983	-0.00448
					(0.0348)	(0.0348)
First			-0.121***	-0.123***	-0.121***	-0.123***
			(0.0341)	(0.0350)	(0.0341)	(0.0351)
Constant	0.119***	0.159***	0.143***	0.183***	0.143***	0.187***
	(0.0215)	(0.0507)	(0.0260)	(0.0526)	(0.0260)	(0.0525)
Controls	No	Yes	No	Yes	No	Yes
Order Dummy	No	No	Yes	Yes	Yes	Yes
Mean of Dep.	0.02	0.02	0.02	0.02	0.02	0.02
Observations	1091	1091	1091	1091	1091	1091

Notes: This table presents the long-term effect of being informed about police alternatives on the propensity to dial 988 in the “suicidal ideation” scenario, compared to the likelihood for individuals not exposed to this information. The dependent variable equals one if the respondent reported that they would dial 988, and zero otherwise. We report robust standard errors in parentheses. The treatment arm, *Police Alternatives*, encompasses several distinct components: information about emergency service numbers in the active control group *988,211,311*, the *DCTP* treatment and the *Police Violence* treatment. Both the *DCTP* treatment and the *Police Violence* treatment groups receive the emergency service numbers information that is provided to the active control group. Participants assigned to the *Police Alternatives* treatment were surveyed six months after exposure to the information on police alternatives, in contrast to the *No Information* control group, which was surveyed one month after the initial survey without having been provided information about 988. We report the mean of the dependent variable of the omitted category—those who did not receive any information about police alternatives and were presented with the “suicidal ideation” scenario first. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Contents

Supplementary Materials

A Additional Analysis

A.1 Dontcallthepolice.com

In June 2020, in the wake of George Floyd's death, dontcallthepolice.com was established as a directory for specialized crisis intervention services, aiming to offer alternatives to law enforcement involvement. The site lists vetted organizations across North America that attend to an array of crises and provide resources on housing assistance, mental health services, substance abuse treatment, LGBTQ+ support, youth and elder care, and conflict resolution, reflecting a wide array of community needs.

The website has cataloged over 500 organizations across 82 cities in 42 states and Canada and has seen significant engagement, with over 1,173,547 visits since its inception.[1] The organizations listed are individually vetted to ensure that they meet specific criteria, including confidentiality, financial accessibility, and appropriateness of policies regarding their interaction with law enforcement.

A.1.1 Other Samples

A.1.2 Insights from Nonbinary and Youth Groups

To help inform our study, we performed exploratory analysis using data from the Cooperative Congressional Election Study (CCES) collected in 2022 in Section A.2. This analysis included a survey question on respondents' perceptions of safety around police. Key demographic patterns emerged in Figure A.6: (1) Black or African American respondents generally feel less safe around police than do other racial groups, (2) nonbinary and transgender individuals report feeling significantly less safe than people in other gender groups, and (3) younger respondents, particularly those aged 18–24, tend to feel less safe around police. To understand how these trends could influence our study's outcomes, we gathered additional data from nonbinary individuals and young adults, along with our main sample. The representation of Black respondents in our main sample was sufficient to examine potential systematic differences through heterogeneity analysis.

Nonbinary Sample To understand how nonbinary individuals responded to the information, we conducted a separate analysis, the results of which are presented in Table A.6, which presents the family-wise error-adjusted p-values. Notably, even before exposure to the information, nonbinary respondents were significantly less likely to call the police, with their average likelihood being

[1] As of December 16, 2023.

$10 - 20$ pp lower than that of their peers in the main and youth samples (see Figure A.9). This highlights a baseline reluctance to involve law enforcement among nonbinary individuals.

In Panel A, the KLK index indicates that the *DCTP* treatment meaningfully decreases both the general police demand index and the violent scenario–specific index, with a pronounced effect size of 0.286σ for the latter, albeit with a family-wise adjusted p-value of 0.070. Panel B reveals that this reduction is predominantly influenced by the the "screaming woman" scenario, where the *DCTP* treatment reduces the likelihood of calling the police by 11.3 pp. This effect is statistically significant even after we account for the family-wise error rate ($p = 0.048$). In contrast, for the "armed robbery," "disruptive begging," and "suicidal ideation" scenarios, the treatments yield negative effects, but these are not statistically reliable enough to confirm any definitive outcomes.

The analysis highlights marked differences in how the main sample and nonbinary group respond to the information treatment, particularly in their baseline attitudes toward police involvement. Nonbinary individuals demonstrate a greater initial reluctance to engage law enforcement. Furthermore, while the main sample shows a general decline in police demand following exposure to police alternative information, especially for the nonviolent scenarios, nonbinary individuals display a more significant decrease in their propensity to call the police in the case featuring gender-based violence, that is, the "screaming woman" scenario.

Youth Sample In contrast to the nonbinary group, respondents aged 18–24 exhibit an average propensity to call the police that aligns closely with that of the control group in the main sample (see Figure A.9). The KLK index from Panel A of Table A.7 indicates that the *DCTP* treatment has a significant negative effect on the indexes of general police demand with an effect size of -0.158σ for violent incidents and a family-wise adjusted p-value of 0.003. Panel B of this table underscores the impact of the *DCTP* treatment on the propensity to call the police, which is particularly notable in the "screaming woman" scenario with a significant decrease of 6.2 pp and a family-wise error-adjusted p-value of 0.016. However, for the "armed robbery" and "naked man" scenarios, the effect is not statistically significant. The "suicidal ideation" and "disruptive begging" scenarios show a considerable decrease in the likelihood of calling the police with exposure to the *Police Violence* information, with p-values of 0.007 and 0.009, respectively, indicating that the effects are robust even after adjustment for multiple hypothesis testing. This table implies that the youth sample's response to the information treatments varies by scenario, with the most pronounced effects in scenarios involving potential gender-based violence and mental health crises.

A.2 Attitudes toward Police

A.2.1 Perceptions of Police Safety

We use nationally representative survey data from the Cooperative Congressional Election Study (CCES) to depict the attitudes of different sociodemographic groups toward the police. Figure A.6

reveals a large amount of heterogeneity in how safe the different groups feel in their interactions with police. We find that the group identifying as nonbinary feels the most unsafe and reports feeling significantly less safe than do respondents in the Black and Hispanic groups. In our supplementary analysis examining a nonbinary-only sample, we confirm that this group ranks its baseline likelihood to call the police much lower (by 10–20 pp) than that of the main sample. The potential for gender-based violence in police interactions may drive this result. In contrast, identifying as Republican, white or a man is correlated with feeling the most safe in police interactions.

A.2.2 Support for "Defund the Police" by Partisanship

We replicate Ba et al. (2023a) and use data from the CCES to examine how the Defund movement influences public sentiment on police budgets by partisanship. Using an event study approach, Figure A.7 shows the impact of George Floyd's murder on the public support for reducing police funding, differentiated by political affiliation and the intensity of Google searches for "defund the police." The figure reveals that George Floyd's murder did not significantly alter Republican support for reducing police funding. Despite the increased salience of the Defund movement, indicated by the varying levels of Google search activity, there is no discernible impact on Republicans' stance on the issue. This is in stark contrast to what we observe for Democrats, who, particularly in areas with high search interest, showed a marked increase in support for reducing police funding after George Floyd's murder. This suggests a significant partisan divide in the response to the incident and subsequent reform movements, with Republicans remaining largely unaffected in their views on police budget adjustments.

A.3 Quantile Regressions

Violent Scenarios Using quantile regression, Figure A.8 explores whether the treatment effects vary by quantile for the violent scenarios. For the "armed robbery" scenario, the *DCTP* treatment is associated with increased demand for police, particularly at the lower end of the distribution, with a significant peak at the 5th–15th percentiles, up to 0.3086σ ($p < 0.1$). Meanwhile, exposure to the police violence information has a more muted impact on police demand across the quantiles for "armed robbery." In contrast, for the "screaming woman" scenario, exposure to the DCTP information consistently reduces the demand for police, especially at lower quantiles, with notable decreases between the 5th and 25th percentiles. Conversely, the *Police Violence* treatment has a marginal and generally insignificant effect. The findings indicate that the *DCTP* treatment substantially influences those with initially low demand for police services. However, the direction of the effect varies between scenarios: it increases demand in the "armed robbery" case while decreasing it in the "screaming woman" scenario.

Nonviolent Scenarios Figure A.10 analyzes whether the treatment effects vary by quantile for the nonviolent scenarios. Across these situations—"naked man," "suicidal ideation" and "disruptive begging"—the quantile regression analyses demonstrate that the *DCTP* and *Police Violence* information treatments consistently lead to a reduction in public demand for police intervention.

For the "naked man" scenario, the middle quantiles exhibit the most substantial decreases, signaling an effective shift in public preference away from police involvement due to the treatments. Similarly, in the "suicidal ideation" scenario, there is a significant and persistent decline in demand for police from the lower to higher quantiles, particularly in the middle of the distribution for the *DCTP* treatment. The "disruptive begging" scenario also shows a pronounced decrease in police demand with an increase in quantiles, with significant reductions evident from the middle to the upper quantiles for both treatments. Overall, the findings suggest that both the *DCTP* and *Police Violence* information treatments significantly influence public attitudes, with a notable decrease in the preference for police response in the various nonviolent crises.

Overall, for the violent scenarios, our information treatments predominantly affect the lower quantiles, suggesting that those less inclined to call the police are influenced by exposure to additional information, particularly in the "armed robbery" situation. In contrast, for the nonviolent "naked man," "suicidal ideation," and "disruptive begging" scenarios, the middle quantiles show the most substantial shifts in demand, highlighting the treatments' impact on those with moderate initial demand for police services.

B How Does Perceived Danger Influence Demand for Police?

Perceived danger plays a pivotal role in both civilian decisions and law enforcement behavior during emergencies. Civilians' perceptions of danger influence their choice to call 911 (Ang et al., 2021), and officers' perceptions of danger affect their propensity to use force (Fryer, 2019; Annan-Phan and Ba, 2023). Understanding how the effects of information about police alternatives and perceived danger interact is key for developing policies that optimize emergency response, reduce excessive force, and build community trust in police services. This analysis examines how perceived danger shapes responses to information about police alternatives and police violence statistics.

Our approach involves exposing different groups to information about police alternatives and measuring the impact on perceived danger and response preferences. After constructing a measure of perceived danger using a combination of AI classification and human coding, we follow the methodology of Heckman et al. (2013) and Heckman and Pinto (2015), using a mediation model to understand these mechanisms. Our goal is to distinguish the average causal effects that occur through two channels: (a) indirect effects due to the impact of the treatment on perceived danger and (b) direct effects arising through other means, including unobserved changes in attitudes or the relationship between perceived danger and response preferences.

B.1 Research Design

B.1.1 Coding Procedures for Open-Text Responses

To qualitatively analyze the reasoning behind respondents' demand for police involvement, we leverage the fact that our surveys included open-ended questions where respondents could explain their response rationales (Andre et al., 2021, 2022; Stantcheva, 2023; Ba et al., 2023a). Our approach combines manual classification and large-language models to effectively capture the often nuanced rationales embedded in these responses. We take the following steps.

- **Step 1: Classification Scheme** We define an open-text response classification scheme with two categories: (1) *danger*, indicating perceived danger, and (2) *no danger*, indicating no perceived danger. Responses suggesting a high likelihood of violence, potential escalation, or fear for safety are coded under *danger*. Responses highlighting mental health concerns or low-priority issues are coded under *no danger*. This latter category also includes responses advocating for police alternatives or expressing concerns about police intervention worsening the situation. These responses indicate that the respondent did not perceive the situation to be dangerous enough to require police involvement.

- **Step 2: Manual Classification** We manually code responses from over 350 pilot respondents using the above classification schema. Three coders independently classified each open-text response and achieved a 94% matching rate. Table A.10 displays the classification scheme and examples provided to the coders.

- **Step 3: Zero-Shot Classification** We use Facebook's pretrained BART model for zero-shot classification to classify the main sample's open-text responses for each scenario, after validating its performance against the pilot manual classification results. The model assigns scores from 0 to 1, indicating whether the explanation falls into a particular category. A score of 0 indicates irrelevance, while 1 implies perfect classification. We include a main category of *danger* and additional categories such as *mental health issues* and *low priority for police*, where a high score in these categories lowers the *danger* score. The final score for *danger* represents the level of perceived danger reflected in the explanation.

Having established the measure of perceived danger, in the following section, we outline the methodology used to ascertain the effect of the randomized exposure to information about police alternatives and the perceived danger measure on demand for police among the respondents in our sample.

B.1.2 Mediation Analysis

For the mediation analysis model, we follow Heckman et al. (2013) and Heckman and Pinto (2015). Let D denote the respondent's treatment status, the multivalued treatment variable corresponding to the *Control*, *DCTP*, or *Police Violence* groups defined previously. To streamline the notation, we suppress the individual index. Similarly to the setup in Heckman et al. (2013), Fagereng et al. (2021), and Goncalves et al. (2023), let y_d denote the potential outcome if the respondent is assigned to information treatment $D = d$. We consider the following linear model:

$$\begin{aligned} y_d &= \kappa_d + \alpha_d S_d + \sum_{j \in J} \gamma_d^j \theta_d^j + X' \beta_d + u_d \\ y_d &= \tau_d + \alpha_d S_d + X' \beta_d + \epsilon_d \end{aligned} \tag{4}$$

such that κ_d is a treatment-specific intercept, X is the set of preassigned covariates from Table 2, S_d is our measured mediator for the perceived danger score, and θ_d is a vector of the unmeasured mediator. The error term, u_d, is assumed to be uncorrelated with X or the mediator variables. Although the treatment does not alter the background variables X, it can influence their relationship with the outcome y, a dynamic reflected in the treatment-specific coefficients β_d. The second expression can rearrange the components that we do not observe into an intercept and a mean-zero error term, $\tau_d = \kappa_d + \sum_{j \in J} \gamma_d^j E[\theta_d^j]$ and $\epsilon_d = u_d + \sum_{j \in J} \gamma_d^j (\theta_d^j - E[\theta_d^j])$. Hence, any difference in the error terms if information is assigned to one type of respondent family versus another can be attributed to differences in the mediator variables that we do not observe. We specify linear models for the treatment-specific intercept τ_d, the observed mediators α_d, and the covariate variables β_d:

$$\tau_d = \tau_0 + \tau d \qquad \alpha_d = \alpha_0 + \alpha d \qquad \beta_d = \beta_0 + \beta d \tag{5}$$

We also use a linear model for our observed mediator variable measuring perceived danger:

$$S_d = \mu_0 + X' \mu_1 + \mu_2 d + \eta \tag{6}$$

where η is a mean-zero error term. To estimate the parameters $\alpha_0, \alpha, \beta_0, \beta$ accurately, we must assume that neither the observed nor the unobserved mediator variables are correlated with the covariates X or with the perceived danger mediator. This assumption of noncorrelation allows identification of these parameters, as demonstrated by Heckman and Pinto (2015). It should be noted, however, that any correlation between the observable and unobservable mediators would introduce bias into the estimated coefficients of the mediator variables. Assuming that the treatment influences the perceived danger mediator without altering the effect of these variables or the background variables on outcomes (i.e., assuming $\alpha = 0$ and $\beta = 0$), we can streamline the mediation model.

As per Heckman and Pinto (2015), these restrictions are testable under the uncorrelatedness assumption. Table A.9 reports the tests for the uncorrelatedness assumption within a mediation analysis for various response outcomes, following Heckman et al. (2013); Heckman and Pinto (2015). The results show that for the "woman screaming" and "suicidal ideation" scenarios, the assumption does not hold when we consider demand for police, as indicated by the p-values of 0.00. Conversely, for "armed robbery" and "naked man," we observe p-values well above conventional significance levels, suggesting that the uncorrelatedness assumption may hold. Given some caveats, for our primary analysis, we adopt the simplifying assumptions of $\alpha = 0$ and $\beta = 0$. With these restrictions, equations 4—6 lead to the following mediation model:

$$
\begin{aligned}
y_d &= \tau_0 + \tau d + \alpha_0 S_d + X'\beta_0 + \epsilon_d \\
y_d &= \tau_0 + \tau d + \alpha_0(\mu_0 + X'\mu_1 + \mu_2 d + \eta) + X'\beta_0 + \epsilon_d
\end{aligned} \tag{7}
$$

where we derive the second part of equation 7 by incorporating the linear formulation of our perceived danger mediator from equation 6. Utilizing equation 7, we can break down the average treatment effect of being assigned to one information treatment d' over the other d:

$$
\begin{aligned}
E[y_{d'} - y_d] &= (d' - d)\tau + \alpha_0 E[S_{d'} - S_d] \\
E[y_{d'} - y_d] &= \underbrace{(d' - d)\tau}_{\text{Direct Effect}} + \underbrace{\alpha_0(d' - d)\mu_2}_{\text{Indirect Effect}}
\end{aligned} \tag{8}
$$

Our goal is to separate the indirect effect, which originates from the treatment's influence on the specifically measured mediator—perceived danger—and the direct effect, which functions through other avenues not associated with changes in perceived danger. Concurrently, a secondary objective is to evaluate the proportional significance of perceived danger as an observed mediator in our analytical context. The estimation proceeds in two steps. The first step consists of the estimating equation given by:

$$
y = \tau_0 + D\tau + \alpha_0 S + X'\beta_0 + \varepsilon \tag{9}
$$

Applying OLS to equation 9 provides consistent parameter estimates $(\tau_0, \tau, \alpha_0, \beta_0)$ under the assumptions that inform equation 7. The next step entails using OLS to estimate a linear model for perceived danger, with S as the dependent variable and X and D as independent variables. The outcomes of these regressions offer estimates of the parameters specified in equation 6, which are essential for determining the direct and indirect effects in the model.

B.2 Results

Descriptives Our analysis begins with descriptive statistics related to perceived danger across the various scenarios. As illustrated in Figure A.11, the cumulative probability of perceiving danger increases with the danger score. The "armed robbery" and "woman screaming" scenarios invoke an immediate sense of threat with minimal score increments, whereas the "naked man," "suicidal ideation," and "disruptive begging" scenarios require higher danger scores to be perceived as equally threatening. Hence, threat assessment is heavily influenced by the scenario context, with some situations inherently perceived as more dangerous.

Section B.3 in the appendix further explores how demographic factors such as race and political orientation, as well as attitudes towards police, shape perceptions of danger. Moreover, we show a pronounced preference for police intervention in scenarios with high perceived danger, particularly violent ones, under the *DCTP* and *Police Violence* treatments. Nevertheless, there is a notable openness to alternative responses in the less threatening or nonviolent scenarios, underscoring the public's discernment in crisis response preferences.

B.3 Measures of Perceived Danger

B.3.1 Descriptives

Correlates of Perceived Danger Table A.8 demonstrates how respondents' demographics and baseline attitudes toward police impact their perception of danger in different scenarios. Factors such as age, race, political affiliation, education, and marital status play a role. For instance, Black respondents perceive less danger in the "armed robbery" and "screaming woman" scenarios but more in the "naked man" and "suicidal ideation" situations. Political leanings and educational levels also show varied effects on danger perception. Marital status, particularly being single, influences perceived danger, especially in the domestic violence scenario. The initial police demand index positively correlates with danger and is a consistent predictor across scenarios, indicating that established attitudes toward police are linked to perceptions of danger. This highlights the strong influence of individual characteristics and preconceived notions about police on how danger is perceived in various crises.

Relationship between Propensity to Call the Police and Perceived Danger In Figure A.12, we present the relationship between perceived danger and the likelihood of calling the police in each scenario. As perceived danger increases, the likelihood of calling the police also increases. However, the strength of this correlation varies depending on the scenario. For example, there is a strong correlation between perceived danger and calling the police in the "naked man" case but a weaker correlation in the case of "disruptive begging." Overall, people are more likely to call the police when they perceive a situation to be dangerous. However, the specific likelihood of calling the police depends on the nature of the situation.

Reasoning, Information, and Demand for Police and Alternatives Figures A.13 and A.14 summarize participant preferences for police involvement versus alternatives across various scenarios, influenced by the perceived danger.

In scenarios perceived as dangerous, a high percentage of respondents prefer police intervention, especially in "armed robbery" and "woman screaming" cases, where over 80% opt for police officers after receiving the *DCTP* or *Police Violence* information treatments. When danger is not perceived, there is a higher inclination toward social workers or no intervention, particularly in the control group.

For the "naked man" and "suicidal ideation" scenarios, even with perceived danger, there is a notable preference for social workers, reaching 87% for the "suicidal ideation" scenario when it is perceived as nondangerous. This suggests discernment regarding when police intervention may be unnecessary or less appropriate. In the "disruptive begging" case, even with perceived danger, there is less demand for police, and a considerable percentage favor nonintervention or intervention by a social worker when no danger is perceived.

The prevalent tendency to call the police is closely linked to perceived risk. However, there is a notable willingness to consider other options, particularly where the threat level is low or in nonviolent circumstances. This trend suggests that policy initiatives could focus on raising awareness and facilitating access to alternative crisis management solutions.

Impact of Information on Perceived Danger Table A.11 presents the results from the first step of the mediation analysis by estimating the impact of the information treatments on perceived danger. This table demonstrates that the *DCTP* and *Police Violence* information treatments have a significant effect on how danger is perceived in different scenarios. In the "armed robbery" case, exposure to police alternatives information raises the perceived danger by 4.4 to 4.8 pp ($p < 0.01$)—a considerable increase over the control group's average danger perception of 70.05. The "screaming woman" scenario sees a more substantial rise in perceived danger from the *Police Violence* treatment alone, 3.4 pp ($p < 0.05$). Conversely, both treatments substantially lower the perceived danger in the "naked man" and "suicidal ideation" scenarios, with the *DCTP* treatment having the most marked effect on the latter. Additionally, *DCTP* is the only treatment that significantly lessens the perceived danger in the "disruptive begging" scenario. The key insight is that these treatments influence danger perceptions diversely, intensifying them in potentially criminal situations while lessening them in nonviolent or minor scenarios.

Likelihood of Calling the Police Table A.12 presents the results of the mediation analysis on how information about police alternatives influences the propensity to call the police, with perceived danger acting as the mediating factor.

In the "armed robbery" scenario, a significant portion of the effect is indirect, particularly for the *Police Violence* treatment, with this indirect effect accounting for over 90% of the total effect, indicating that changes in demand for police are largely due to shifts in perceived danger. For the (nonviolent) "naked man," "suicidal ideation," and "disruptive begging" cases, the *DCTP* treatment results in a substantial direct effect, indicating that the reduction in the propensity to call the police is not primarily driven by changes in perceived danger. Similarly, the *Police Violence* treatment in these scenarios also operates through channels other than perceived danger, as evidenced by its significant direct effects.

We transition next to the "screaming woman" scenario, where a case of inconsistent mediation emerges, with the direct and indirect effects contradicting each other (MacKinnon et al., 2007). The majority of the reduction in police demand is driven by the direct effect, whereas the indirect effects, despite being smaller, have positive coefficients. This suggests that while the direct information from the treatments persuades individuals not to call the police, the increased perception of danger has a smaller yet countervailing effect.

Our results indicate that the danger mechanism explains the impact of information about police alternatives on the decision to involve police. In the violent situations such as the "armed robbery" scenario, perceived danger significantly mediates the impact of information on police alternatives, whereas in the nonviolent scenarios, direct information plays a more decisive role, overriding the influence of perceived danger.

Police as First Responders Table A.13 presents a mediation analysis of the various effects of information about police alternatives on the preference for police as first responders, mediated by perceived danger. This table shows that the *DCTP* and *Police Violence* information treatments differentially impact the preference for police intervention, with perceived danger's mediation effect varying by scenario. In the "armed robbery" situation, the indirect effects of both treatments are statistically significant, but the high baseline mean of the control group (0.97) underscores a strong initial preference for police as first responders in such situations. For the "screaming woman" case, the *DCTP* treatment directly decreases preferences for police, while for the "naked man" and "disruptive begging" cases, this treatment's effects are both direct and indirect. For the "suicidal ideation" scenario, we see a significant reduction in the preference for police through perceived danger with the *DCTP* treatment. Overall, while information impacts the likelihood of involving police, the extent and nature of this impact are scenario dependent, with a particularly strong baseline inclination toward police response in the "armed robbery" case.

Social Workers as First Responders Table A.14 conducts a mediation analysis to assess the impact of the *DCTP* and *Police Violence* information treatments on the preference for social workers as first responders, with perceived danger as a mediator. The results contrast with previous findings on preferences for police intervention. In the "armed robbery" scenario, there is a slight decrease in the demand for social workers under the *DCTP* treatment, in constrast to the strong preference for police noted in the earlier analysis. For the "screaming woman" scenario, there is an increase in the direct demand for social workers under the *DCTP* treatment, differing from the decrease in police preference for the same scenario. In the "naked man" and "suicidal ideation" cases, both the *DCTP* and *Police Violence* treatments lead to an increased demand for social workers, which contrasts with the earlier observation of a reduced preference for police in the "suicidal ideation" case. The "disruptive begging" case similarly shows an increased demand for social workers under the *DCTP* treatment, albeit slight, compared to the direct and indirect effects on police preference previously discussed.

The findings indicate that public preferences for police and social workers as first responders can vary depending on the type of incident and associated perception of danger. There appears to be a tendency toward police intervention in scenarios such as "armed robbery," while for incidents that are nonviolent or related to mental health issues, we tend to see an inclination toward social worker involvement, reflecting a potential preference for specialized care in certain situations.

No Respondent as First Responder Table A.15 shows that the *DCTP* and *Police Violence* treatments slightly decrease the preference for no first responder in the "armed robbery" case when perceived danger is low. There is a mixed impact in other scenarios, with *DCTP* increasing the likelihood of calling a responder for the "naked man" and "disruptive begging" cases. The direct effects are generally insignificant. The key insight is that the information treatments tend to discourage opting out of first responder services, especially in situations with potential danger.

C Simple 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 either be 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 depend on her decision to call the police in instances devoid of alternatives, thus 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 a 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 of 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 as $e \in [0, 1]$, affects the probability r of choosing the non-police 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 choses the level of effort, e, that maximize the following value function

$$\begin{aligned} max_e\{V(r,\theta,\pi) - c(e)\} &= max_e\{V(f(e),\theta,\pi) - c(e)\} \\ &= max_e\{\pi + (1-\pi) \cdot (1-f(e)) \cdot (-\theta) - c(e)\} \end{aligned} \tag{10}$$

We assume 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 level of effort, which is given by:

$$(1\text{-}\pi) \cdot \theta \cdot f'(e) = c'(e) \Rightarrow e^* = (1-\pi) \cdot \theta \tag{11}$$

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's 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 non-police necessary scenario $(1-\pi)$ and the severity of the mistake θ.

The Role of Information Equation 11 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: emergency service numbers $\{988, 211, 311\}$, *DCTP*, and *Police Violence*. Each treatment corresponds to a distinct θ value, representing the perceived severity of erroneously calling the police when alternatives are available: θ_N, θ_E, θ_D, and θ_P for the control group (no information), the $\{988, 211, 311\}$

numbers, *DCTP*, and *Police Violence*, respectively.

Our findings suggest that for non-violent scenarios, the sequence of severity perceptions is $\theta_N < \theta_E < \theta_P < \theta_D$, leading to corresponding effort levels $e_N < e_E < e_P < e_D$ and probabilities of selecting non-police actions $r_N < r_E < r_P < r_D$. This indicates that information, particularly from *DCTP* significantly increases respondents' propensity to choose non-police alternatives in situations where alternatives are viable.

D Video Transcripts

D.1 Control

Link to the video: Control 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

D.2 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 non-violent 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 non-violent 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."

D.3 Police Violence

Link to the video: Police Violence 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? Despite this small number, police are armed first responders, and calling them for help can end up escalating tragically into violence.

- **Narrator:** Every year, more than a thousand people are killed by police. In 2022, around half of these killings began with police responding to suspected non-violent offenses. Even worse, the impact of police violence is not uniform across the U.S. population. For people of color, and for young men of color in particular, the risk of being killed by police is far greater than for any other demographic, and remains a leading cause of death. This risk is similarly greater for other vulnerable groups; individuals struggling with poverty, severe mental illness, substance addiction, or homelessness are more likely to have contact with police, and are more likely to become victims of police violence.
- **Narrator:** Rates of police violence are also notably higher in the U.S. than in other countries. In 2019, the U.S. accounted for 13.2% of all deaths due to police conflict, while only accounting for 4% of the global population.
- **Narrator:** Fortunately, for many situations, alternative sources of help are available instead of relying on police.
- **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 chose an active control group design, as it guarantees that all participants receive pertinent information, though the specifics vary. This contrasts with a pure control setup and yields a diverse range of belief changes, not only for those with initial misconceptions but also for individuals with initially accurate beliefs, thereby facilitating the determination of beliefs' average causal impact on a wider demographic (Bottan and Perez-Truglia, 2022; Roth et al., 2022; Haaland et al., 2023). However, we later compare our results to the outcomes from a pure control that did not receive any information on police alternatives.

E 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."*

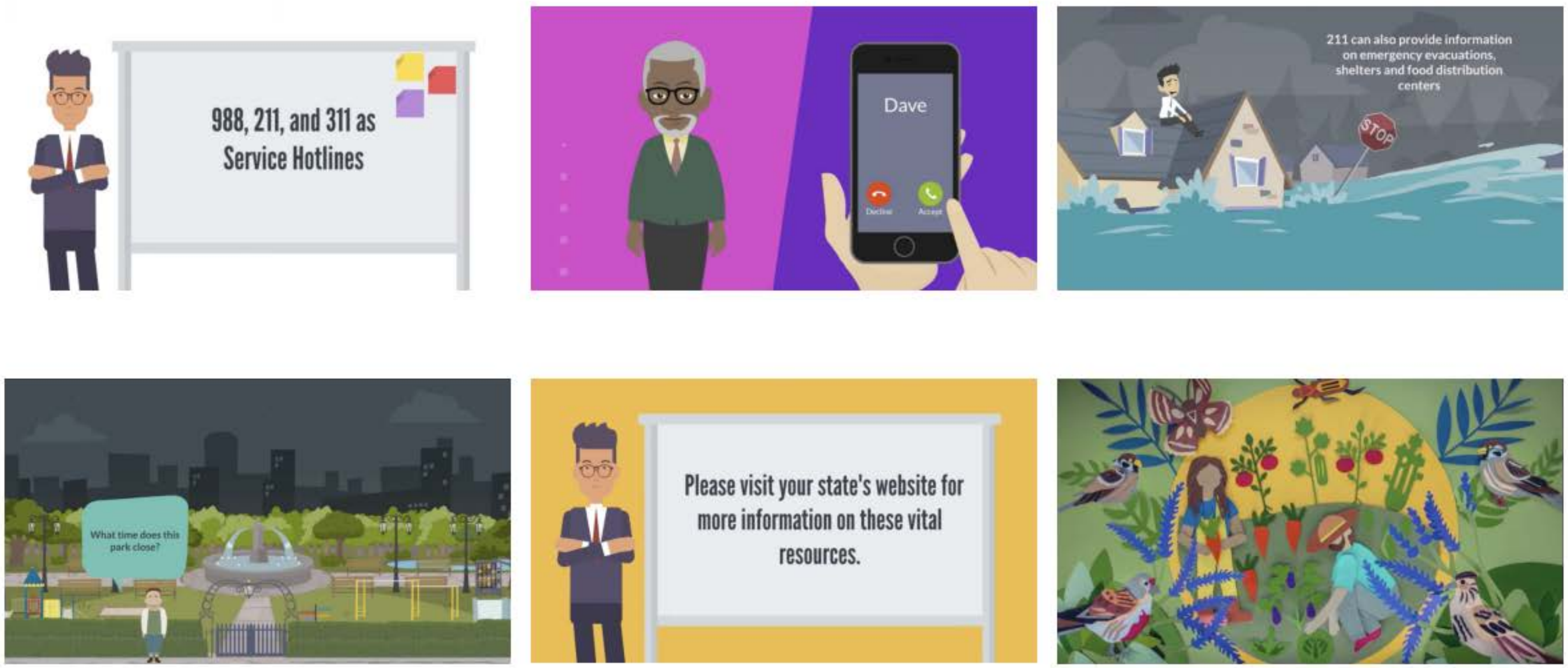
- **Suicide:** *"A neighbor seems really upset and says he is 'thinking about ending things'."*

Homelessness. Fictional story

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

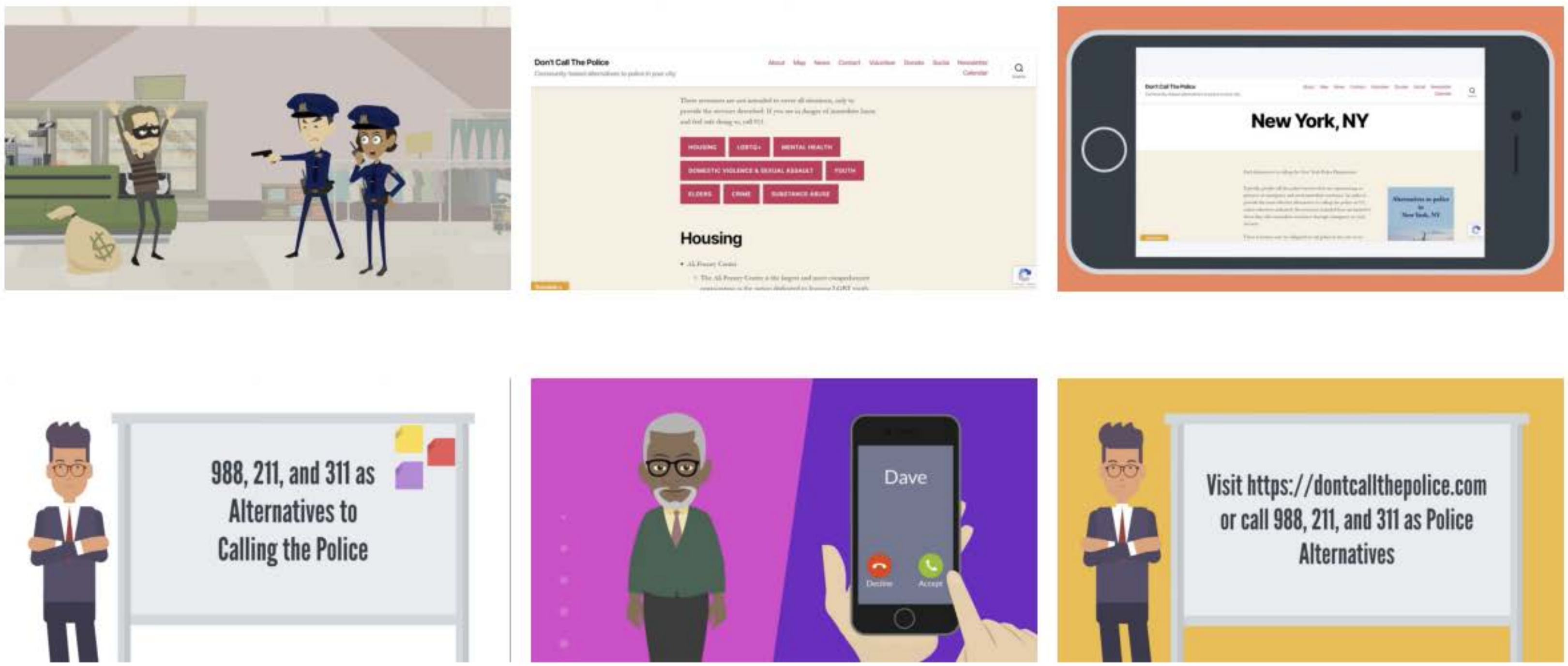
F Additional Figures and Tables

Figure A.1: Screenshots from the Control Video



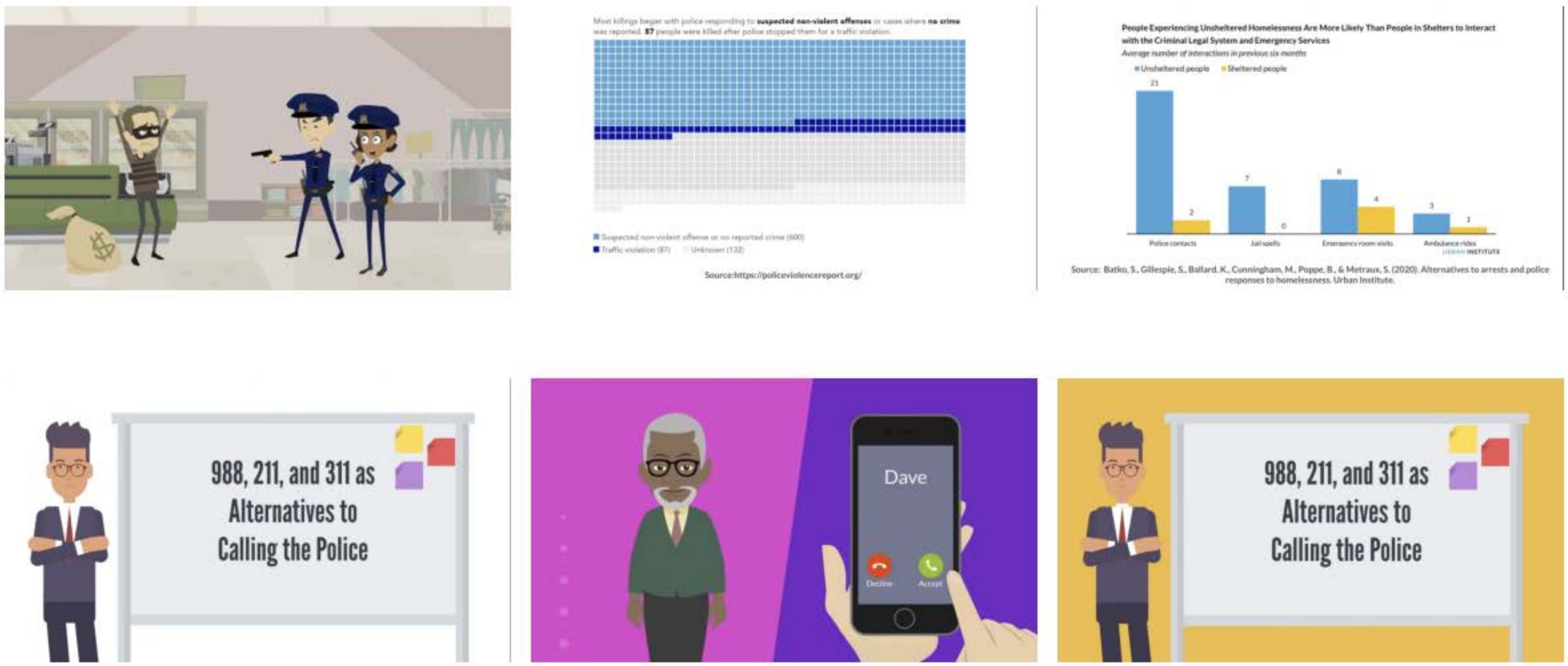
Notes: This figure presents screenshots from the control video.

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



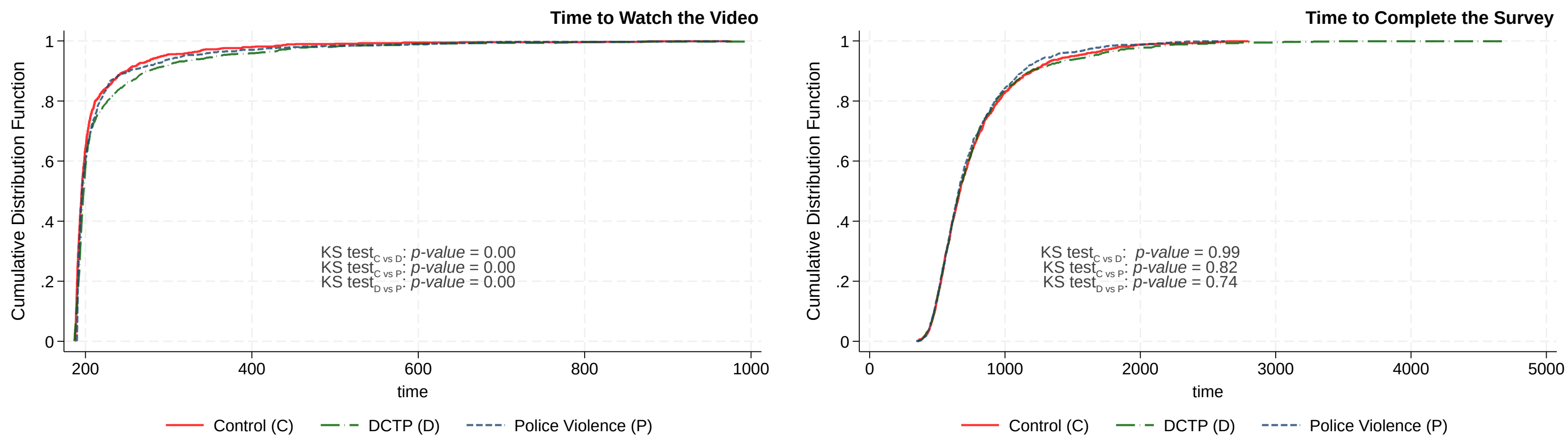
Notes: This figure presents screenshots from the *Don’t Call the Police* video.

Figure A.3: Screenshots from the *Police Violence* Video



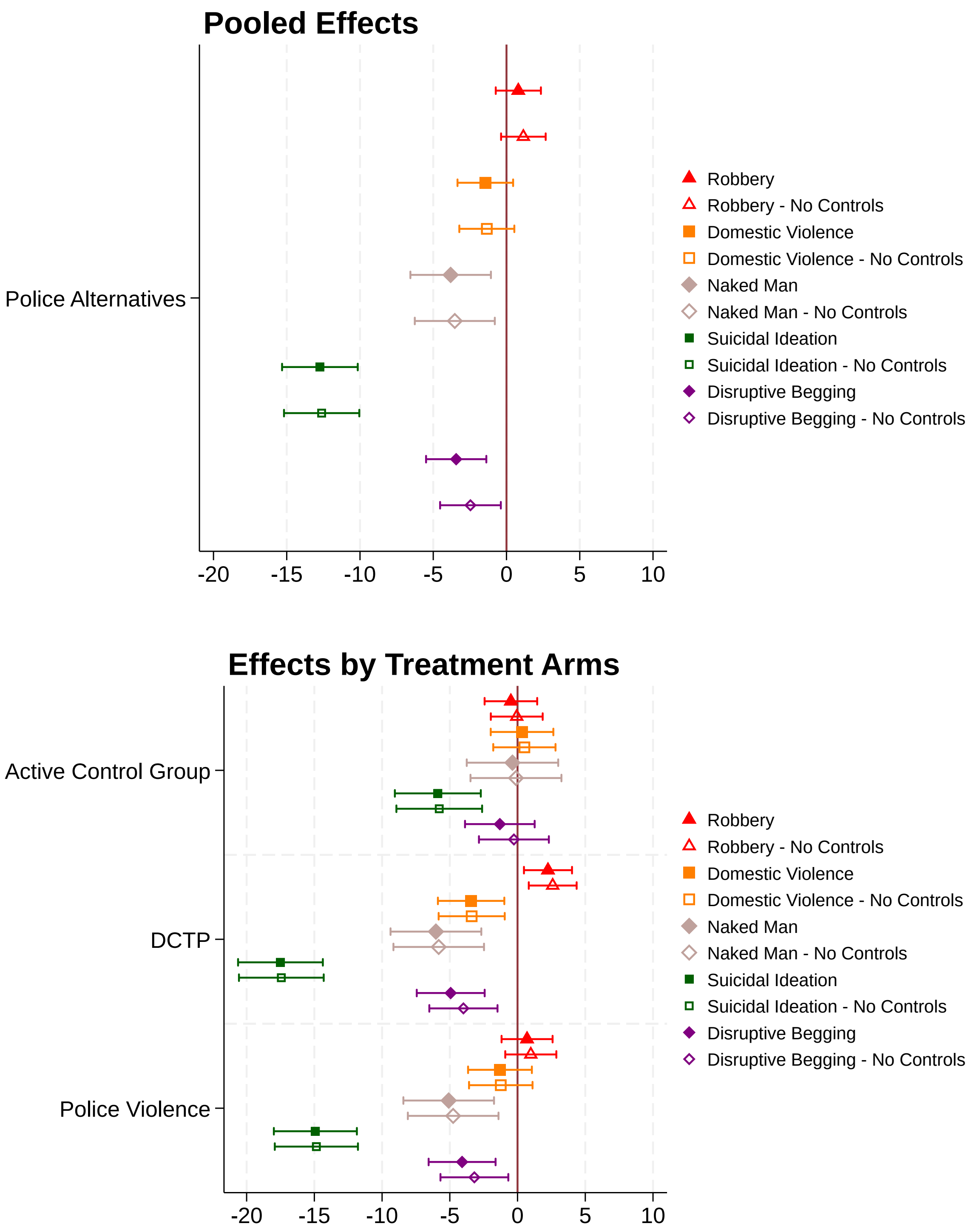
Notes: This figure presents screenshots from the *Police Violence* video.

Figure A.4: CDFs of Time to Watch the Informational Video and Complete the Survey, by Treatment Arm



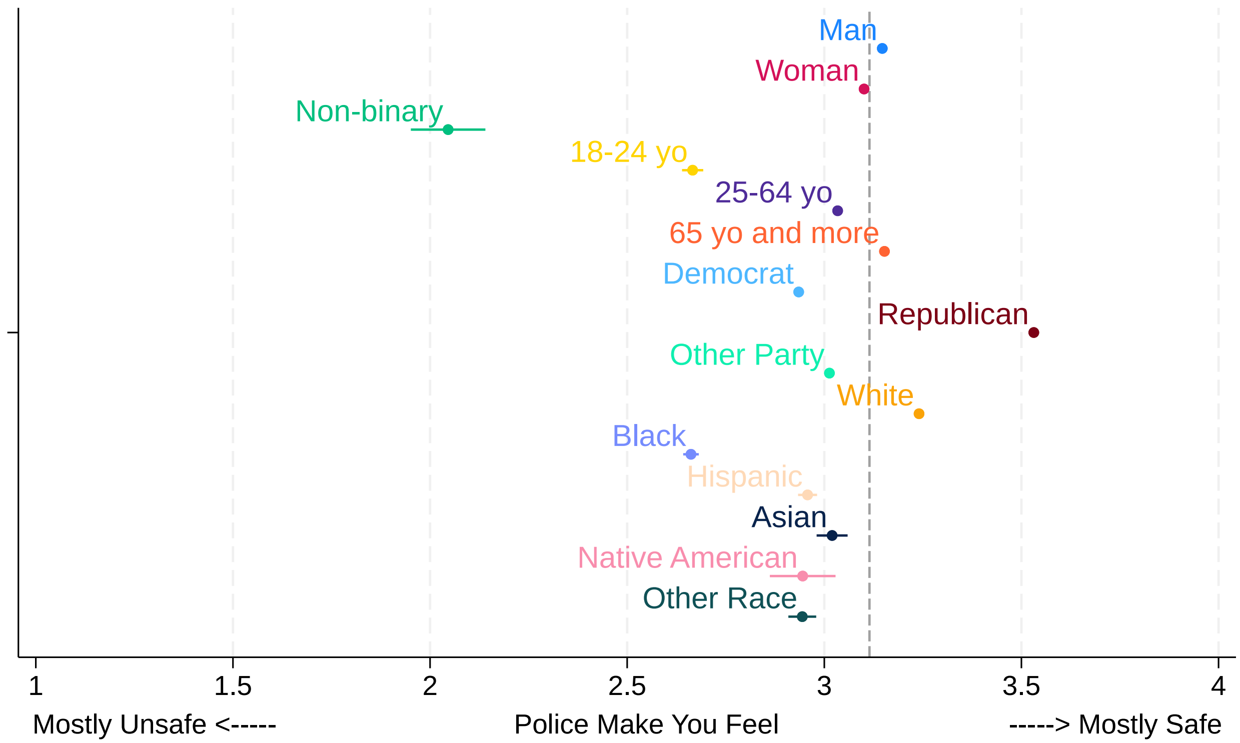
Notes: Empirical cumulative distribution functions of the time to watch the informational video and to complete the survey by treatment arm. We also report the p-value of a Kolmogorov–Smirnov (KS) test of equality for pairs of distributions among the control (C), *DCTP* (D), and *Police Violence* (P) treatments.

Figure A.5: Robustness: Knowledge about Police Alternatives on Demand for Police by Scenario



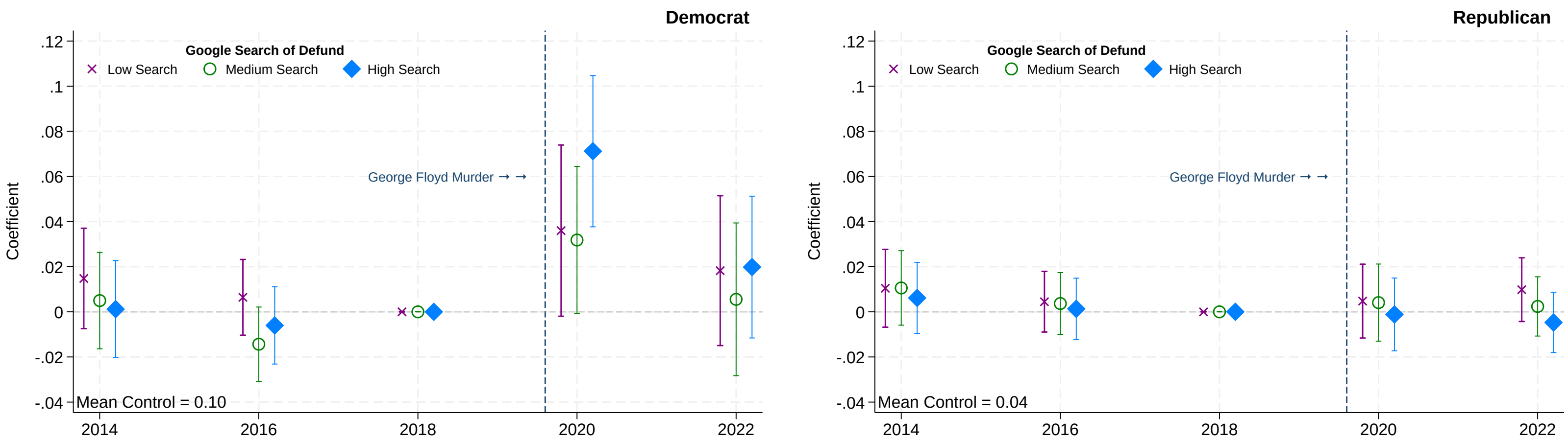
Notes: These figures present the effect of being informed about police alternatives on the propensity to request police assistance across various scenarios, compared to the propensity for individuals not exposed to no such information. The dependent variable indicates the likelihood of calling the police in the proposed situation (0–100). We report robust standard errors in parentheses. The treatment arm, *Police Alernatives*, encompasses several distinct components: information on emergency service numbers *988,211,311*, the *DCTP* treatment and the *Police Violence* treatment. Our control group consists of individuals not provided with any details regarding these alternatives. In our analysis, we compare estimates with and without control variables. We report the 95% confidence intervals using robust standard errors.

Figure A.6: Attitudes Toward Police by Sample



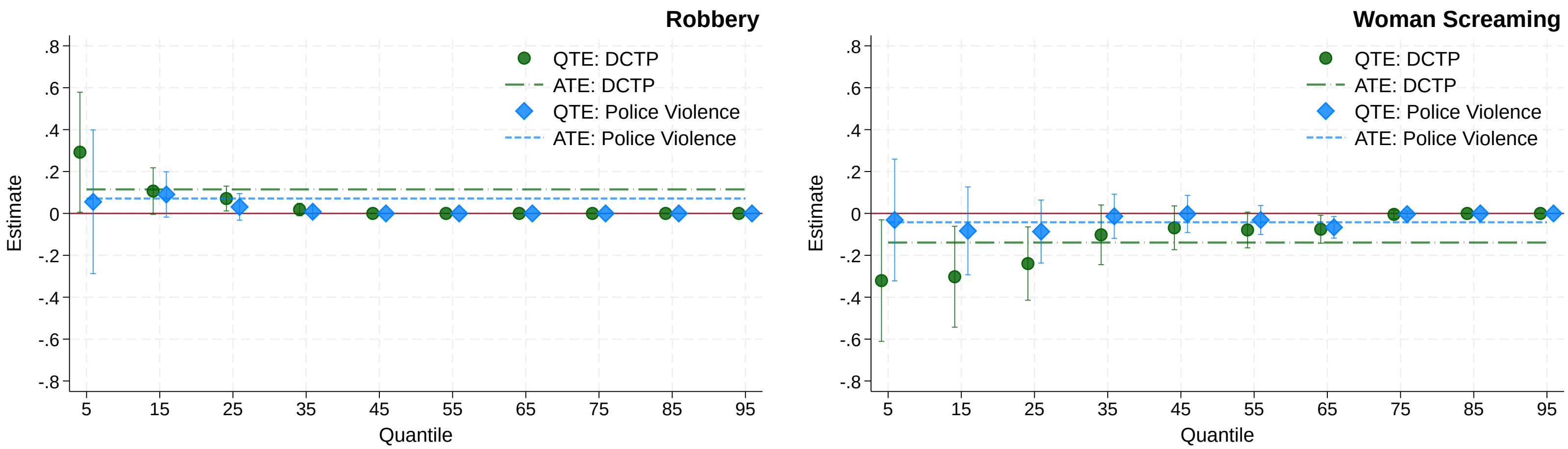
Notes: This figure presents the attitudes of respondents toward police, based on data from the 2022 Cooperative Congressional Election Study (CCES), segmented by various respondent characteristics. The primary variable of interest is the respondent's answer to the question "Do the police make you feel safe?" The response options range from 5 ("mostly safe") to 1 ("mostly unsafe"), including intermediate perceptions of safety. The vertical line corresponds to the mean of the full CCES sample. We provide 95% confidence intervals.

Figure A.7: George Floyd's Murder and Public Support for Reducing Police Funding by Partisanship



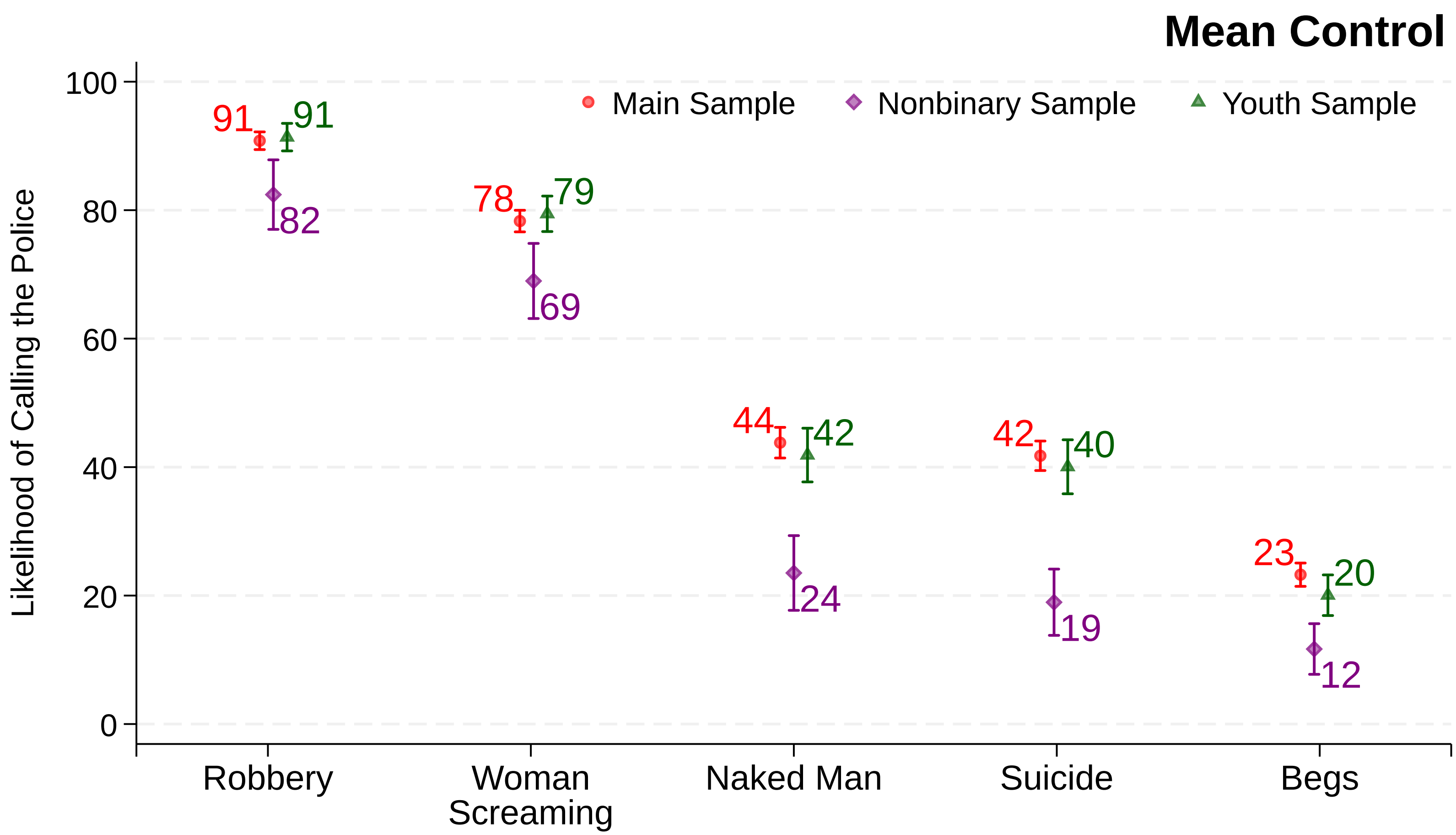
Notes: This figure presents the impact of George Floyd's murder on support for reducing police funding by partisanship status, categorized by quartiles of Google search activity for "defund the police." We report 95% confidence intervals, with standard errors clustered at the designated market area level.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

Figure A.8: Quantile Regressions for Violent Scenarios



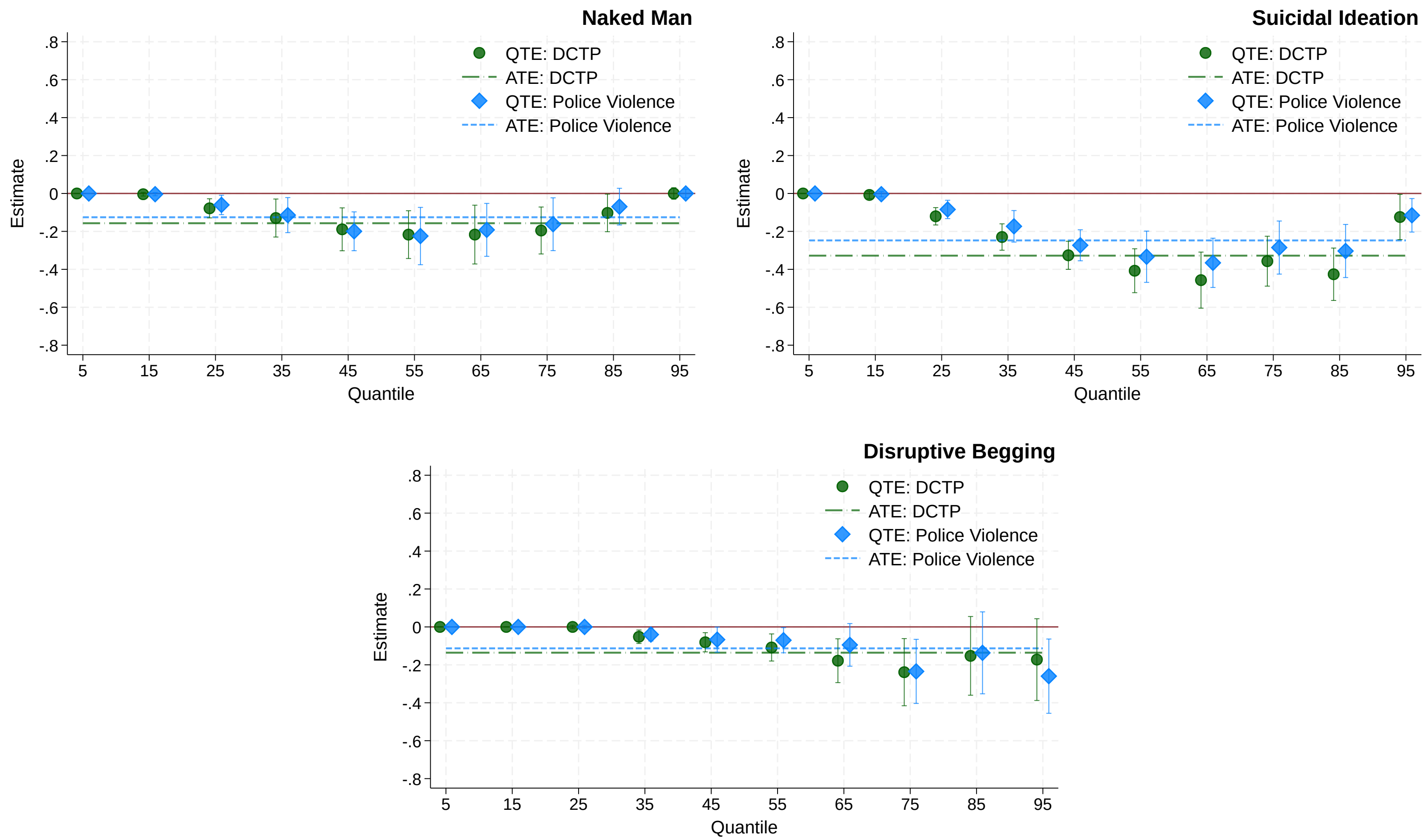
Notes: This figure reports the results of ordinary least squares and quantile regressions estimating the impact of the *DCTP* and *Police Violence* information treatments on the demand for police in each violent scenario. The dependent variable is a Kling–Liebman–Katz index, i.e., a z-score computed by subtracting the control group's mean and dividing by its standard deviation. A higher score indicates greater demand for police. The omitted category, i.e., the control group, comprises individuals receiving information about 988, 311, and 211 only. We provide the estimates and their 95% confidence intervals using bootstrap standard errors with 100 replications.

Figure A.9: Propensity to Call the Police for Control Group by Sample Type



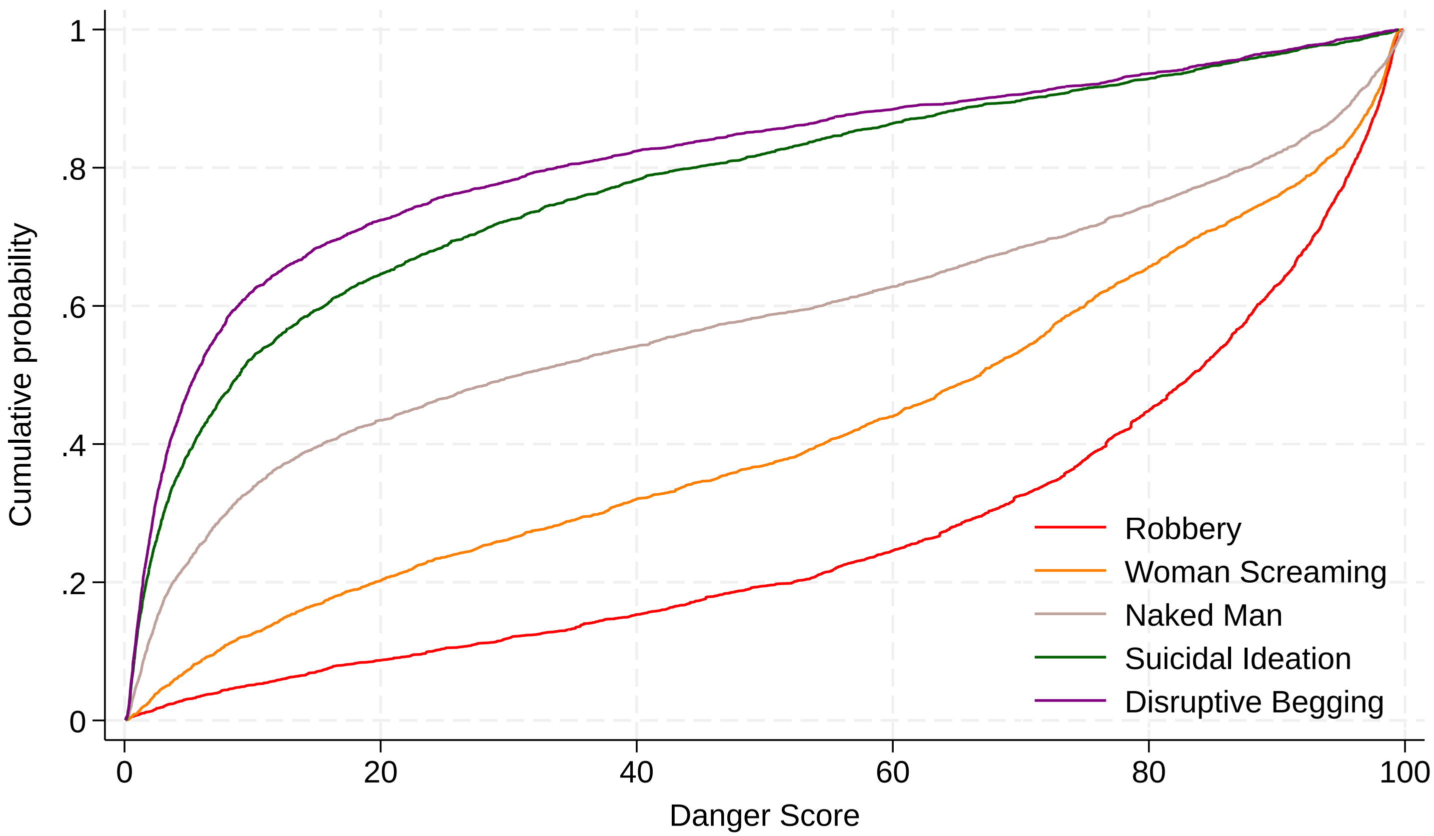
Notes: This figure presents the mean propensity to call the police by scenario for the control group for the main, nonbinary, and youth samples. The control group is composed of individuals receiving information about 988, 311, and 211 only.

Figure A.10: Quantile Regressions for Nonviolent Scenarios



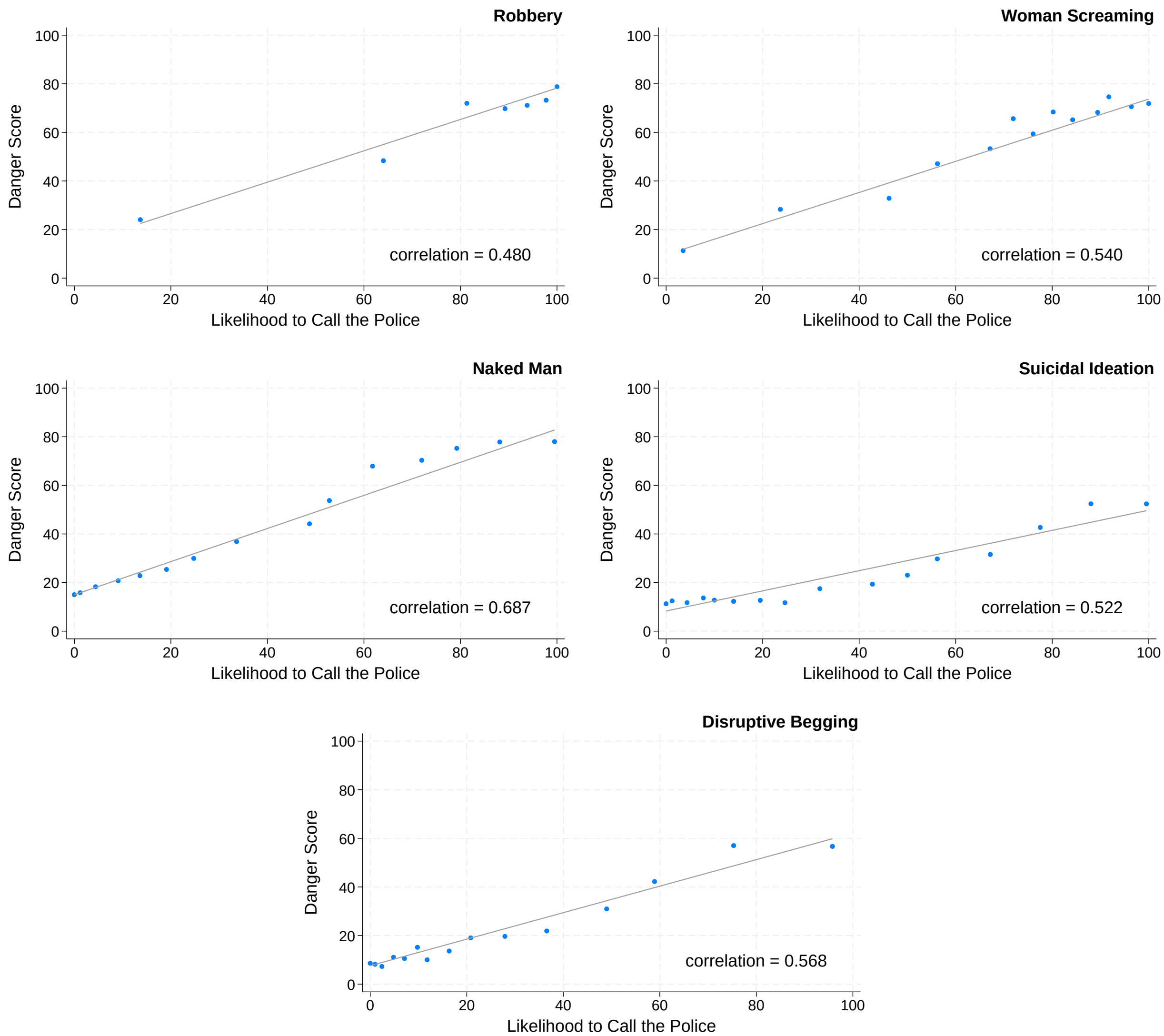
Notes: This figure reports the results of ordinary least squares and quantile regressions estimating the impact of the *DCTP* and *Police Violence* information treatments on the demand for police in each nonviolent scenario. The dependent variable is a Kling–Liebman–Katz index, i.e., a z-score computed by subtracting the control group's mean and dividing by its standard deviation. A higher score indicates greater demand for police. The omitted category, i.e., the control group, comprises individuals receiving information about 988, 311, and 211 only. We provide the estimates and their 95% confidence intervals using bootstrap standard errors with 100 replications.

Figure A.11: CDFs of Danger Score by Scenario



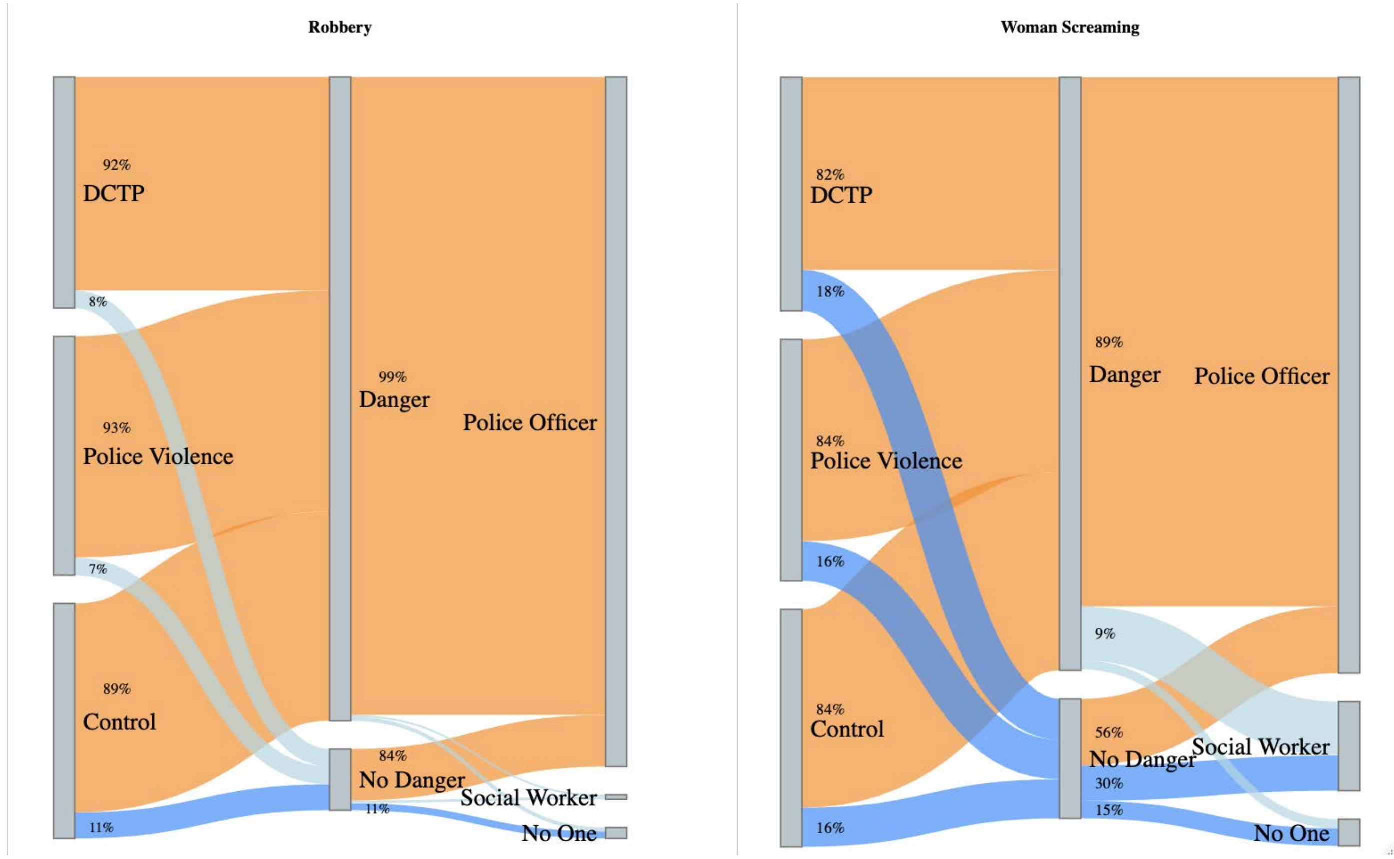
Notes: Empirical cumulative distribution functions of the variable "Danger," a score variable that takes values between 0 and 1, where higher values mean a situation is perceived as more dangerous for each scenario.

Figure A.12: Relationship between Perceived Danger and Propensity to Call the Police by Scenario



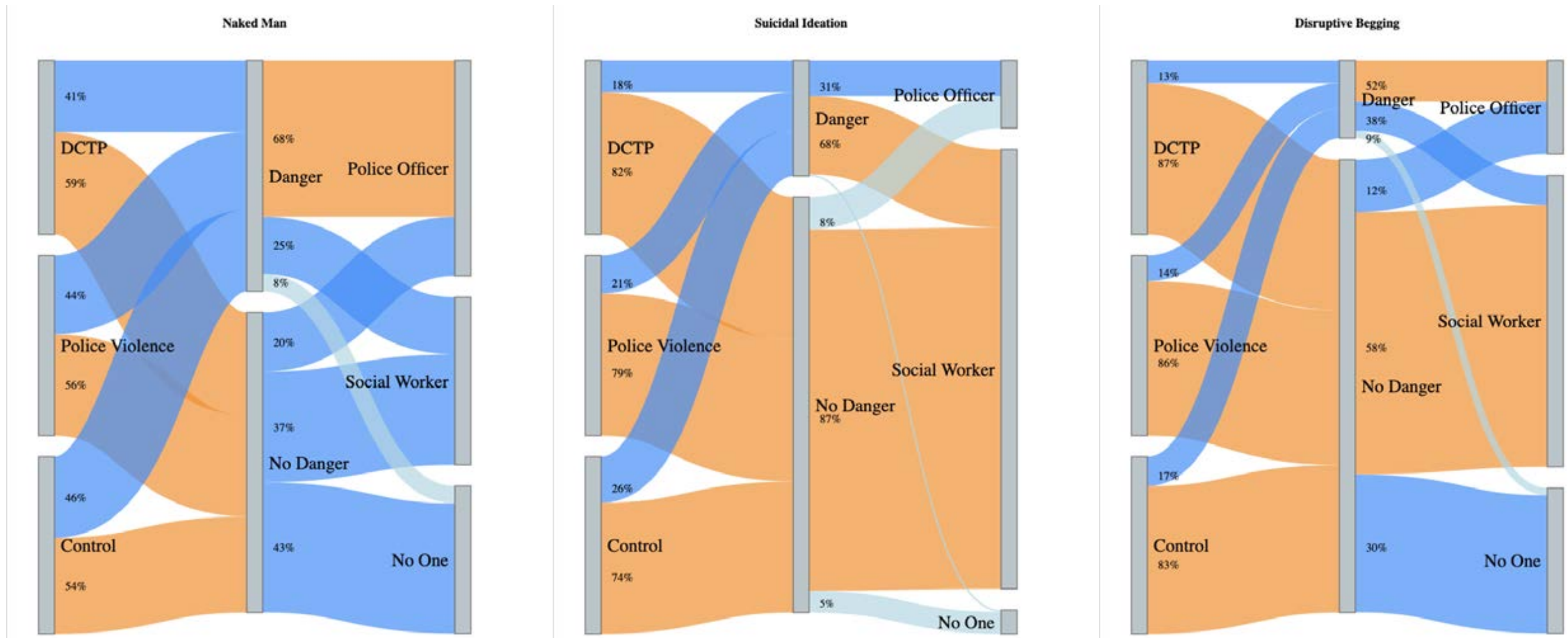
Notes: This figure presents the relationship perceived danger and propensity to call the police by scenario. The variable "Danger" is a score variable that takes values between 0 and 1, where higher values mean a situation is perceived as more dangerous for each scenario.

Figure A.13: Reasoning, Information, and Demand for Police and Alternatives for Violent Scenarios



Notes: This figure depicts the distribution of how perceived danger plays a role in the reported propensity to call the police. The *danger/no danger* classification of participants' free responses is coded through a zero-shot text classifier. Flows between 0% and 10% are in light blue, between 10% and 50% are in darker blue and above 50% are in orange.

Figure A.14: Reasoning, Information, and Demand for Police and Alternatives for Nonviolent Scenarios



Notes: This figure depicts the distribution of how perceived danger plays a role in the reported propensity to call the police. The *danger/no danger* classification of participants' free responses is coded through a zero-shot text classifier. Flows between 0% and 10% are in light blue, between 10% and 50% are in darker blue and above 50% are in orange.

Table A.1: Heterogeneity Analysis: Impact of Information Treatments on Demand for Police

	(1) Main Sample	(2) Female	(3) Male	(4) White	(5) Black	(6) Other Race	(7) 39yo or less	(8) 40yo or more	(9) Less than college	(10) More than college
DCTP	-0.129***	-0.198***	-0.0567*	-0.164***	-0.101	-0.00759	-0.0793**	-0.179***	-0.0978**	-0.144***
	(0.0240)	(0.0337)	(0.0342)	(0.0283)	(0.0755)	(0.0542)	(0.0331)	(0.0347)	(0.0430)	(0.0289)
Police Violence	-0.0931***	-0.154***	-0.0315	-0.115***	-0.0793	-0.0233	-0.0790**	-0.113***	-0.0243	-0.129***
	(0.0240)	(0.0331)	(0.0347)	(0.0277)	(0.0797)	(0.0585)	(0.0344)	(0.0335)	(0.0429)	(0.0289)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value:DCTP=Police Violence	0.13	0.16	0.47	0.08	0.76	0.77	0.99	0.05	0.09	0.61
Observations	2910	1479	1431	2012	379	519	1453	1457	1033	1877

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 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 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., individuals receiving information about 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.2: 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) Other Race	(7) 39yo or less	(8) 40yo or more	(9) Less than college	(10) More than college
DCTP	-0.0122	-0.0861*	0.0682	-0.0662*	-0.0124	0.199***	0.0455	-0.0647	-0.0259	-0.0000350
	(0.0341)	(0.0488)	(0.0477)	(0.0398)	(0.111)	(0.0759)	(0.0494)	(0.0471)	(0.0624)	(0.0402)
Police Violence	0.0144	0.000392	0.0270	0.0152	0.0318	-0.00200	0.0325	-0.00389	0.0602	-0.0111
	(0.0340)	(0.0477)	(0.0484)	(0.0380)	(0.115)	(0.0867)	(0.0530)	(0.0428)	(0.0630)	(0.0399)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value:DCTP=Police Violence	0.43	0.07	0.40	0.04	0.70	0.01	0.80	0.18	0.17	0.78
Observations	2910	1479	1431	2012	379	519	1453	1457	1033	1877

Notes: This table presents the impact of the *DCTP* and *Police Violence* 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 Kling–Liebman–Katz 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 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., individuals receiving information about 988, 311, and 211, only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.3: 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) Other Race	(7) 39yo or less	(8) 40yo or more	(9) Less than college	(10) More than college
DCTP	-0.207***	-0.273***	-0.140***	-0.229***	-0.160*	-0.145**	-0.163***	-0.255***	-0.146***	-0.239***
	(0.0287)	(0.0391)	(0.0422)	(0.0341)	(0.0899)	(0.0648)	(0.0380)	(0.0431)	(0.0486)	(0.0359)
Police Violence	-0.165***	-0.257***	-0.0706*	-0.202***	-0.153*	-0.0375	-0.153***	-0.185***	-0.0806*	-0.208***
	(0.0285)	(0.0383)	(0.0420)	(0.0339)	(0.0900)	(0.0637)	(0.0380)	(0.0422)	(0.0467)	(0.0360)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value:DCTP=Police Violence	0.13	0.68	0.10	0.43	0.93	0.09	0.80	0.09	0.18	0.37
Observations	2910	1479	1431	2012	379	519	1453	1457	1033	1877

Notes: This table presents the impact of the *DCTP* and *Police Violence* 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 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 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., individuals receiving information about 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.4: Impact of Information Treatments on Demand for Experts' Advice

	(1) Police	(2) Community Orgs	(3) Lawyers	(4) Academics	(5) Not Interested
DCTP	0.0991*	-0.00255	-0.0979	0.135**	-0.134**
	(0.0601)	(0.0542)	(0.0597)	(0.0538)	(0.0571)
Police Violence	0.0562	0.0299	-0.0386	0.0586	-0.106*
	(0.0592)	(0.0539)	(0.0596)	(0.0536)	(0.0562)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	3.18	3.43	3.39	3.12	1.87
p-value:DCTP=Police Violence	0.47	0.55	0.31	0.15	0.62
Observations	2910	2910	2910	2910	2910

Notes: This table presents the impact of the *DCTP* and *Police Violence* information treatments on the willingness to receive expert advice. The dependent variable is a score corresponding to the average ranking of each group. A higher score indicates a greater overall preference (1 = bottom choice, 5 = top choice). 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 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.5: Summary of Main Results Accounting for Family-Wise Error Rate

Outcome	**Treatment**	**Mean Dep. Var Control Group**	**Coef**	**SE**	**p-value**	**Family-Wise p-value**
A) Kling-Liebman-Katz Index						
Police Index	DCTP	—	-0.129	0.024	0.000	0.000
Violent Index	DCTP	—	-0.012	0.034	0.721	0.879
Nonviolent Index	DCTP	—	-0.207	0.029	0.000	0.000
Police Index	Police Violence	—	-0.093	0.024	0.000	0.001
Violent Index	Police Violence	—	0.014	0.034	0.671	0.879
Nonviolent Index	Police Violence	—	-0.165	0.028	0.000	0.000
B) Likelihood to Call the Police (0-100)						
Robbery	DCTP	90.81	2.516	0.871	0.004	0.016
Woman Screaming	DCTP	78.30	-3.718	1.186	0.002	0.010
Naked Man	DCTP	43.80	-5.918	1.562	0.000	0.001
Suicidal Ideation	DCTP	41.77	-11.949	1.456	0.000	0.000
Disruptive Begging	DCTP	23.25	-3.923	1.200	0.001	0.007
Robbery	Police Violence	90.81	1.558	0.900	0.084	0.152
Woman Screaming	Police Violence	78.30	-1.128	1.133	0.319	0.322
Naked Man	Police Violence	43.80	-4.854	1.555	0.002	0.010
Suicidal Ideation	Police Violence	41.77	-9.134	1.442	0.000	0.000
Disruptive Begging	Police Violence	23.25	-3.340	1.193	0.005	0.016

Notes: This table presents the impact of the *DCTP* and *Police Violence* information treatments on the demand for police with p-values controlling for the family-wise error rate on our primary outcome, following the Westfall and Young (1993) approach. The first set of outcomes 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 second set of outcomes indicates the likelihood of calling the police in the proposed situation (0–100). We report robust standard errors in parentheses. Family-wise p-values adjust for the number of outcome variables in each family and are estimated with 10,000 bootstraps.

Table A.6: Summary of Main Results Accounting for Family-Wise Error Rate in the Nonbinary Sample

Outcome	Treatment	Mean Dep. Var Control Group	Coef	SE	p-value	Family-Wise p-value
A) Kling-Liebman-Katz Index						
Police Index	DCTP	—	-0.153	0.074	0.039	0.135
Violent Index	DCTP	—	-0.286	0.118	0.016	0.070
Nonviolent Index	DCTP	—	-0.064	0.079	0.419	0.661
Police Index	Police Violence	—	-0.096	0.074	0.192	0.442
Violent Index	Police Violence	—	-0.086	0.114	0.453	0.661
Nonviolent Index	Police Violence	—	-0.103	0.083	0.212	0.462
B) Likelihood to Call the Police (0-100)						
Robbery	DCTP	82.427	-5.885	4.111	0.153	0.632
Woman Screaming	DCTP	68.982	-11.334	3.986	0.005	0.048
Naked Man	DCTP	23.518	1.734	3.811	0.649	0.943
Suicidal Ideation	DCTP	18.964	-2.544	3.105	0.413	0.859
Disruptive Begging	DCTP	11.682	-3.248	2.045	0.113	0.601
Robbery	Police Violence	82.427	-1.506	3.923	0.701	0.943
Woman Screaming	Police Violence	68.982	-3.684	3.981	0.356	0.859
Naked Man	Police Violence	23.518	-0.079	4.022	0.984	0.985
Suicidal Ideation	Police Violence	18.964	-4.056	3.148	0.199	0.678
Disruptive Begging	Police Violence	11.682	-3.315	2.135	0.121	0.601

Notes: This table presents the impact of the *DCTP* and *Police Violence* information treatments on the demand for police for the nonbinary sample with p-values controlling for the family-wise error rate on our primary outcome, following the Westfall and Young (1993) approach. The first set of outcomes 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 second set of outcomes indicates the likelihood of calling the police in the proposed situation (0–100). We report robust standard errors in parentheses. Family-wise p-values adjust for the number of outcome variables in each family and are estimated with 10,000 bootstraps.

Table A.7: Summary of Main Results Accounting for Family-Wise Error Rate in the Youth Sample

Outcome	Treatment	Mean Dep. Var Control Group	Coef	SE	p-value	Family-Wise p-value
A) Kling-Liebman-Katz Index						
Police Index	DCTP	—	-0.158	0.046	0.001	0.003
Violent Index	DCTP	—	-0.163	0.069	0.019	0.034
Nonviolent Index	DCTP	—	-0.155	0.052	0.003	0.009
Police Index	Police Violence	—	-0.153	0.046	0.001	0.004
Violent Index	Police Violence	—	-0.093	0.071	0.190	0.190
Nonviolent Index	Police Violence	—	-0.193	0.052	0.000	0.002
B) Likelihood to Call the Police (0-100)						
Robbery	DCTP	91.371	-0.943	1.523	0.536	0.852
Screaming Woman	DCTP	79.436	-6.210	2.029	0.002	0.016
Naked Man	DCTP	41.875	-1.905	2.808	0.498	0.852
Suicide	DCTP	40.049	-9.327	2.560	0.000	0.003
Begs	DCTP	20.057	-3.637	2.000	0.069	0.324
Robbery	Police Violence	91.371	-0.998	1.543	0.518	0.852
Screaming Woman	Police Violence	79.436	-2.960	1.976	0.135	0.473
Naked Man	Police Violence	41.875	-2.778	2.847	0.329	0.761
Suicide	Police Violence	40.049	-8.938	2.624	0.001	0.007
Begs	Police Violence	20.057	-6.248	1.902	0.001	0.009

Notes: This table presents the impact of the *DCTP* and *Police Violence* information treatments on the demand for police for the youth sample (18–24 years old) with p-values controlling for the family-wise error rate on our primary outcome, following the Westfall and Young (1993) approach. The first set of outcomes 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 second set of outcomes indicates the likelihood of calling the police in the proposed situation (0–100). We report robust standard errors in parentheses. Family-wise p-values adjust for the number of outcome variables in each family and are estimated with 10,000 bootstraps.

Table A.8: Correlation between Perceived Danger and Covariates

	(1) Robbery	(2) Screaming Woman	(3) Naked Man	(4) Suicidal Ideation	(5) Disruptive Begging
Age	0.0465	0.0462	-0.00128	0.00581	0.0764*
	(0.0433)	(0.0503)	(0.0547)	(0.0410)	(0.0422)
Black	-5.753***	-6.087***	5.700***	6.637***	1.978
	(1.606)	(1.895)	(2.087)	(1.643)	(1.548)
Other race	-0.148	-0.647	3.377*	4.120***	1.457
	(1.351)	(1.657)	(1.834)	(1.411)	(1.316)
Male	-0.733	-2.450**	0.360	3.261***	2.081**
	(1.046)	(1.238)	(1.371)	(1.031)	(0.980)
High School or Less	0.926	-0.554	4.404**	1.700	-1.093
	(1.507)	(1.882)	(2.129)	(1.613)	(1.584)
Some college	-2.691*	-2.389	2.542	0.678	-1.744
	(1.388)	(1.603)	(1.768)	(1.299)	(1.226)
Graduate Degree	1.609	0.0856	-1.750	-1.202	-1.883
	(1.516)	(1.752)	(1.960)	(1.489)	(1.411)
No party	-0.695	-2.105	-8.538***	-4.582***	-2.144
	(1.636)	(1.882)	(2.114)	(1.551)	(1.627)
Democratic	3.523***	3.454**	-11.35***	-1.253	-5.098***
	(1.268)	(1.554)	(1.733)	(1.355)	(1.323)
High income	-0.365	-1.152	-4.226**	0.825	-0.0984
	(1.498)	(1.750)	(1.948)	(1.564)	(1.475)
Low income	-0.682	-3.978**	-0.168	-3.174**	1.948
	(1.453)	(1.683)	(1.835)	(1.268)	(1.341)
Single	1.998	2.773*	-3.609**	-2.497**	-0.0807
	(1.233)	(1.439)	(1.563)	(1.161)	(1.098)
Baseline Police index	6.409***	7.118***	8.657***	4.507***	4.537***
	(0.778)	(0.841)	(0.898)	(0.672)	(0.641)
Mean of Dep.	72.92	58.47	42.03	22.52	18.79
Observations	2910	2910	2910	2910	2910

Notes: The table presents the relationship between the covariates and the "Danger" score variable, which takes values between 0 and 1, where higher values mean a more dangerous situation for each scenario. We report the mean of the dependent variable. We report robust standard errors in parentheses. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.9: Test of Uncorrelatedness Assumption, i.e., $\alpha = 0$ and $\beta = 0$

Outcome	Demand for Police	Send Police	Send Social Worker	Send No Responder
Robbery	0.62	0.69	0.99	0.31
Woman Screaming	0.00	0.00	0.00	0.50
Naked Man	0.94	0.29	0.16	0.17
Suicidal Ideation	0.00	0.00	0.05	0.12
Disruptive Begging	0.09	0.15	0.87	0.48

Notes: This table presents the p-values the uncorrelatnedness assumption for various outcomes of interests. We estimate an extended version of the model in equation 9, interacting the treatment variable D with the observed mediators S and with the covariates X. The null hypothesis $\alpha = 0$ and $\beta = 0$ is assessed by verifying whether the interaction coefficients are statistically indistinguishable from zero, as detailed in Heckman et al. (2013) and Heckman and Pinto (2015); Fagereng et al. (2021) provide more details.

Table A.10: Open-Text Classification Scheme

Category	Description	Example
Danger	The response mentions fear, threats, or concerns for their own safety or that of the victim or bystanders. Mentions being afraid or says things along the lines of "this is the police's job", or "this is what the police are meant to do". Mentions potential for escalation. If the response mentions a mental health issue, it also references concerns that the person is dangerous, unstable, in distress, or causing a disturbance, or the situation has the potential to escalate.	"This is a dangerous situation and the police need to handle it immediately." "This man is obviously not in his right state of mind and could hurt someone."
No Danger	The response mentions a mental health issue and nothing more. Mentions that the issue is not a priority or not a serious concern. Response expresses concern that a police response might make the situation worse or mentions that other alternatives might be better (which suggests that the situation is not sufficiently dangerous or provoking of fear to warrant a police response).	"This man needs a mental health check—having the police show up would only make him more upset." "This isn't a situation where the police are needed."

Notes: This table provides details of the different categories of reasons mentioned by respondents to explain their choices of police involvement.

Table A.11: Impact of Information Treatments on Perceived Danger

	(1) Robbery	(2) Screaming Woman	(3) Naked Man	(4) Suicidal Ideation	(5) Disruptive Begging
DCTP	4.820***	1.064	-3.600**	-5.106***	-2.265*
	(1.255)	(1.473)	(1.635)	(1.244)	(1.197)
Police Violence	4.497***	3.495**	-2.298	-3.875***	-1.473
	(1.244)	(1.464)	(1.628)	(1.241)	(1.199)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	70.05	57.21	44.32	25.68	20.17
p-value:DCTP=Police Violence	0.79	0.10	0.43	0.31	0.50
Observations	2910	2910	2910	2910	2910

Notes: This table presents the impact of the *DCTP* and *Police Violence* information treatments on perceived danger. The dependent variable "Danger" is a score variable that takes values between 0 and 1, where higher values mean a situation is perceived as more dangerous for each scenario. 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 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.12: Information, Perceived Danger, and Police Demand

	(1) Robbery	(2) Screaming Woman	(3) Naked Man	(4) Suicidal Ideation	(5) Disruptive Begging
Indirect Effect					
DCTP	1.357***	0.499	-2.237**	-3.259***	-1.210*
	(0.381)	(0.676)	(1.012)	(0.811)	(0.648)
Police Violence	1.521***	1.486**	-1.419	-2.213***	-0.819
	(0.439)	(0.621)	(1.052)	(0.730)	(0.679)
Direct Effect					
DCTP	1.151	-4.224***	-3.719***	-8.695***	-2.712***
	(0.864)	(1.031)	(1.201)	(1.285)	(1.033)
Police Violence	0.0467	-2.634***	-3.335***	-6.826***	-2.437**
	(0.886)	(1.010)	(1.164)	(1.282)	(0.998)
ATE: Total Effect					
DCTP	2.508***	-3.725***	-5.956***	-11.95***	-3.921***
	(0.869)	(1.183)	(1.561)	(1.454)	(1.195)
Police Violence	1.568*	-1.148	-4.754***	-9.039***	-3.256***
	(0.898)	(1.131)	(1.549)	(1.438)	(1.186)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	90.81	78.30	43.80	41.77	23.25
Observations	2910	2910	2910	2910	2910

Notes: This table presents the results of a mediation analysis assessing the direct, indirect, and total effects of the *DCTP* and *Police Violence* information treatments, with perceived danger as the mediator, on police demand for each situation. 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 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.13: Information, Perceived Danger, and Police as First Responders

	(1) Robbery	(2) Screaming Woman	(3) Naked Man	(4) Suicidal Ideation	(5) Disruptive Begging
Indirect Effect					
DCTP	0.00488**	0.00576	-0.0237**	-0.0235***	-0.0141*
	(0.00193)	(0.00782)	(0.0108)	(0.00623)	(0.00756)
Police Violence	0.00417**	0.0139**	-0.0142	-0.0183***	-0.00792
	(0.00172)	(0.00592)	(0.0105)	(0.00618)	(0.00657)
Direct Effect					
DCTP	0.00447	-0.0572***	-0.0343*	0.0106	-0.0437***
	(0.00742)	(0.0157)	(0.0186)	(0.0153)	(0.0160)
Police Violence	0.00617	-0.0231	-0.0325*	0.0198	-0.0563***
	(0.00719)	(0.0153)	(0.0183)	(0.0151)	(0.0157)
ATE: Total Effect					
DCTP	0.00936	-0.0514***	-0.0580***	-0.0130	-0.0578***
	(0.00675)	(0.0165)	(0.0211)	(0.0147)	(0.0172)
Police Violence	0.0103	-0.00916	-0.0467**	0.00147	-0.0642***
	(0.00660)	(0.0154)	(0.0209)	(0.0148)	(0.0169)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	0.97	0.86	0.45	0.13	0.22
Observations	2910	2910	2910	2910	2910

Notes: This table presents the results of a mediation analysis assessing the direct, indirect, and total effects of the *DCTP* and *Police Violence* information treatments, with perceived danger as the mediator, on demand for police as first responders for each situation. The dependent variable is a binary variable that equals 1 if the respondent prefers that police respond to the situation 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 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.14: Information, Perceived Danger, and Social Worker as Preferred First Responder

	(1) Robbery	(2) Screaming Woman	(3) Naked Man	(4) Suicidal Ideation	(5) Disruptive Begging
Indirect Effect					
DCTP	-0.00197*	-0.00426	0.00667**	0.0211***	0.00657*
	(0.00117)	(0.00579)	(0.00334)	(0.00571)	(0.00372)
Police Violence	-0.000627	-0.00924**	0.00365	0.0162***	0.00307
	(0.000613)	(0.00403)	(0.00277)	(0.00554)	(0.00262)
Direct Effect					
DCTP	0.00144	0.0612***	0.0511**	0.00222	0.0327
	(0.00458)	(0.0147)	(0.0204)	(0.0175)	(0.0219)
Police Violence	-0.00192	0.0232*	0.0494**	-0.000135	0.0355
	(0.00381)	(0.0138)	(0.0201)	(0.0172)	(0.0218)
ATE: Total Effect					
DCTP	-0.000538	0.0569***	0.0578***	0.0233	0.0393*
	(0.00394)	(0.0149)	(0.0207)	(0.0170)	(0.0222)
Police Violence	-0.00255	0.0139	0.0530***	0.0161	0.0386*
	(0.00359)	(0.0136)	(0.0203)	(0.0169)	(0.0220)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	0.01	0.10	0.28	0.81	0.52
Observations	2910	2910	2910	2910	2910

Notes: This table presents the results of a mediation analysis assessing the direct, indirect, and total effects of the *DCTP* and *Police Violence* information treatments, with perceived danger as the mediator, on demand for a social worker as first responder for each situation. The dependent variable is a binary variable that equals 1 if the respondent prefers that a social worker respond to the situation 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 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.15: Information, Perceived Danger, and No First Responder

	(1) Robbery	(2) Screaming Woman	(3) Naked Man	(4) Suicidal Ideation	(5) Disruptive Begging
Indirect Effect					
DCTP	-0.00291**	-0.00151	0.0170**	0.00248**	0.00741*
	(0.00136)	(0.00205)	(0.00775)	(0.00124)	(0.00405)
Police Violence	-0.00354**	-0.00474**	0.0106	0.00215**	0.00485
	(0.00153)	(0.00213)	(0.00788)	(0.000978)	(0.00407)
Direct Effect					
DCTP	-0.00591	-0.00291	-0.0157	-0.0128	0.0121
	(0.00612)	(0.00855)	(0.0179)	(0.00952)	(0.0196)
Police Violence	-0.00425	0.000962	-0.0168	-0.0197**	0.0229
	(0.00627)	(0.00887)	(0.0177)	(0.00911)	(0.0195)
ATE: Total Effect					
DCTP	-0.00882	-0.00442	0.00127	-0.0103	0.0196
	(0.00560)	(0.00860)	(0.0199)	(0.00976)	(0.0201)
Police Violence	-0.00779	-0.00378	-0.00623	-0.0175*	0.0277
	(0.00565)	(0.00855)	(0.0197)	(0.00936)	(0.0201)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of Dep.	0.02	0.04	0.28	0.05	0.26
Observations	2910	2910	2910	2910	2910

Notes: This table presents the results of a mediation analysis assessing the direct, indirect, and total effects of the *DCTP* and *Police Violence* information treatments, with perceived danger as the mediator, on demand for no first responder for each situation. The dependent variable is a binary variable that equals 1 if the respondent prefers no responder to the situation 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 988, 311, and 211 only. * Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.16: Pure Control Group vs. Sample with Information

	(1) All	(2) No Information	(3) Control	(4) Police Violence	(5) DCTP	(6) p-value
Age	41.78	40.96	42.41	41.78	42.25	0.048
Black	0.13	0.14	0.12	0.13	0.14	0.481
Other Race	0.18	0.19	0.18	0.17	0.18	0.847
Male	0.47	0.43	0.50	0.49	0.49	0.004
High School or Less	0.13	0.13	0.14	0.13	0.14	0.976
Some College	0.22	0.21	0.23	0.21	0.23	0.712
Graduate Degree	0.15	0.16	0.13	0.16	0.15	0.175
High Income	0.16	0.18	0.14	0.16	0.13	0.005
Low Income	0.18	0.18	0.18	0.19	0.18	0.933
Single	0.43	0.44	0.41	0.43	0.41	0.416
Baseline Police Demand Index	-0.02	-0.00	-0.00	-0.06	-0.01	0.303
Observations	4204	1294	971	954	985	4204

Notes: The table presents the descriptive statistics by treatment arm. Column (1) provides the mean of each variable for the full sample. Columns (2) to (5) report the mean of each variable by treatment arm. Column (5) reports the p-value from a test of the hypothesis of equal means across the experimental conditions.