Emotions and Policy Views*

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Abstract

This paper investigates the growing role of emotions in shaping policy views. Analyzing social citizens' media postings and political party messaging over a large variety of policy issues from 2013 to 2024, we document a sharp rise in negative emotions, particularly anger. Content generating anger drives significantly more engagement. We then conduct two nationwide online experiments in the U.S, exposing participants to video treatments that induce positive or negative emotions to measure their causal effects on policy views. The results show that negative emotions increase support for protectionism, restrictive immigration policies, redistribution, and climate policies but do not reinforce populist attitudes. In contrast, positive emotions have little effect on policy preferences but reduce populist inclinations. Finally, distinguishing between fear and anger, we find that anger exerts a much stronger influence on citizens' policy views, in line with its growing presence in the political rhetoric.

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1 Introduction

How do emotions shape policy views? Existing research has traditionally emphasized the role of economic factors (Algan et al., 2017; Autor et al., 2020; Guriev and Papaioannou, 2022) and cultural influences (Bonomi et al., 2021; Norris and Inglehart, 2019) in understanding political attitudes, polarization, and the rise of populism. As economists, we usually shy away from analyzing emotions, but they have become critical and omnipresent in the policy discourse and have potentially important implications for economic policies. This paper studies the link between emotions – both positive and negative ones– on policy views.

There has been widespread anger and indignation expressed both in the growing support for anti-establishment votes across Western democracies, as well as in specific recent social movements such as Black Lives Matter, MeToo, and the *Gilets Jaunes* in France. These movements defy conventional political categorizations, transcending established party lines and union structures, and challenging explanations grounded purely in socio-demographic characteristics, class dynamics, or ideological positions. Instead, recent insights from political science literature Bakker et al. (2016), Forgas and Crano (2021), Gaffney et al. (2018), Gootjes et al. (2021), Magni (2017), and Rosanvallon (2021) highlight that such movements appear predominantly driven by "emotional communities" characterized by shared experiences of anger, outrage, and resentment. As stressed by Ward et al. (2024), the expansion of populist support over the past two decades has also coincided with a striking 20-percentage-point increase in reported experiences of negative emotions.

Recent research also shows that political leaders themselves are increasingly employing emotional rhetoric to sway voters (Gennaro and Ash, 2022; Grosjean et al., 2023; Webster and Albertson, 2022). This is especially evident among populist parties, which reject the conventional left-right divide in favor of a new fault line between "the people" and "the elite," a distinction rooted not only in material interests but also in deeply felt emotions of anger and resentment. There is thus a need to better understand the affective, emotional dimension of the political process, that cannot fit neatly into rational and cognitive frameworks.[1]

Despite extensive research in political science documenting the correlation between specific emotions and political preferences, especially for authoritarian or populist parties (for a synthesis of this growing literature, see Marcus et al. (2019) and Redlawsk and Pierce (2017)), no robust causal relationship has been established between emotions and different political views. Moreover, systematic efforts to distinguish between the differential impacts of positive and negative emotions on policy attitudes have thus far been limited.

This paper aims to bridge this critical research gap through a three-step approach. First, we examine the role of emotions in U.S. citizens' online conversations and in official Democratic and Republican social media accounts from 2013 to 2024, as well as in candidates' speeches during the 2024 U.S. presidential election. We then investigate whether emotional rhetoric is strategically employed by political leaders to amplify engagement, as reflected in higher retweet rates for emotionally charged policy messages on social media. To achieve this, we construct two distinct Twitter-based datasets. The first captures the political landscape by analyzing tweets from official Democratic and Republican party accounts, providing insights into their communication strategies. The second focuses on partisan discourse, examining tweets from individual users whose political affiliation is inferred based on their retweeting behavior. Our citizens' dataset includes 679,760

[1]The famous left-populist theorist (Mouffe, 2018) argues: "The lack of understanding of the affective dimension in the processes of identity politics is, in my view, one of the main reasons for which the left, locked in a rationalist framework, is unable to grasp the dynamics of politics".

tweets from a random sample of 762 users who retweeted at least once from official party accounts. These tweets, spanning from 2013 to November 2024, contain keywords related to trade, immigration, taxes and redistribution, democracy and governance, societal issues and climate change. We complement this analysis with official speeches delivered by Trump, Biden, and Harris during the 2024 campaign. To systematically analyze emotional content in policy-related texts, including political speeches and tweets, we employ large language models (LLM) combined with embedding-based representations and supervised machine learning classifications.

As a second step, we design and run a large-scale survey and experiment that systematically induces both positive and negative emotions through video treatments and framed questions, enabling us to identify the causal effects of emotions on a broad range of policy attitudes, encompassing views on immigration, trade, taxation and redistribution, democracy and governance, as well as key societal issues such as abortion, the MeToo movement, and gun control. The study was conducted in November 2024, using a nationally representative survey of 3,800 citizens. Respondents were randomly assigned to different experimental conditions, combining video stimuli and variations in the framing of open-ended questions to elicit either positive or negative emotions, or to serve as a neutral control group. Participants in the treatment groups were exposed to an initial video and framed question immediately before being asked about their policy views, thereby ensuring that their emotional state was actively influenced at the moment of response. The videos designed to induce positive emotions feature serene landscapes accompanied by peaceful music. In contrast, the videos intended to elicit negative emotions depict individuals trapped in California wildfires, emphasizing government corruption and corporate greed as contributing factors to the worsening disasters. A potential issue is that emotions may be associated with other significant values or beliefs that also shape political preferences. To verify that our findings are not biased by omitted factors, we measure the most relevant and commonly-studied factors in the literature, such as moral universalism, generalized trust, and we do control for previous voting behaviors.

As a third step, we dive deeper into the nature of negative emotions by distinguishing between fear and anger. We focus on these two emotions in relation to a specific policy issue: climate change. As shown in our social media analysis, while climate change primarily evoked fear in the early 2010s, this has gradually given way to anger—either directed at climate inaction among pro-climate advocates or at restrictive policies among climate skeptics. This shift makes climate change an excellent case setting to examine the contrasting effects of fear and anger on perceptions and policy attitudes toward environmental action. In this second experiment, we build upon the previous negative emotion-inducing images but introduce a key distinction. In the first set of videos, we emphasize the devastating threat of climate change by depicting desperate individuals trapped in California wildfires. This video is designed solely to evoke fear in response to an imminent and destructive danger. In the second treatment aimed at inducing anger, we not only depict the devastation caused by the California wildfires but also highlight systemic failures and culpability. The video underscores how PG&E's negligence—specifically, its failure to replace aging electrical line hooks—ignited the fire, while also exposing government favoritism toward corporations and the lack of meaningful accountability. This framing shifts the emotional response from fear of an impending disaster to anger at those perceived as responsible for it. We also compare the effects of these emotions with those of cognitive videos that share simple facts about climate change, as well as with the positive emotion video featuring serene landscapes.

Our paper yields three key findings. First, our analysis documents a sharp increase in emotionality within policy-related tweets over time, with anger emerging as the dominant emotion. The proportion of tweets

containing emotional content rose from 40% to 85%, while fact-based, non-emotional tweets declined from 60% to 15% over the same period. This trend has intensified significantly since 2016, particularly among Republican-affiliated users, where anger now constitutes nearly 90% of all emotional tweets, compared to 70% among Democratic-affiliated users. A similar evolution is observed in official party accounts, where emotional content surged starting in June 2024, coinciding with the first Biden-Trump debate. This increase appears consistent across both parties, suggesting a strategic shift in communication tactics as the election approached.

Furthermore, we demonstrate that tweets from party official accounts expressing anger generate significantly higher engagement, even after controlling for time fixed effects, user fixed effects, and tweet topics. On average, tweets classified as conveying anger receive 62% more retweets than neutral (non-emotional) tweets. This effect is particularly prominent for tweets on emotionally charged topics such as immigration. In contrast, tweets expressing gratitude, joy, or hope are associated with significantly lower engagement, suggesting that positive emotions do not drive interactions to the same extent. This could provide a demand-driven explanation for why political parties are increasingly using a rhetoric based on negative emotions, and in particular on anger.

Our paper then addresses the issue of causality by conducting the first experimental survey during the 2024 U.S. presidential election, focusing on the campaign's key policy issues. This approach aligns with our previous analyses of social media discourse and political speeches, allowing us to systematically assess the impact of emotional rhetoric on public opinion formation. We find that exposure to negative emotions significantly increases anger and outrage, and to a lesser extent fear and sadness, while reducing feelings of joy and tranquility. This emotional shift has substantial consequences for policy preferences: individuals exposed to negative emotions develop more pessimistic views on trade and are more likely to support protectionist policies. Similarly, they exhibit greater support for restrictive immigration measures, though their general perceptions of immigration remain unchanged. Interestingly, negative emotions also foster more favorable attitudes toward redistribution and increased backing for redistributive policies. Contrary to prior research, however, negative emotions do not appear to heighten support for populist attitudes.

In contrast, exposure to positive emotions significantly increases joy and tranquility, while reducing negative emotions such as outrage. Positive emotions diminish pessimistic perceptions regarding trade and immigration but do not significantly influence policy preferences in these areas. However, while positive emotions do not alter attitudes toward redistribution, they significantly reduce populist inclinations. These findings underscore the asymmetrical and nuanced role of emotions in shaping political perspectives, highlighting how different emotional states can drive distinct policy orientations.

While the first experiment contrasts the effects of positive and negative emotions on policy views, the second experiment dives deeper into two key negative emotions, fear and anger. The topic focus of this second survey is on climate change. We first confirm that our experimental treatments effectively elicit distinct negative emotions. The anger-inducing video significantly increases feelings of anger while having a much weaker impact on fear, whereas the fear-inducing video produces the opposite effect. We then measure the impact of these emotional treatments on four key outcomes: general attitudes toward climate change, policy views, preferences for redistributive climate policies, and willingness to take individual pro-climate actions. Findings indicate that anger exerts a positive and statistically significant effect across all indices, leading to stronger beliefs in human-caused climate change, increased support for climate policies (e.g., carbon taxes or subsidies for electric vehicles), redistributive climate measures, and greater willingness to

adopt individual behavioral changes (e.g., reducing meat consumption or limiting air travel). By contrast, the fear treatment produces no significant effects for any of these outcomes. These findings underscore the importance of differentiating between negative emotions: while both fear and anger are commonly classified as negative, only anger substantially influences climate-related attitudes and policy preferences. This result aligns with our findings on the rise of anger in political speeches and social media messages in Section 3: Political parties and leaders are likely to adopt rhetoric infused with anger, as it proves more effective in driving citizen engagement.

Our paper contributes to multiple strands of the literature. First, extensive research across different social sciences has documented the pivotal role of emotions in shaping judgments, decisions, and choices. Psychology has particularly advanced our understanding of emotions in politics, building on Lazarus' (1991) Cognitive Appraisal Theory and Marcus' (2002) Affective Intelligence Theory. Both perspectives conceptualize emotions as intuitive heuristics (Loewenstein, 1996; Loewenstein, 2000) that act as critical filters through which individuals interpret their experiences and make decisions. They are used as intuitive heuristics to simplify judgment, and guide decision-making, even when individuals are unaware of its source. Within this framework, a new strand in political sciences suggest that emotions may have become a more powerful explanatory paradigm for political attitudes than traditional class-based or ideological frameworks, particularly in increasingly fragmented societies. While industrial-era institutions—such as unions, firms, families, and churches—shaped political views, post-industrial societies are marked by social fragmentation and loneliness (Putnam, 2020), making emotions, a more salient force in shaping political preferences (Rosanvallon, 2021). In lines with the affect-as-information framework Clore, Gasper, et al. (2001) and Clore and Huntsinger (2007), isolated individuals have thus replaced social class and ideological identity with affective heuristics as a way to ease the cognitive burden and complexity of political decision-making Rahn (2000), making emotions an important driver of electoral behavior.

This framework has spurred a rich body of empirical research on the correlation between emotions and political behavior. Studies have examined the distinction between voting and protesting (van Zomeren, 2021), political participation in partisan versus deliberative contexts (MacKuen et al., 2010), and the role of emotions in political polarization in the U.S. (Boxell et al., 2024). Complementary research explores how specific emotions shape citizen behavior: anxiety has been linked to increased political information-seeking and voter participation, whereas anger is associated with higher distrust of new information and greater involvement in violent demonstrations (Ladd and Podkul, 2018). Recent research has also stressed the link between emotions and populist attitudes (Jost, 2019; Marcus et al., 2019; Vasilopoulou and Wagner, 2017), whereby anger has been identified as a key correlate of populist support (Rico et al., 2017; Widmann, 2021; Ward et al., 2024). All this research in political sciences is mainly focused on voting behavior or political preferences, especially for authoritarian or populist parties, while we analyze the impact of emotions on a variety of policy views that could ultimately explain citizens votes. And much of this literature remains correlational, lacking robust causal identification of the impact of emotions on policy views.

More recently, a strand of economic research has sought to address this limitation by employing experimental designs to explore the role of negative emotions in shaping policy views, particularly on immigration and democracy. In contemporaneous work, Manzoni et al. (2024) examine how sensationalized news affects anti-immigration attitudes in Italy. They find that negative emotions triggered by these news about immigrants increase support for restrictive policies, even when statistical facts are provided. However, their study does not isolate specific emotions or test the impact of positive emotions, and focuses only on policy views

towards immigration. Tilley and Hobolt (2024) analyze how emotions shape perceptions of electoral fairness, showing that anger reduces democratic consent among election losers in the context of Brexit and the 2019 UK election. While they find a strong link between anger and rejection of election outcomes, our results suggest that negative emotions do not necessarily undermine perceptions of electoral legitimacy. Fewer studies address emotions in trade and redistribution. Lo et al. (2022) find that outrage over U.S.-China trade war news reduces support for Chinese government policies and increases U.S. product boycotts. Gonthier (2023) demonstrates that anger toward wealth inequality is linked to perceptions of unfair income distribution and increased support for economically progressive populist parties.

The experimental part of our paper makes several contributions to this growing body of work. Unlike existing studies, which focus on specific policies in isolation, our research provides a comprehensive analysis of how emotions influence multiple policy domains, allowing us to identify which issues are most affected by emotional states. In addition, our study experimentally induces both positive and negative emotions through video treatments and framed questions, an approach that contrasts with existing studies that primarily focus on negative emotions. Prior research has extensively examined the link between anger or anxiety with policy preferences, either in correlational studies (e.g., Albertson and Gadarian (2015)) or with experiments (Manzoni et al., 2024). By examining both positive and negative emotions, we can see that their effects are not symmetric and can identify which policy topics are more likely to be affected by specific emotions.

Importantly, we also identify the causal general impact of emotions, in a context-independent way. Previous studies have relied on news articles to generate emotions, which limits control over the type of emotions elicited. Moreover, these studies typically induce emotions directly tied to the policy in question—for instance, by presenting alarming news about rapes committed by immigrants (Manzoni et al., 2024) — making it impossible to disentangle the effect of emotions from that of policy content. In contrast, we take a different approach: to elicit negative (positive) emotions, we expose respondents to video content that is unrelated to the policies under consideration. This method generates emotions unrelated to the policy being assessed. Participants are then asked about issues such as immigration and other topics, allowing us to isolate the impact of emotions from the influence of policy content itself and to estimate the general (not context-specific) effect of emotions on policy views.

Our findings also contribute to the growing body of literature seeking to understand the determinants of policy preferences, traditionally framed through factual knowledge, in-group-out-group bias, efficiency-equity trade-offs, and self-interest versus redistributive concerns. Previous work has used experimental survey methods to examine how individuals perceive, reason about, and learn different economic policies—including taxation, trade, insurance, inflation, climate change or government spending (Stantcheva, 2020; Stantcheva, 2021; Stantcheva, 2022; Binetti et al., 2024; Dechezlepretre et al., Forthcoming; Roth et al., 2022; Sawulski et al., 2024; Bremer and Bürgisser, 2023). These studies primarily emphasize deliberative, cognitively driven processes in shaping policy attitudes. This is true even in the more recent focus on narratives about the economy (Andre et al., 2023; Giglio et al., 2021; Bailey et al., 2019; Goetzmann et al., 2022). Comparatively little is known about the role of emotions in shaping policy attitudes. Understanding how emotions interact with rational considerations is crucial for developing a more comprehensive framework of policy preferences and political behavior. This perspective aligns with a long-standing philosophical debate between Descartes and Spinoza, where the latter argued that emotions do not oppose but rather complement cognitive reasoning in shaping human beliefs and behaviors—an insight later formalized in neuroscience by Damasio (2006).

The rest of the paper is structured as follows. Section 2 presents our data sources, from social media

and political speeches during the 2024 U.S. elections and from our two surveys and experiments to identify the causal impact of positive and negative emotions—specifically distinguishing between anger and fear—on policy views. Section 3 examines the demand side of emotions and documents the rise of emotional rhetoric, especially negative emotions, in citizens' conversation related policy issues on social media. Section 4 analyzes the supply side of emotion in public and political discourse over the past decade and how policymakers strategically leverage emotions to persuade and mobilize citizens. Section 5 presents the experimental results, analyzing how positive and negative emotions, including the distinction between anger and fear, shape perceptions and policy preferences across six key issues: trade, immigration, taxation and redistribution, democracy, societal issues, and climate change.

2 Data, Sample, and Surveys

In this section, we describe the survey design, data collection procedure, and treatments of the experimental component of this study. We designed and ran two surveys and experiments. The first survey, referred to hereafter as Survey A, investigates the effects of positive and negative emotions on perceptions and policy preferences across five broad areas (immigration, taxation and inequality, trade, societal issues, and democracy). The second survey, Survey B, zooms in on two key negative emotions–fear and anger– on attitudes toward climate change.

2.1 Survey Data Collection and Sample

Data Collection. Data for Survey A were collected in early November 2024, during the days immediately preceding the US Presidential election. Data collection for Survey B took place between November to December 2024. Both surveys were administered through *Bilendi*, a professional survey company that maintains respondent panels and distributes survey invitations to panelists targeting socioeconomic characteristics. Respondents who fully completed the survey were compensated by the company with various incentives, including monetary rewards, charitable donations, and loyalty points redeemable at partner companies. After excluding inattentive respondents—those failing attention checks or not fully viewing the treatment videos (as detailed below)—the final sample size for Survey A comprised 3,512 participants, while Survey B included 6,366 respondents. Prior to being assigned to a treatment branch, respondents were filtered through screening questions to ensure national representativeness across key demographic dimensions, namely gender, age, income and race/ethnicity. For an extensive discussion of methodologies related to online survey administration, participant recruitment, incentive structures, and the comparability of online samples to traditional sampling methods, see Stantcheva (2023).

Sample. Table 1 demonstrates that our sample is relatively representative with respect to the targeted demographic characteristics. Notably, due to the necessity of completing Survey A prior to the elections, the demographic quotas achieved are slightly less representative compared to those of Survey B, which was conducted without time constraints. Additionally, while Survey A included questions regarding voting behavior in the 2020 election as well as voting intentions for 2024, Survey B exclusively inquired about actual voting behavior in the 2024 election.

Table 1: Sample Representativeness

	Survey A	Survey B	US Population
Targeted characteristics			
Gender			
Male (%)	43	49	50
Female (%)	57	51	50
Age			
18-29 years old (%)	14	24	22
30-39 years old (%)	14	18	19
40-49 years old (%)	19	20	17
50-59 years old (%)	21	19	17
60-75 years old (%)	32	18	24
Annual Household Income			
0-19,999 (%)	15	12	11
20,000-39,999 (%)	19	13	13
40,000-69,999 (%)	27	20	19
70,000-89,999 (%)	10	11	11
90,000-109,999 (%)	7	7	9
110,000-149,999 (%)	8	13	13
150,000-199,999 (%)	9	10	10
200,000 or more (%)	5	14	14
Race/Ethnicity			
White (%)	72	61	60
African American/Black (%)	12	13	12
Hispanic/Latino (%)	8	17	18
Asian/Asian American (%)	5	5	7
Mixed/Others (%)	3	4	3
Non-targeted characteristics			
Education			
No College (%)	25	23	36
Some College/College Degree (%)	60	59	51
Master's Degree (%)	11	13	9
Doctoral/Professional Degree (%)	3	5	4
Employment Status			
Employed (%)	53	69	67
Unemployed (%)	8	8	3
Not in labor force (%)	37	23	30
Survey A: Voted in 2020			
Yes (%)	78	-	66
No (%)	22	-	34
Survey A: Voted whom in 2020 (% of all 18+ voters)			
Biden (%)	55	-	51
Trump (%)	41	-	47
Others (%)	2	-	2
Prefer not to say/Don't know (%)	2	-	0
Survey B: Voted in 2024 (Survey B)			
Yes (%)	-	83	64
No (%)	-	17	36
Survey B: Voted whom in 2024 (% of all 18+ voters)			
Harris (%)	-	52	50
Trump (%)	-	43	48
Others (%)	-	3	2
Prefer not to say/Don't know (%)	-	2	0
Observations	3,512	6,366	240,630,903

Notes. The table displays statistics the respondent samples from survey A and B, compared to the overall U.S. population. Summary statistics for the U.S. population are constructed using IPUMS-CPS-ASEC data from 2023 for individuals aged 18 to 75 and using the Federal Election Commission data from 2020. 'Targeted characteristics' refers to those for which quotas are imposed to match the overall U.S. population. Quotas are not set for the non-targeted characteristics.

Data Quality. To ensure the highest possible data quality, we implemented several measures. On the introductory consent page, we emphasized the importance of careful and honest responses, appealing to participants' sense of social responsibility. Additionally, we informed respondents that monetary compensation would be withheld if their answers failed to meet our quality control standards—a policy reinforced by the survey company's own quality checks, of which participants were aware. We recorded the time taken to complete different sections of the survey, as well as the overall survey duration. The median completion time was 21 minutes for Survey A and 15 minutes for Survey B (see Appendix A1 for the full distribution of survey durations). Furthermore, we included an attention-check question to filter out inattentive respondents. The representative samples (as reported in Table 1) were obtained after excluding participants who failed the attention check, exceeded quota limits, abandoned the survey before completion, or did not fully watch the treatment video. In total, for Survey A, 62% of all respondents (N=6,010) who initially began the survey were ultimately excluded. Appendix A1 details the attrition process at each stage: 4% of respondents (N=408) were screened out, 29% (N=2,803) exceeded quota limits, 8% (N=763) dropped out during the survey, and 16% (N=1,531) failed either one of the attention checks or the video technical check.

2.2 The Surveys

The full survey questionnaires can be found at https://socialeconomicslab.org/wp-content/uploads/2025/03/emotions_Q.pdf.

2.2.1 Survey A

As shown in Figure 1, the questionnaire of survey A is structured in ten parts: questions on the background of the respondent, emotional videos and framed questions, questions on trade, questions on immigration, questions on taxes and redistribution, questions on democracy and governance, questions on societal attitudes, questions on emotions, questions on affective polarization, and feedback questions.

Background of respondents The initial part of the survey collects respondents' socio-demographic characteristics, including gender, age, ethnicity, region of residence, household income, education, employment status, and religion. We assess political leanings by asking respondents to place themselves on the liberal-conservative spectrum, report whether they voted in the 2020 presidential election, and indicate the candidate they voted for or would have preferred if they did not vote. We also ask about their voting intention for the 2024 presidential election. We also collect data on psychological correlates of voting behavior, including interpersonal trust, trust in government, perceptions of government waste, compassion, views on wealth inheritance, and respect for authority. Finally, we assess social connectedness by asking about teamwork experiences, social support networks, and financial resilience.

Emotional videos and framed questions Respondents are randomly assigned to different experimental branches, detailed below, combining video treatments and variations in the framing of open-ended questions. The videos are designed to put the respondent in a neutral or emotional state. The first video is shown just before the trade block and a second video just before the taxes and redistribution block. They are described in further details in Section 2.3. The open-ended framed questions are designed to further reinforce the emotional or neutral state triggered by the video. They are asked at the start of each policy block. They invite respondents to briefly describe their initial thoughts about a specific policy topic in either an emotional

or neutral manner. For example, the framed trade question began with the prompt: "When you think about U.S. trade with other countries...", the neutral framing then asks: "...what are the main considerations that come to your mind ?" In contrast, the positively framed version asks: "...what are some of the things, if any, that make you feel optimistic ?" while the negatively framed version asks: "...such as China, what makes you really angry and revolted ?". See Appendix Section A.1.2 for the complete list of framed questions.

Trade We measure perceptions about trade's effects on the economy, including whether respondents view trade as beneficial for all or as creating winners and losers. We also assess beliefs about trade's contribution to unemployment and inequality. For policy views, we ask about support for reducing trade barriers, maintaining relationships with allies, and implementing tariffs on Chinese imports.

Immigration We elicit perceptions about immigration's economic and social consequences, including beliefs about unemployment rates among native-born Americans versus legal immigrants, and whether immigrant poverty stems from personal effort or external circumstances. Respondents evaluate immigration's threat to the economy and culture. Policy questions address support for changing immigration levels, deportation operations, addressing root causes of migration, and requirements for pathways to citizenship.

Taxes and Redistribution We measure perceptions about poverty's causes, government's role in reducing inequality, tax burden distribution, and effective approaches to reducing income differences. Policy questions focus on support for raising the corporate minimum tax, restoring higher top federal income tax rates, and implementing a federal ban on corporate price gouging.

Democracy and Governance Respondents evaluate different governance approaches, including having a strong leader who bypasses democratic processes, decision-making by experts versus elected officials, and the value of democratic systems. We also assess confidence in election fairness and perceptions of politicians' priorities.

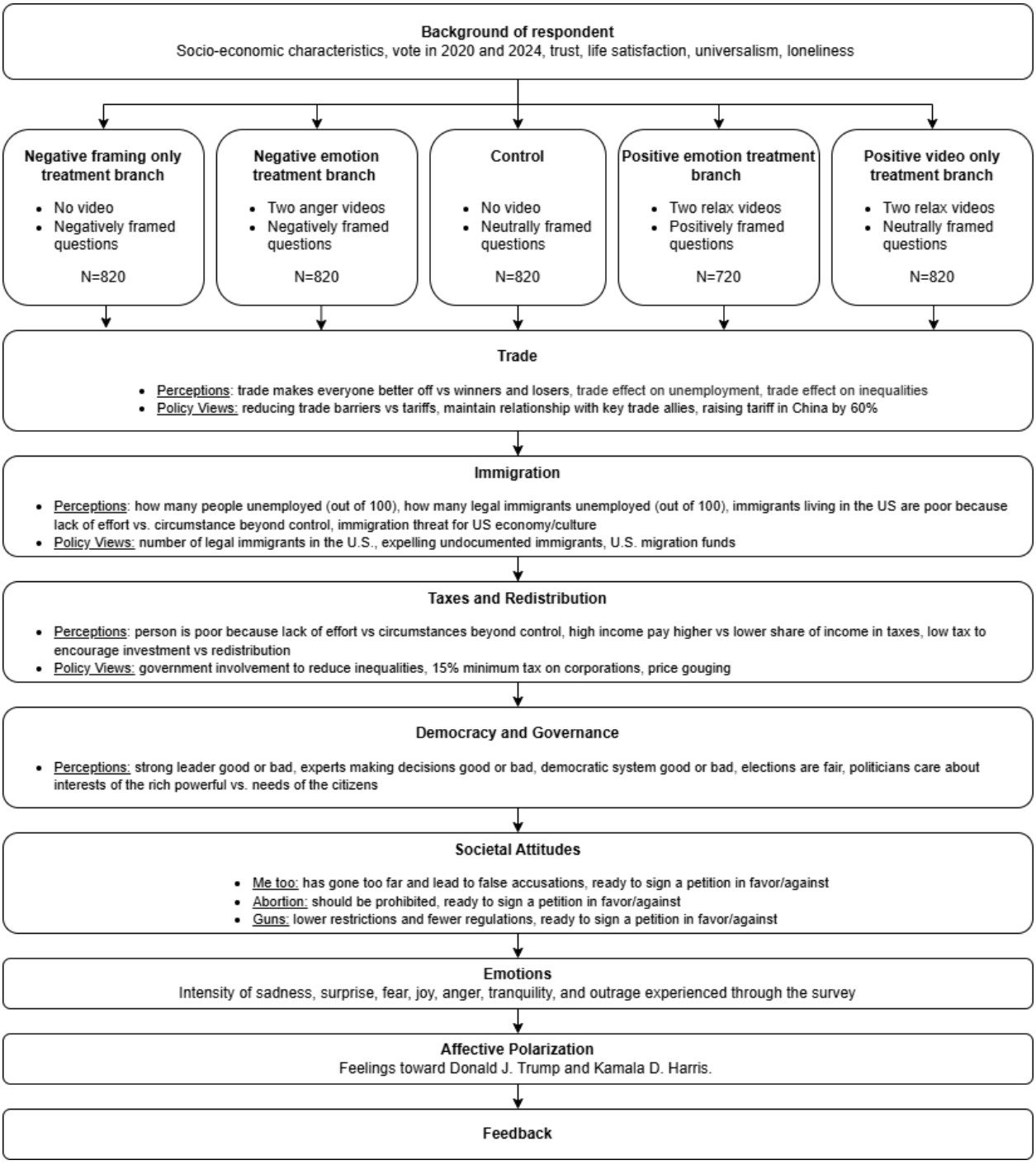
Societal Attitudes We gauge agreement with statements on prominent social issues including the MeToo movement, abortion restrictions, and firearm regulations. For each issue, respondents are also asked to indicate whether they would sign a petition supporting or opposing the position.

Emotions Respondents rate the intensity of their emotional experiences during the survey, including sadness, surprise, fear, joy, anger, tranquility, and outrage, using a 7-point scale.

Affective Polarization To measure affective polarization, we ask respondents to rate their feelings toward Donald Trump and Kamala Harris using a "feeling thermometer" scale from 0 (very cold/unfavorable) to 100 (very warm/favorable).

Feedback Finally, respondents provide feedback on the survey, including whether they perceived any political bias.

Figure 1: Survey A Experimental Design



Notes. The figure illustrates the experimental design used to elicit the effects of the video treatment on the policy views. Participants are randomly selected into the positive, negative or neutral emotion treatment. After the treatments we elicits participants' policy views about trade, immigration, redistribution, government and society.

Experimental Treatments In survey A, respondents are randomly assigned to one of five treatment arms. We primarily focus on the three following treatments arms:

1. Positive emotion treatment branch: Respondents watch two one-minute relaxation videos (before the trade and wealth & taxation blocks) designed to induce calm, and the open-ended policy questions in each policy block are framed in a positive way, prompting optimism.

2. Control branch: The open-ended policy questions at the beginning of each policy block are framed in a neutral way.

3. Negative emotion treatment branch: Respondents watch two one-minute videos (before the trade and wealth & taxation blocks) designed to evoke negative emotions, and the open-ended policy questions in each policy block are framed negatively.

   Then say, for robustness we also included these X other arms, that do "variations" on the main arms. One arm for instance only has the framing without the video etc.. We use these for additional analyses and robustness.

   The primary treatments are designed to evoke either positive or negative emotions by combining a video with a framed question. For robustness we also include two other treatment arms, that are slight variations of these main arms:

4. Negative framing only treatment branch: The open-ended policy questions at the beginning of each policy block are framed in a negative way.

5. Positive video only treatment branch: Respondents watch the two relaxation videos but the open-ended policy questions are framed neutrally.

2.2.2 Survey B

As illustrated in Figure 2, the Survey B questionnaire is structured into eight sections: respondent background information, emotional video treatments, general attitudes toward climate change, opinions on specific climate policies, views on redistributive aspects of climate policies, willingness to undertake private actions against climate change, self-reported emotional responses, and survey feedback.

Background of Respondents. The initial part of the survey collects respondents' socio-demographic characteristics, including gender, age, ethnicity, region of residence, household income, education, and employment status. Political leanings are assessed by asking respondents to self-position on the liberal-conservative spectrum and report their voting behavior in the 2024 presidential election or indicate their preferred candidate if they did not vote.

Emotional Videos and Framed Questions. Respondents are randomly assigned to different video treatment branches designed to induce emotional or neutral states. The first video is presented before assessing general attitudes toward climate change, and a second video precedes questions eliciting emotional states. Detailed descriptions of these videos are provided in Section 2.3.

General Attitudes Toward Climate Change. Respondents' attitudes toward climate change are measured through questions about their beliefs regarding the causes of climate change and whether economic slowdown is justified to mitigate climate change.

Climate Policies. Opinions are elicited on various climate policies, including support for the Paris Agreement, the Inflation Reduction Act, electric vehicles, fossil fuels, costly renewable energy, bans on certain activities, and the implementation of a carbon tax.

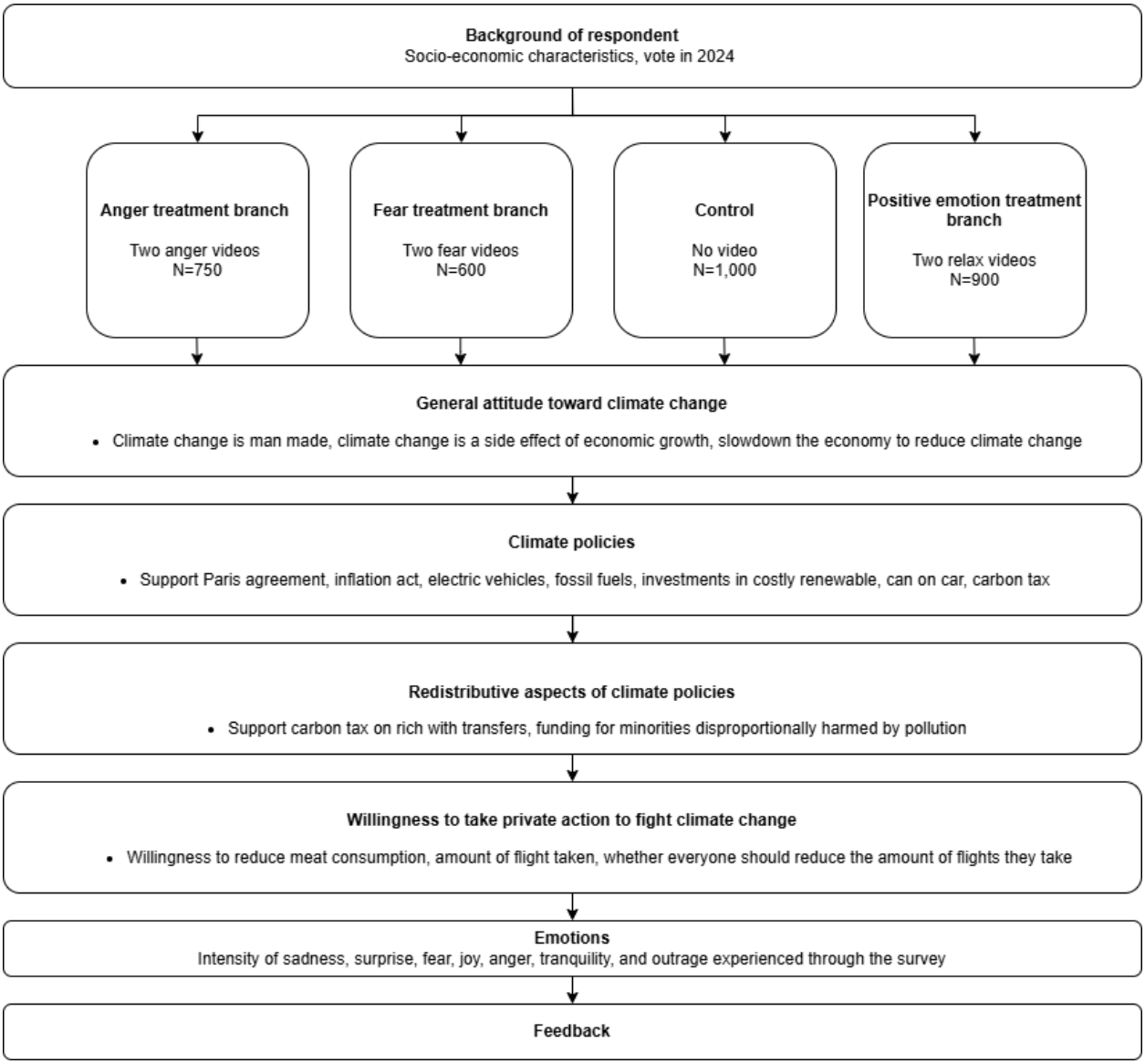
Redistributive Aspects of Climate Policies. Preferences for redistributive climate policies are assessed by measuring respondents' support for a redistributive carbon tax and increased assistance to minorities disproportionately harmed by pollution.

Willingness to Take Private Actions Against Climate Change. Respondents' willingness to engage in private actions to mitigate climate change is evaluated, such as reducing meat consumption, limiting air travel, or advocating for collective reductions in air travel.

Emotions. Respondents rate the intensity of emotional experiences during the survey—including sadness, surprise, fear, joy, anger, tranquility, and disgust—using a 7-point scale.

Feedback. Respondents provide feedback regarding the survey, including perceptions of potential political bias.

Figure 2: Survey B Experimental Design



Notes. The figure illustrates the experimental design of survey B used to elicit the effects of the video treatment on climate change attitudes. Participants are randomized into the anger treatment branche, the fear treatment branch, the positive emotion treatment branch or no video at all. After the treatments we elicits participants' general attitude toward climate change, views on climate policies, views on the redistributive aspect of climate policies and their willingness to take private action to fight climate change.

Experimental Treatments In survey B, respondents are randomly assigned to one of four treatment arms:

1. Positive emotion treatment branch: Respondents watch the same two one-minute relaxation videos of survey A, described in details in Section 2.3.

2. Control branch: No video is shown to respondents.

3. Anger treatment branch: Respondents watch the same two one-minute video of survey A designed to evoke negative emotion and particularly anger, described in details in Section 2.3.

4. Fear treatment branch: Respondents watch two one-minute videos designed to be similar in content as the anger treatment branch video but emphasizing fear sentiments rather than anger.

2.3 Video treatments

As previously explain through the Section, Survey A includes the positive and negative video treatments only, while Survey B additionally includes a fear-based treatment.

The positive treatment consists of two videos. The first positive video features serene imagery, including green fields, a tranquil lake, an eagle in flight, a cyclist beside water, lavender fields, and snow-capped mountains, accompanied by peaceful music. The second positive video similarly presents calm mountain scenery, clear blue skies, a flowing river, and an aerial view of a lush forest, also with peaceful music. Screenshots of these videos are shown in Figure 3.

The negative treatment similarly comprises two videos. The first video emphasizes government corruption and corporate negligence by focusing on a wildfire caused by PG&E's failure to maintain aging electrical equipment, resulting in 84 corporate homicide charges. It vividly illustrates the resulting devastation and victims. The second video underscores governmental favoritism toward corporations and the lack of accountability, specifically highlighting how PG&E received only a minimal fine despite substantial negligence. It further details how the California Public Utility Commission withheld evidence beneficial to prosecution. Screenshots of these videos appear in Figure 4.

Survey B further investigates negative emotions by introducing an additional treatment designed to induce fear rather than anger. This fear-based treatment also comprises two parts. The first part portrays the dangerous, frightening consequences of increasingly frequent climate disasters, including dramatic footage of a woman trapped in her car during a forest fire, accentuated by dramatic music and textual warnings. The second part features a distressing conversation between firefighters and a woman trapped in her burning home. Unlike the anger-focused videos, these emphasize the terrifying nature of the disasters without attributing blame or responsibility. Screenshots from the fear-based videos are provided in Figure 5.

Figure 3: Positive emotion treatment videos



(a) First relax video (i)



(b) First relax video (ii)



(c) Second relax video

Figure 4: Negative emotion treatment videos



(a) First anger video (i)



(b) First anger video (ii)



(c) Second anger video

Figure 5: Fear treatment videos



(a) First fear video (i)



(b) First fear video (ii)



(c) Second fear video

2.4 Twitter data

We construct three distinct databases using Twitter data. The first database captures the political landscape by analyzing tweets from official party accounts. This dataset provides insights into the communication strategies and messaging of political parties. The second database focuses on the discourse of the citizens by analyzing tweets from individual accounts, where the political affiliation of each account is inferred based on the tweets they engage with. This approach allows us to examine the perspectives and affiliations of the broader public, as reflected through their interactions with political content. The third database focuses on tweets related to climate change, as explored in Survey B.

Official party tweets. We extracted all the tweets and retweets from the main official accounts for each part. These are, for the Republican Party @GOP, @HouseGOP, @SenateGOP and for the Democratic Party, @TheDemocrats, @HouseDemocrats and @SenateDems. Table 2) shows a breakdown of the data by source. Our database is comprised of 395,272 tweets sent between January 2013 and November 2024.

Table 2: Twitter Official Account

Twitter Account	Party	Followers	Tweets
@GOP	Republican	3,386,083	60,115
@HouseGOP	Republican	1,657,590	55,353
@SenateGOP	Republican	1,570,256	43,323
@TheDemocrat	Democrat	2,404,691	44,349
@HouseDemocrats	Democrat	1,294,898	21,828
@SenateDems	Democrat	1,269,012	39,897

Citizens' tweets. We then select a random sample of 762 users who have retweeted at least one time a tweet from these official accounts. For these users, we extract all tweets they have sent between January

2013 and November 2024 that contain one or more of the following keywords: immigration, terrorism, crime, war, justice, injustice, inequality, abortion, gun, education, climate, inflation, price, job, tax, trade, economy, growth, budget, deficit, debt, health, healthcare, Medicare, Supreme Court, policy, government, congress, or senate. The resulting dataset comprises 679,760 tweets on a variety of policy issues.

Climate change tweets. We extract a random sample of 1/12th of all tweets containing the keywords "climate change" and "global warming" sent on Twitter between January 2013 and April 2023.[2] Our dataset is composed of 3.7 millions tweets from 1.5 million distinct users.

2.5 Political speech data

We gather all public interventions from Kamala Harris, Joe Biden, and Donald Trump between January 2023 and November 2024 by extracting transcripts from Factba.se / Rollcall. One key advantage of this database is that all transcripts are timestamped, with speakers clearly identified. This makes it easy to distinguish between journalist questions, remarks from other participants, and statements made by the U.S. presidential candidates themselves. The database includes a diverse range of interventions, including interviews, press briefings, press conferences, press gaggles, remarks, speeches, and vlogs. Our database consists of 1,992 interventions and 274,921 segments.[3]

3 The Demand Side of Emotions: the Rise of the Emotional Voter

3.1 Methods for Analyzing Emotions in Policy-Related Textual Data

This section examines the rising role of emotions in U.S. citizens' policy-related discussions, using the case study of the social media platform X (formerly known as "Twitter."). To systematically analyze emotional content in policy-related textual data (political speeches and tweets), we use a large language model (LLMs) combined with embedding-based representations and supervised machine learning classification. Initially, we apply GPT-4o-mini to a randomly selected sample comprising 100,000 tweets and 50,000 segments extracted from political speeches, classifying each along three principal dimensions: cognition versus affect, specific emotional category, and primary topic. The precise prompt formulations are detailed in Appendix A.5.

We then use the GPT-4o-mini-generated classifications as labeled training data for a supervised classifier designed to systematically categorize the entire corpus of text data. To achieve consistency across all subsequent classifications, each document is first converted into a standardized numerical representation (embedding) via the "all-mpnet-base-v2" model, implemented within the Sentence Transformers (SBERT) framework. These embeddings are then used as inputs in the supervised machine learning classifier to provide a prediction of emotions and topics within the dataset.

3.2 Emotional Expressions of Citizens : Analyzing Tweets on policy issues

Figure 6 presents the distribution of tweets classified into each emotional category, disaggregated by political affiliation. The sample is restricted to tweets primarily addressing the topics covered in survey A, but similar patterns emerge when extending the analysis to the entire tweet sample.

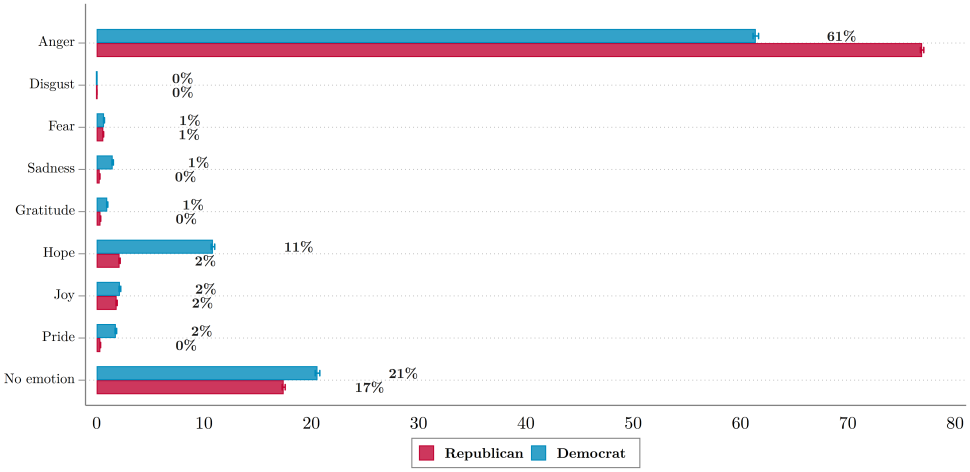
[2]While we have data up to November 2024 for the other two datasets, collected via the Pro Twitter API, the climate change sample was created using the Academic API, access to which was discontinued by X following Elon Musk's acquisition.

[3]Factba.se / Rollcall automatically split intervention and speeches into distinct, complete segments for analysis. A segment can be a sentence of a group of sentences. The average number of words per segment is 40.

The findings reveal that the overwhelming majority of tweets convey emotions. Only 17% of the tweets of Republican users and 21% of those of Democrat users are classified as non-emotional. Among emotional tweets, anger by far stands out as the dominant sentiment, with a striking disparity between the two groups: close to 80% of emotionally charged tweets by Republicans express anger, compared to 60% among Democrats. On the other hand, 11% of Democrat followers' tweets express hope, while only 2% of Republican followers' tweets do.

Figure 7 illustrates the share of affective tweets for each policy topic. Issues such as abortion, democracy, or gender equality have the highest share of tweets that are emotional; on the other end of the spectrum, tax and inequality-related topics or trade issues have the lowest share of affective tweets with 45% and 25% respectively.

FIGURE 6: CITIZENS' TWEETS ON POLICY ISSUES: EMOTIONS BY POLITICAL AFFILIATION



Notes.

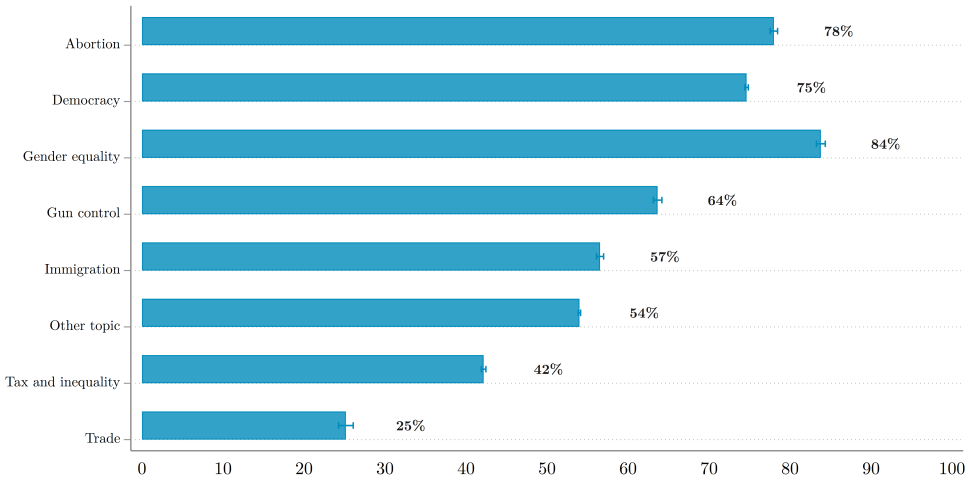
The figure shows, for each emotion, the share of tweets classified in a given emotional category by political affiliation. The numerator represents the number of tweets by X users within a given political affiliation classified in that emotion category, while the denominator is the total number of tweets by X users in that political affiliation. The sample is restricted to citizens' tweets whose primary topic is either 'abortion', 'democracy', 'gender equality', 'gun control', 'immigration', 'tax and inequality' or 'trade'.

3.3 The Evolution of Emotional Expression in Citizen Discourse

Figure 8 illustrates the evolution of emotional expression in citizens' tweets on the policy issues from Survey A since 2013. The most striking finding is the sharp increase in the share of tweets expressing anger, which surged from around 40% to 80% over the period. Simultaneously, the proportion of tweets centered on facts and reasoning, devoid of emotional content, has undergone a significant decline, dropping from nearly 58% to less than 20%. In contrast, other emotional expressions in tweets have remained relatively stable over time, especially positive emotions (staying under 10% over the period).

Figure 9 illustrates the evolution of negative emotions and their nature in discussions on the key policy issue covered in Survey B, namely, climate change. While this topic was relatively unemotional in the early 2010s, it became a major source of anger, sadness, and disgust starting in 2016–2017. Anger expressed about climate change doubles between 2013 and 2023, a result that is consistent with what we observe on the other policy issues presented above. At the same time, the overall level of fear about climate change

FIGURE 7: CITIZENS' TWEETS ON POLICY ISSUES: SHARE OF AFFECTIVE TWEETS BY TOPIC

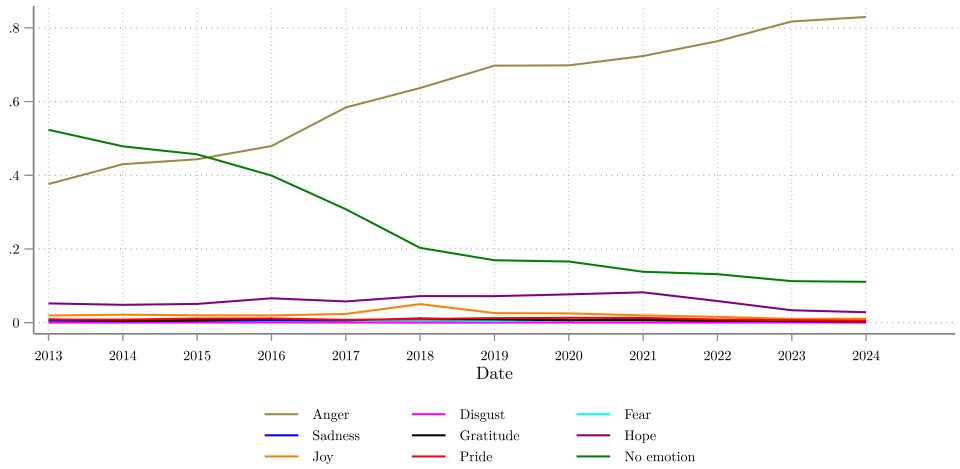


Notes. The figure shows the share of affective tweets by topic. The numerator represents the number of tweets by X users within a given topic classified as affective, while the denominator is the total number of tweets by X users in that topic. The sample is restricted to citizens' tweets classified as 'affective' or 'cognitive'.

has not significantly changed. The rise in sadness, anger, and disgust may indicate growing frustration with perceived inaction but also a rise of anti-climate policies and opinion, while the stagnation of fear implies a steady awareness of the risks associated with climate change. This highlights the importance of differentiating among various types of emotions – even among negative ones– when analyzing their impact on policy views, as we do in Survey B.

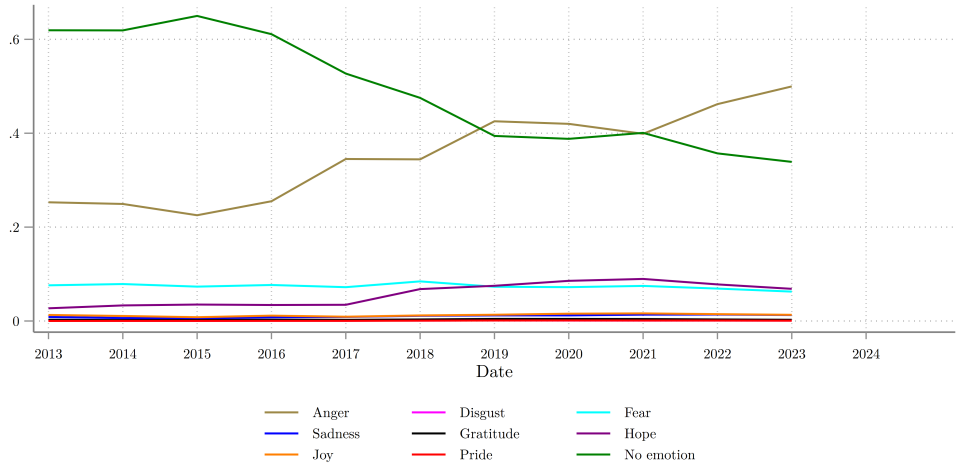
Finally, Figure 10 illustrates the evolution of the share of anger— the most prominent emotion, among Democratic and Republican followers. Anger surged in both camps starting in 2015, from an initial level of 45%. However, while Republican followers have shown a continuous rise in anger, reaching nearly 90% of all expressed emotions by 2024, the share of anger among Democrat followers' tweets has stabilized around 70%.

Figure 8: Evolution of Emotional Content in Citizens' Tweets on Policy Issues



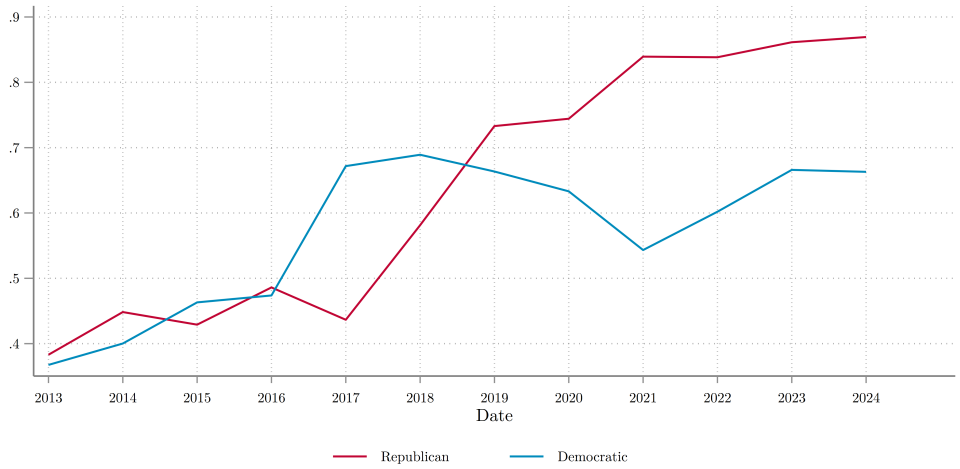
Notes. The figure shows, for each year, the share of tweets classified in a given emotional. The numerator represents the number of tweets by X users within a given year classified in that emotion category, while the denominator is the total number of tweets by X users in that year. The sample is restricted to citizens' tweets whose primary topic is either 'abortion', 'democracy', 'gender equality', 'gun control', 'immigration', 'tax and inequality' or 'trade'.

Figure 9: Evolution of Emotional Content in Tweets on Climate Change



Notes. The figure shows the evolution of emotional content in climate change-related tweets, expressed as a base 1 index in 2013. The share of tweets classified in a given emotional is computed as the number of tweets by X users within a given year classified in that emotion category divided by the total number of tweets by X users in that year. The sample is restricted to tweets about climate change.

FIGURE 10: EVOLUTION OF ANGER IN CITIZENS' TWEETS: DEMOCRATS VERSUS REPUBLICANS



Notes. The figure shows, for each year, the share of tweets classified as anger by political affiliation. The numerator represents the number of tweets by X users within a given political affiliation classified anger, while the denominator is the total number of tweets by X users in that political affiliation. The sample is restricted to citizens' tweets whose primary topic is either 'abortion', 'democracy', 'gender equality', 'gun control', 'immigration', 'tax and inequality' or 'trade'.

4 The Supply Side of Emotions by Political Parties

4.1 Emotional Expressions of Political Parties: Analyzing Tweets and Speeches

Tweets from official accounts. When analyzing tweets from the official Republican and Democratic party accounts, we see a similar pattern in the role of emotions to that in citizens' tweets. Figure 11 reveals that 42% of official Republican Party tweets and 38% of Democratic Party tweets are classified as non-emotional. Interestingly, Republican Party communications exhibit slightly lower levels of emotional expression than those of the Democratic Party.

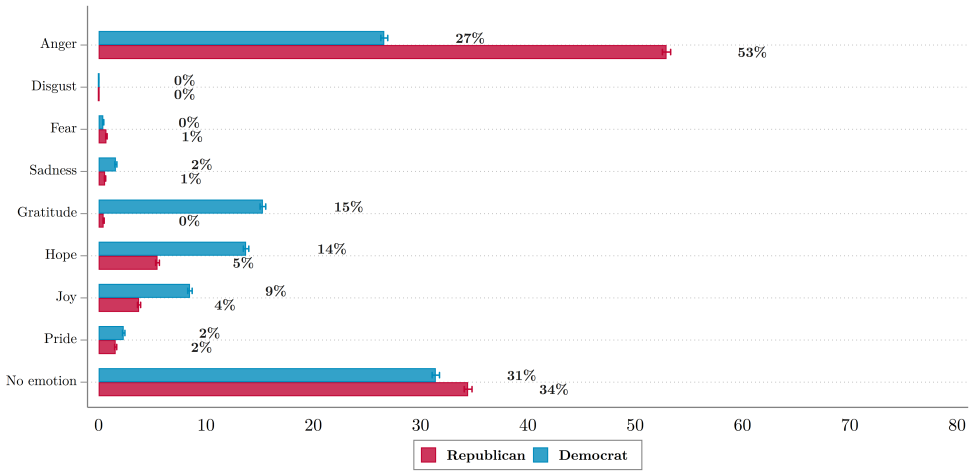
However, the distribution of emotions varies significantly across the two parties. While 53% of Republican Party tweets convey anger, compared to 27% among Democratic Party tweets, the latter are markedly more likely to express positive emotions (including hope, gratitude, and joy). Specifically, 38% of Democratic Party tweets contain positive emotional content, with a notable emphasis on gratitude (15%), hope (14%), joy (9%). In contrast, only 15% of Republican Party tweets express positive emotions, with hope (7%) and gratitude (3%) appearing far less frequently.

The analysis of speeches delivered by Donald Trump and Joe Biden/Kamala Harris during the last U.S. presidential campaign offers a complementary yet consistent perspective on the role of emotions in political discourse (Figure 12). While the proportion of speeches devoid of emotional content is similar for both Trump (20%) and Harris (18%), the distribution of emotions in the remaining speeches differs markedly between candidates from the two parties. Anger was present in 62% of Trump's speeches, compared to 33% in Harris's (and 31% in Biden's). Conversely, hope was a more prominent theme in Harris's speeches,

appearing in 41% of them, compared to only 8% in Trump's addresses.

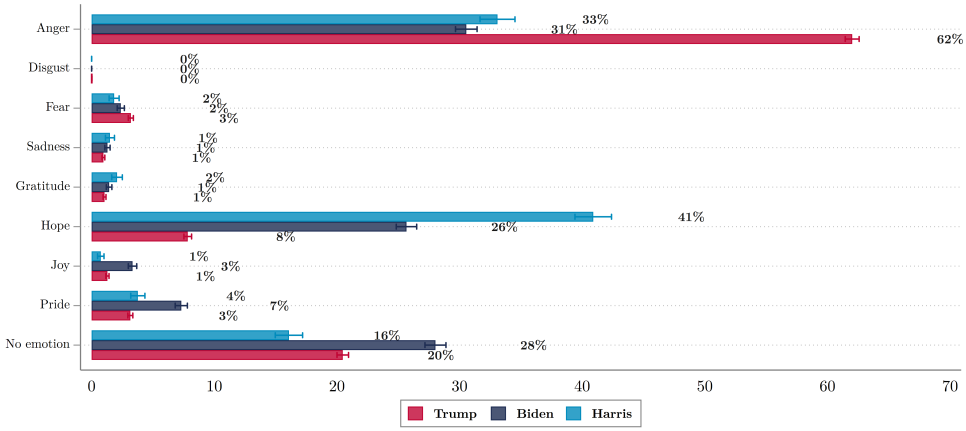
Figure 13 analyzes the distribution of topics where political parties and politicians most frequently employ emotional rhetoric. The findings reveal that societal issues and topics related to American democracy exhibit the highest levels of emotional rhetoric (70%–80%). These are followed by immigration, while more technical and economic topics, such as international trade and taxation, tend to be less emotionally charged. These findings perfectly echo the ones for citizens' tweets above. Thus, the emotional rhetoric in politicians' discourse increases in step with that of citizens, suggesting a mutual reinforcement of emotional narratives in political communication.

Figure 11: Emotional Content of Tweets from Official Democrat and Republican Party Accounts



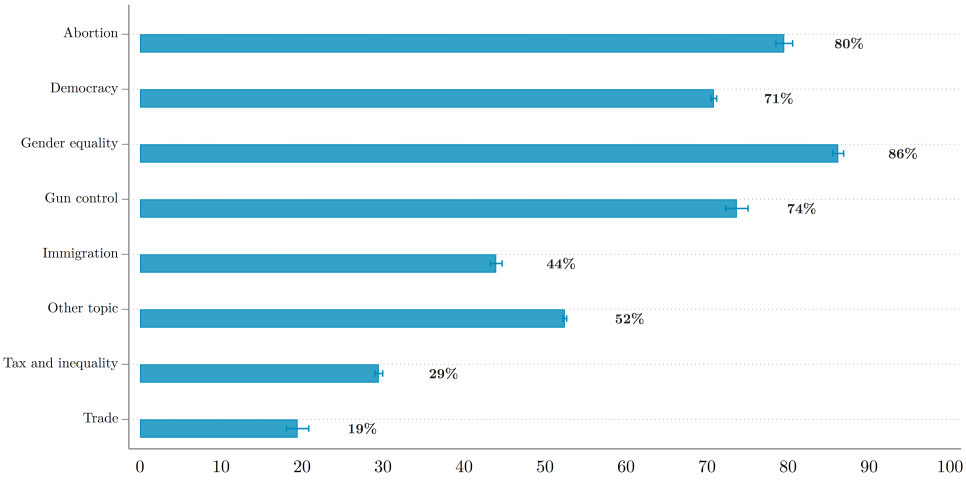
Notes. The figure shows, for each emotion, the share of tweets classified in that emotional category from Democrat and Republican official account. The numerator represents the number of tweets by official account classified in that emotion category, while the denominator is the total number of tweets by the official Democrat and Republican account. The sample is restricted to tweets whose primary topic is either 'abortion', 'democracy', 'gender equality', 'gun control', 'immigration', 'tax and inequality' or 'trade'.

Figure 12: Emotional Content in Speeches During the 2024 U.S. Presidential Election



Notes. The figure shows, for each emotion, the share of speeches classified in that emotional category by speaker. The numerator represents the number of speeches by that speaker classified in the given emotion category, while the denominator is the total number of speeches by that speaker. The sample is restricted to speeches with more than 20 tokens and whose primary topic is either 'abortion', 'democracy', 'gender equality', 'gun control', 'immigration', 'tax and inequality' or 'trade'.

Figure 13: Official tweets on policy issues: share of affective tweets by topic

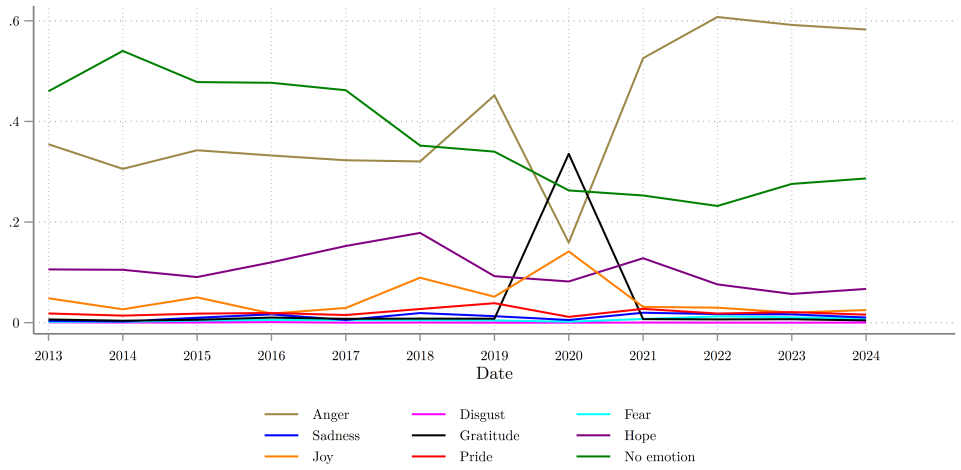


Notes.
The figure shows the share of affective tweets by topic. The numerator represents the number of tweets by X users within a given topic classified as affective, while the denominator is the total number of tweets by X users in that topic. The sample is restricted to tweets from official account of the Democratic and Republican parties and classified as 'affective' or 'cognitive'.

Figure 14 illustrates the evolution of the emotional rhetoric in the tweets from the official Twitter accounts of the Democratic and Republican parties. The share of tweets devoid of emotional content has declined at a rate comparable to that observed in citizen tweets, from 55% in 2014 (peak) to 30% in 2024. In the meantime, the expressions of anger have increased remarkably, in particular after the 2020 US presidential elections

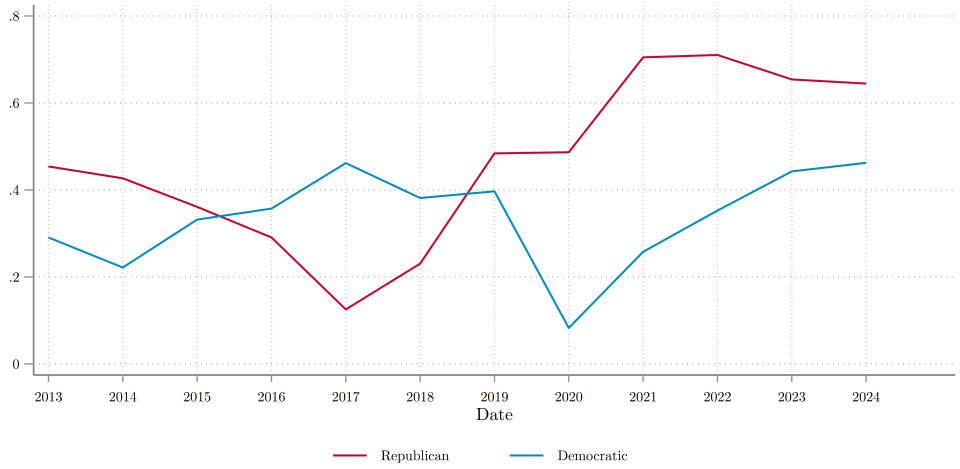
with a surge of 40 percentage periods between 2020 and 2024 (form 18% to 58%). When disaggregating the evolution of anger by party affiliation (Figure 14), two key patterns emerge. Before 2020, anger appeared to fluctuate with electoral cycles: it was higher among Republicans when in opposition and lower when in power, with the reverse pattern for Democrats. This result is consistent with Gennaro and Ash, 2022 who find that across Congress members, emotionality is higher for the opposition party. However, starting in 2017 for Republicans and 2020 for Democrats, anger surged sharply in both parties (and especially among Republicans), indicating a broader shift toward heightened emotional intensity in political discourse.

FIGURE 14: EVOLUTION OF EMOTIONAL CONTENT IN OFFICIAL TWEETS



Notes. The figure shows the proportion of tweets categorized by emotion for each year. The numerator represents the number of tweets within a given year classified in that emotion category, while the denominator is the total number of tweets in that year. The sample is restricted to tweets from the Democrat and Republican official accounts whose primary topic is either 'abortion', 'democracy', 'gender equality', 'gun control', 'immigration', 'tax and inequality' or 'trade'.

Figure 15: Evolution of Anger in Official Tweets



Notes. The figure shows, for each year, the share of tweets classified as anger by political affiliation. The numerator represents the number of tweets by X users within a given political affiliation classified anger, while the denominator is the total number of tweets by X users in that political affiliation. The sample is restricted to officials' tweets whose primary topic is either 'abortion', 'democracy', 'gender equality', 'gun control', 'immigration', 'tax and inequality' or 'trade'.

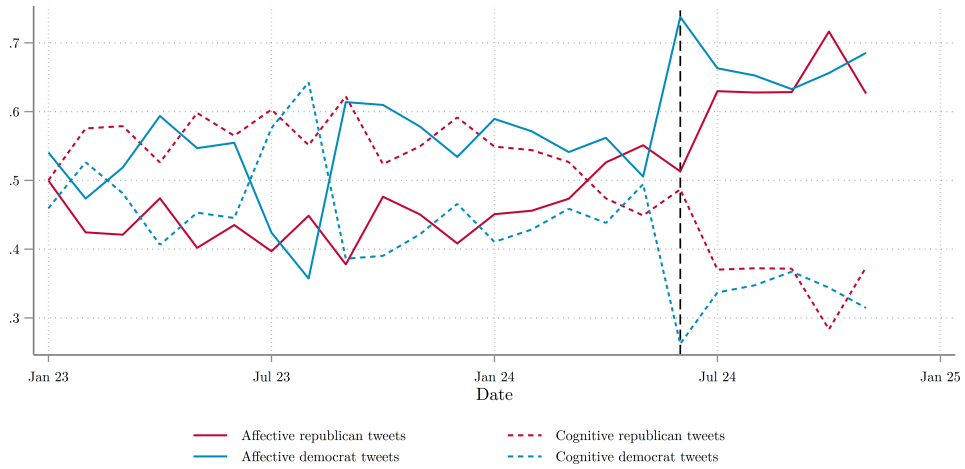
4.2 The strategic supply of emotions by political parties

The preceding sections have demonstrated a notable rise in emotional expression, particularly anger, in both citizen discourse and political messaging. This observation raises a critical question: Do political leaders deliberately employ emotional rhetoric to enhance their influence on the public? In other words, is there a strategic supply of emotions by political parties and leaders aimed at increasing citizen engagement?

To explore this, we begin by analyzing event studies of political speeches, followed by an examination of how the emotional content of messages affects their likelihood of being retweeted.

Focusing on original tweets from the official Republican and Democratic Twitter accounts, we observe a marked increase in emotionality (affective content) and a corresponding decline in rational discourse (cognitive content) starting in June 2024. This shift coincides precisely with the first debate between Trump and Biden, which signaled the official launch of the 2024 presidential campaign (Figure 16). Notably, this increase in emotionality appears similar across both parties, suggesting a strategic shift in communication tactics as the election approached.

FIGURE 16: AFFECT VERSUS COGNITION IN OFFICIAL TWEETS AROUND THE ELECTION, BY POLITICAL AFFILIATION



Notes. The figure shows the share of tweets classified in that affective versus cognitive category by political affiliation. The numerator represents the number of tweets by X users within a given political affiliation classified in that category, while the denominator is the total number of tweets by X users in that political affiliation. The vertical dashed bar marks June 2024, representing the month of the first debate between Trump and Biden.

Next, we explore the underlying drivers of this increasing emotionality by examining the relationship between a tweet's engagement and its predominant emotion. Specifically, we regress the number of retweets on indicators for the emotions expressed in the tweet, while controlling for time (month-year) fixed effects and user fixed effects to account for unobserved temporal variations and individual-specific characteristics. We also include topic fixed effects to control for differences in content themes that may influence emotional expression and engagement. This approach allows us to isolate the impact of emotions on retweet frequency while accounting for persistent differences across users, topics, and broader trends over time. To address potential within-user correlations, standard errors are clustered at the user level. The results of this analysis are presented in Table 3.

Our findings reveal that tweets expressing anger receive significantly higher engagement: on average, tweets from official accounts classified as angry generate 37% more retweets than neutral (non-emotional) tweets. This result aligns with the findings of Lee and Xu, 2018, who showed that during the 2016 U.S. presidential election, Donald Trump's tweets attacking Clinton and the media were far more likely to be retweeted. We observe a similar pattern among users: tweets expressing anger generate 61% more retweets among both Republican and Democratic partisans and 50% more in a broader dataset of climate change-related tweets.

Interestingly, we also find variation in the impact of other emotions on engagement. While pride and gratitude are positively associated with an increase in retweets for official accounts, they show no significant or even negative correlations in the general public sample. For climate change-related tweets, only anger and fear have a statistically significant effect, which justify our focus on those two emotions in the experimental setting (Experiment B).

Table 3: Emotions and retweets on social media

	(1) Official Party Tweets	(2) Citizens' Tweets	(3) Climate Change Tweets
Anger	0.32***	0.48***	0.41***
	(0.07)	(0.05)	(0.06)
Disgust	0.30	0.37	-0.19
	(0.29)	(0.37)	(0.25)
Fear	-0.05	0.10	0.17**
	(0.03)	(0.10)	(0.07)
Gratitude	0.15***	-0.56***	-0.34
	(0.03)	(0.08)	(0.29)
Hope	-0.16	-0.26***	0.02
	(0.10)	(0.06)	(0.07)
Joy	0.09	-0.01	0.10
	(0.06)	(0.12)	(0.10)
Pride	0.19***	-0.22	-0.02
	(0.05)	(0.14)	(0.22)
Sadness	0.04	-0.19	0.09
	(0.13)	(0.13)	(0.09)
Time fixed-effects	Yes	Yes	Yes
User fixed-effects	Yes	Yes	Yes
Topic fixed-effects	Yes	Yes	No
N	110359	387156	1073928

Notes. All regressions are estimated using Poisson Pseudo-Maximum Likelihood (PPML) with user and time fixed-effects. Model [1] and [2] also include topic fixed effect (abortion,' democracy,' gender equality,' gun control,' immigration,' taxation and inequality,' or 'trade.'). Model [3] focuses only on tweets about climate change and thus do not include topic fixed-effects. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5 Experimental Effects of Emotions on Policy views

The previous sections provided evidence that emotions play a dominant role in citizens' discussions on policy issues. Discourse that incorporates more negative emotions appeared to be particularly effective in driving citizen engagement, as it is retweeted at significantly higher rates. However, a crucial question remains: Do emotions also influence citizens' policy views?

This section addresses this question by presenting the results from the experimental part of the paper, composed of two distinct experiments. The first experiment, presented in Section 5.1, investigates how positive and negative emotions influence perceptions and policy preferences across five key topics: trade, immigration, taxation and redistribution, democracy and societal issues. Given that negative emotions appear to exert a stronger influence on perceptions and policy views, we dive into this category more deeply in a second experiment, presented in Section 5.2, specifically distinguishing the effects of two key negative emotions, fear and anger. This experimental analysis provides causal evidence complementing Section 3 and 4, reinforcing the importance of emotions in shaping political discourse and citizens' expectations.

5.1 Negative and Positive Emotions

Effects of the treatments on emotions. Figure 17 summarizes the emotions elicited by the positive and negative emotions treatments. Consistent with our expectations, the negative emotion treatment significantly increases feelings of anger, fear, outrage, and sadness, while substantially reducing joy and tranquility. Conversely, the positive emotion treatment enhances joy and tranquility but has no or very little negative effect on negative emotions.

Effects of the negative emotions treatment on policy views. Figure 18 depicts the effects of the treatments on perceptions and policy views for trade, immigration, redistribution, and democracy.[4] Survey questions on each policy topic were grouped into indices, distinguishing when possible between two types of questions: perceptions about the policy topic and policy views on the topic. For example, survey questions asking about the effects of trade on unemployment or inequality are part of the trade perception index, while the question asking whether the US should increase trade with other countries and reduce barriers to trade is classified in the trade policy index. Appendix Section A.2 shows the results of the treatments separately for each individual variable comprising each index.

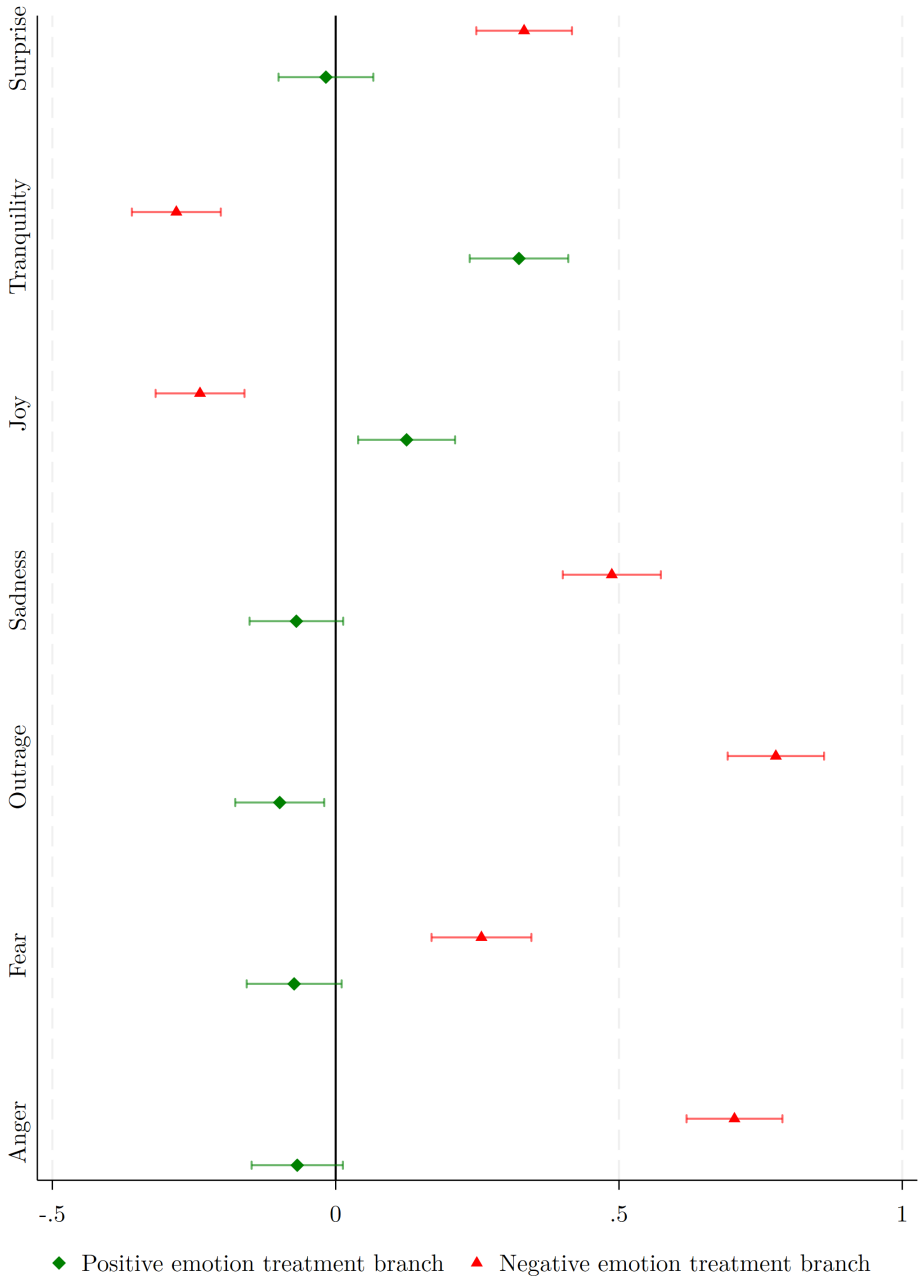
The negative emotion treatment has a positive and statistically significant impact on both the negative trade perception index and the anti-free trade index. Appendix Table A3 shows that the effect on trade perceptions is primarily driven by two of the three variables included in the index: respondents exposed to the negative emotion treatment are more likely to perceive trade as a zero-sum game and to believe that it increases unemployment. Quantitatively, this effect is substantial, equivalent to roughly 48% of the perception gap between Trump and Harris voters. Additionally, Appendix Table A4 shows that the negative emotion treatment heightens opposition to international trade policies, with a magnitude equivalent to about 15% of the Trump-Harris voter difference. These findings suggest that exposure to negative emotions not only intensifies negative perceptions regarding the consequences of trade but also prompts individuals to revise their policy preferences toward greater support for protectionist measures. Similarly, the negative emotion treatment influences individuals' immigration-related policy preferences by increasing their support for restrictive immigration policies, an effect amounting to approximately 14% of the voter gap; although we find no significant impact on perceptions of immigration itself.

Interestingly, while negative emotions encourage unfavorable views on trade and immigration, they concurrently enhance positive perceptions of redistribution and bolster support for redistributive policies; each of these effects corresponds to approximately 11% of the Harris-Trump voter gap. The positive effect on the redistribution perception index is primarily driven by negatively treated respondents being more likely to attribute poverty to external circumstances as shown by Appendix Table A7. Additionally, Appendix Table A8 illustrates that the positive impact on the pro-redistribution policy index arises from negatively treated respondents expressing greater support for policies such as raising the corporate minimum tax and implementing a ban on price gouging. Contrary to prior literature, however, our experimental results reveal no evidence that negative emotions foster greater support for anti-democracy attitudes.

Effects of the positive emotions treatment on policy views. In contrast, the positive emotion treatment significantly reduces the likelihood of negative perceptions concerning trade, corresponding to 42% of the Harris-Trump voter gap, suggesting that positive emotional states mitigate pessimism regarding

[4]The societal issues were too diverse to be grouped into indices, so we present these results separately in Appendix Table A10.

FIGURE 17: EFFECT OF THE TREATMENTS ON EMOTIONS IN SURVEY A



Notes. This figure shows the treatment effect on all emotions (standardized z-score) controlling for personal characteristics, such as gender, age, income, education and vote in 2020 as well as vote correlates, such as interpersonal trust and universalism. Appendix Table A2 displays all the coefficients. Confidence intervals are displayed at the 90% significance level.

trade outcomes. This reduction is primarily driven by positively treated respondents being less likely to view trade as zero-sum and less inclined to believe that trade exacerbates inequality as shown by Appendix Table A3. However, unlike the negative emotion treatment, positive emotions do not significantly alter individuals' policy preferences related to trade, as they do not affect support for or opposition to protectionist measures.

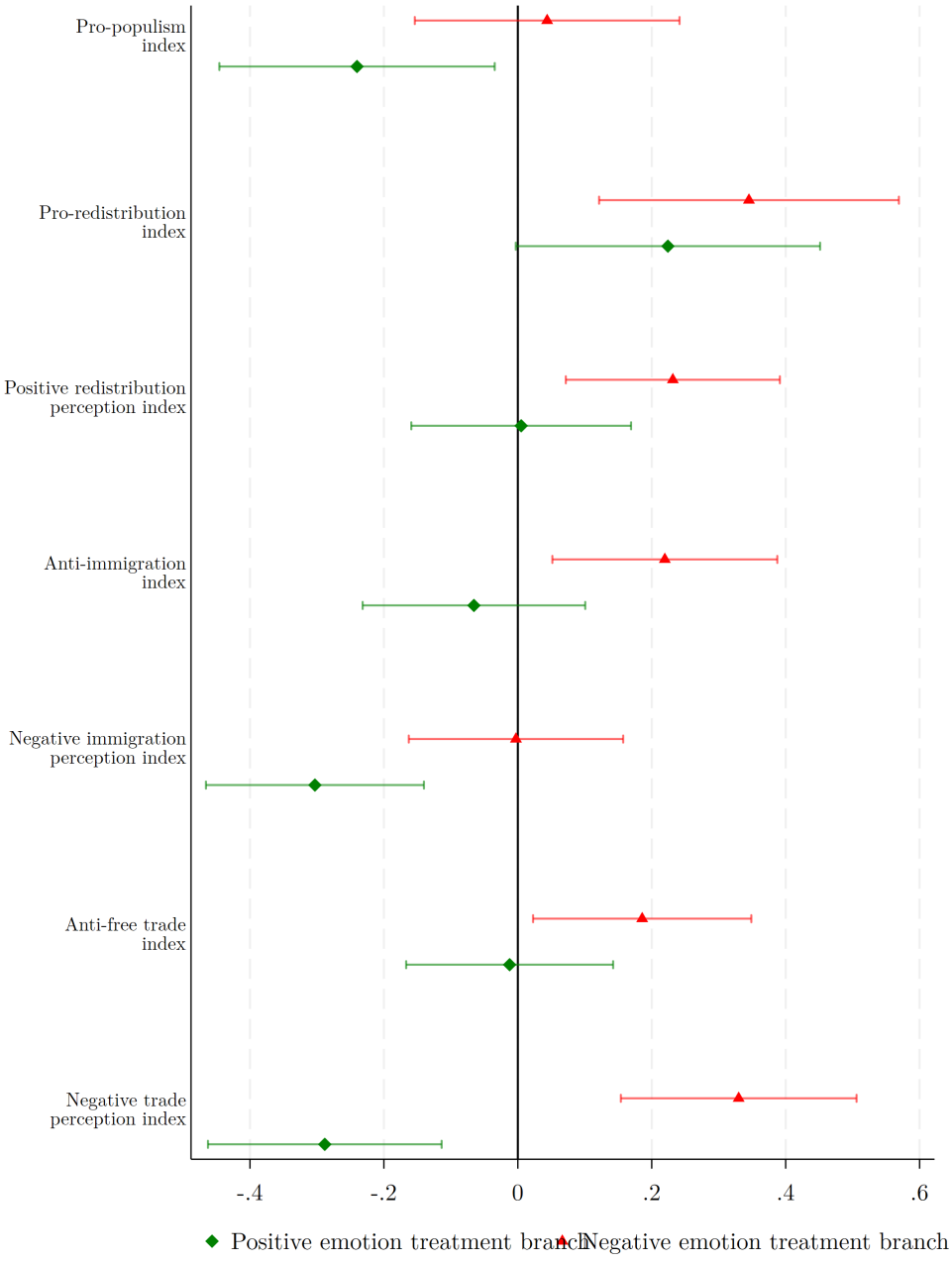
Similarly, Appendix Table A5 illustrates that the positive emotion treatment diminishes negative perceptions toward immigration, by an effect equivalent to 16% of the Harris-Trump voter gap, primarily because positively treated respondents are less likely to view immigration as a threat to the economy or cultural integrity.[5] Nonetheless, this treatment does not influence immigration policy preferences. Regarding redistribution, the positive emotion treatment shows no significant impact.

Lastly, positive emotions significantly reduce anti-democratic, populist attitudes, driven mainly by positively treated respondents being less likely to perceive expert governance as detrimental, an effect representing approximately 16% of the Harris-Trump voter gap. (Appendix Table A9).

Taken together, these findings suggest that positive and negative emotions play asymmetric roles in shaping political perspectives.

[5]Positively treated respondents also estimate lower unemployment rates both for the U.S.-born population and legal immigrants. These two variables are not included in the index because they are expressed as interpretable shares and thus are not transformed into z-scores that can be aggregated into the immigration perception index.

FIGURE 18: EFFECT OF THE TREATMENTS ON PERCEPTIONS AND POLICY VIEWS



Notes. This figure shows the treatment effect on all indices controlling for personal characteristics, such as gender, age, income, education and vote in 2020 as well as vote correlates, such as interpersonal trust and universalism. Appendix Section A.2 displays one table per index, presenting the variables composing each index. Confidence intervals are displayed at a 90% significance level.

5.2 Anger versus fear

We now turn to survey B, which focuses on climate change with the goal of distinguishing between the two key negative emotions, namely anger and fear.

Effects of the anger and fear treatments on emotions. Figure 19 summarizes the emotions elicited by the treatments in survey B, which examines two distinct negative emotions—fear and anger—and, consistently with survey A, includes a positive emotion treatment branch. Reassuringly, the fear treatment branch strongly increases feelings of fear, whereas the anger treatment branch significantly elevates feelings of anger. Interestingly, the fear treatment branch also induces anger, disgust, and sadness but reduces surprise, while the anger treatment branch additionally elicits fear, disgust, sadness, and surprise. As expected, the positive treatment branch enhances feelings of joy and tranquility while significantly reducing all negative emotions as well as surprise.

Effects on policy views. Figure 20 illustrates the effects of the anger and fear treatments on attitudes and policy preferences regarding climate change. Survey questions have been grouped into four distinct indices: general attitudes toward climate change, policy views on climate change, preferences regarding redistributive climate policies, and willingness to take private actions to fight against climate change. Specifically, survey questions assessing beliefs about the causes of climate change comprise the general attitude index; those evaluating support for various climate policies, such as implementing a carbon tax, constitute the policy views index; items measuring support for redistributive climate initiatives, like a redistributive carbon tax, form the redistributive climate policy index; and questions gauging respondents' willingness to engage in individual behaviors, such as reducing meat consumption, create the pro-climate private action index. Appendix Section A.3 provides detailed treatment effects for each individual variable within these indices.

The anger treatment demonstrates a positive and statistically significant impact across all climate change indices, whereas the fear treatment does not produce significant effects on any index. Appendix Table A12 indicates that the effect of the anger treatment on the general attitude index primarily arises from two of the three variables within the index: respondents exposed to the anger treatment are more inclined to believe climate change is caused by humans and to support slowing economic growth to combat climate change. It shifts general climate change attitudes by approximately 22% of the Harris-Trump voter gap. The effect of the anger treatment on the policy view index, accounts for 12% of the voter gap and is driven by increased respondent support for the Paris Agreement, policies promoting electric vehicles, a ban on combustion-engine vehicles, and implementing a carbon tax (see Appendix Tables A13 and A14). Additionally, Appendix Table A15 reveals that the positive effect of anger on the redistributive climate policy index (representing 16% of the voter gap) stems from greater support among respondents for increased funding directed toward minority groups disproportionately affected by pollution. Finally, as illustrated by Appendix Table A16, the anger treatment's influence on pro-climate private actions, corresponds to 24% of the Harris-Trump voter difference and is reflected in respondents' increased willingness to reduce meat consumption, decrease the number of flights taken, and support broader societal reductions in air travel.

In contrast to the first experiment, the positive emotion treatment does not yield opposite effects on climate change attitudes and policy views compared to the negative emotion treatments. Similar to the fear treatment, the positive emotion treatment largely generates insignificant effects across most climate indices, with the notable exception of a positive association with the general attitude index.

These findings highlight the need to distinguish the role different negative emotions: while fear and anger

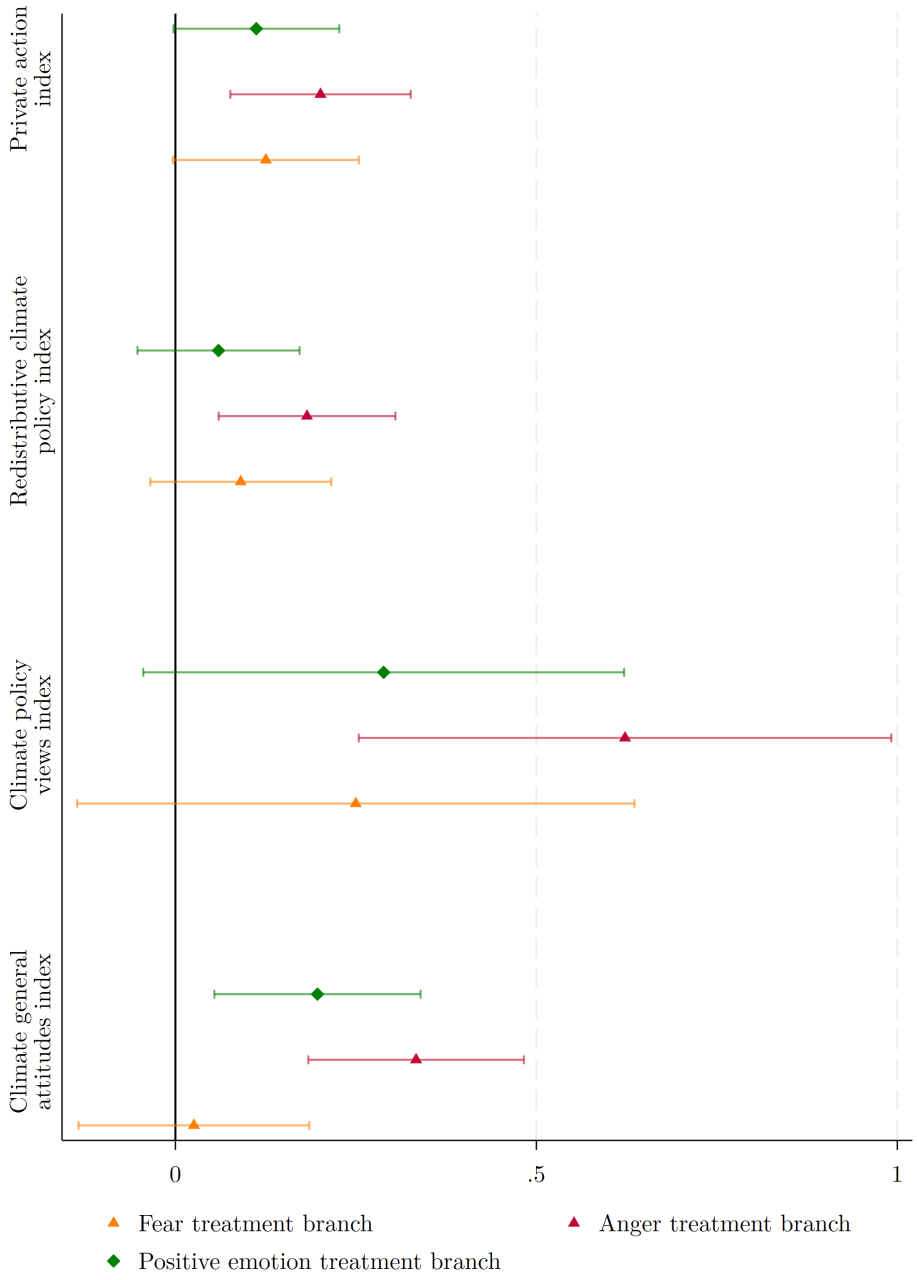
are both typically categorized as negative emotions, anger substantially shapes climate-related attitudes and policy views, whereas fear does not. Furthermore, positive emotions do not systematically produce effects opposite to those elicited by negative emotions.

FIGURE 19: EFFECT OF THE TREATMENTS ON EMOTIONS IN SURVEY B



Notes. This figure shows the treatment effect on all emotions (standardized z-score) controlling for personal characteristics, such as gender, age, income, education and vote in 2024. Appendix Table A11 displays all the coefficients. Confidence intervals are displayed at the 90% significance level.

FIGURE 20: EFFECT OF THE TREATMENTS ON CLIMATE CHANGE ATTITUDES



Notes. This figure shows the treatment effect on all climate indices controlling for personal characteristics, such as gender, age, income, education and vote in 2024. Appendix Section A.3 displays one table per index, presenting the variables composing each index. Confidence intervals are displayed at a 90% significance level.

6 Conclusion

This paper seeks to understand how emotions shape political discourse and influence public opinion through a three-step approach. We first document the evolution of emotional rhetoric in U.S. political discourse on social media and candidate speeches, leveraging advanced machine learning methods and natural language processing. By analyzing nearly 680,000 policy-related tweets from both citizens and official party accounts, combined with key political speeches from the 2024 presidential campaign, we systematically study the emotional content of the political discourse over time and across political leanings. Complementing these observational analyses, we conducted two large-scale experimental surveys designed to establish causality and explore the effects of different emotions on an array of policy attitudes.

Our findings highlight the central role of emotions—particularly anger—in contemporary U.S. political communication. We observed a significant increase in emotional rhetoric over time, marked by a notable surge in anger-driven content since 2016, more prominently among Republican-leaning politicians and citizens. We also find that tweets expressing anger generated substantially higher retweet rates compared to neutral or positively framed messages. Experimentally, exposure to negative emotions significantly intensified pessimistic views on issues such as trade and immigration and boosted support for protective or redistributive policies. Our deeper exploration into negative emotions revealed that anger specifically—and not fear—had a pronounced influence on shaping public attitudes and policy preferences, particularly regarding climate change.

These insights open important avenues for future research. First, it would be interesting to examine whether similar emotional dynamics hold in other democracies and under varying institutional contexts. Furthermore, exploring long-term effects of sustained emotional messaging on democratic norms, voter mobilization, and polarization would offer valuable implications for democratic health.

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ONLINE APPENDIX
for
"Emotions and Policy Views"

by Yann Algan, Eva Davoine, Thomas Renault, and Stefanie Stantcheva

A.1 Sample description

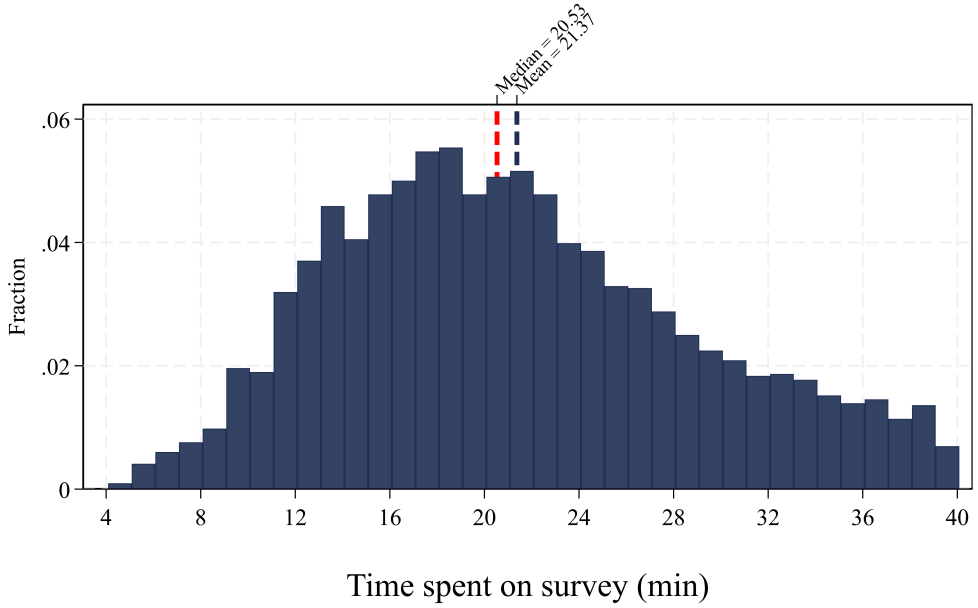
A.1.1 Sample evolution and duration

Table A1: Sample evolution

Sample evolution	N	%
Participants	9714	100%
Respondents screened out	408	4%
Respondents over quotas	2803	29%
Respondents abondoning before completion	763	8%
Respondents failing 1st Attention Check	1147	12%
Respondents failing 2nd Attention Check	325	3%
Respondent failing Video Technical Check	59	1%
Completes	4209	43%
Inattentive respondents manually dropped	392	4%
Respondents not watching full video	115	1%
Final sample	3704	38%
Respondents failing Video Qualitative Check (not dropped from sample)	192	2%
Final sample if all removed	3512	36%

Notes. 'Screened-out respondents' include those who did not provide consent to participate, those younger than 18 or older than 75, and those not residing in the US at the time of the survey. 'Respondents failing the Video Technical Check' are those unable to view the full video due to technical issues; this check applied only to the initial anger and relax video treatments, not to the booster video. 'Inattentive respondents manually excluded' are those who provided poor-quality, inconsistent, or repetitive answers to open-ended questions. 'Respondents not watching the full video' are those who spent less time on the video pages than the actual duration of the video, excluding those already removed due to inattentiveness. Finally, 'Respondents failing the Video Qualitative Check' are those unable to correctly identify the video's content from a set of 3-4 closed-ended options, excluding those who had already been removed due to inattentiveness or failure to watch the entire video.

FIGURE A1: DISTRIBUTION OF TIME SPENT IN THE SURVEY



A.1.2 Details on framed questions.

The exact wording of the framed policy open-ended questions is as follows:

- When you think about US trade with other countries,..
  - Neutral framing: what are the main considerations that come to your mind?
  - Positive framing: what are some of the things, if any, that make you feel optimistic?
  - Negative framing: such as China, what makes you really angry and revolted?
- When you think about current immigration in the US,..
  - Neutral framing: what are the main considerations that come to your mind?
  - Positive framing: especially issues like illegal border crossings, what really scares you and/or makes you really angry?
  - Negative framing: what are some of the things, if any, that make you feel optimistic?
- When you think about income and wealth distribution in the U.S.,..
  - Neutral framing: what are the main considerations that come to your mind?
  - Positive framing: what are some of the things, if any, that make you feel optimistic?
  - Negative framing: what makes you feel really angry and outraged ?
- When you think about how democracy works in the US and its impact on political debates among Americans,..
  - Neutral framing: what are the main considerations that come to your mind?

– Positive framing: what are some of the things, if any, that make you feel optimistic?

– Negative framing: what makes you feel really outraged and angry?

A.2 Experiment 1: Negative and Positive emotions - Individual components

Table A2: Effects of the treatments on emotions

	(1) Anger	(2) Fear	(3) Joy	(4) Tranquility	(5) Outrage	(6) Sadness	(7) Surprise	(8) Negative emotion index	(9) Positive emotion index
Panel A: Treatment effects									
Positive emotion treatment branch	-0.07	-0.07	0.13**	0.32***	-0.10**	-0.07	-0.02	-0.30*	0.45***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.17)	(0.09)
Negative emotion treatment branch	0.70***	0.26***	-0.24***	-0.28***	0.78***	0.49***	0.33***	2.23***	-0.53***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.18)	(0.08)
Panel B: Personal Characteristics									
Female	0.08*	0.05	-0.26***	-0.14***	0.01	0.03	-0.13***	0.18	-0.40***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.15)	(0.07)
30-49 years old	0.14**	0.13*	0.03	0.09	0.19***	0.17**	0.01	0.62***	0.11
	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.24)	(0.12)
50-75 years old	0.04	-0.13*	-0.32***	-0.06	0.08	-0.07	-0.38***	-0.09	-0.38***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.23)	(0.11)
Middle income: 40,000-89,999	-0.02	-0.06	-0.08*	-0.07	-0.02	-0.08	-0.07	-0.19	-0.15*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.18)	(0.09)
High income: 90,000 and above	-0.14**	-0.14**	-0.04	-0.01	-0.17***	-0.22***	-0.03	-0.66***	-0.04
	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.18)	(0.09)
College and above	-0.03	-0.15***	-0.14***	0.05	-0.09	-0.04	-0.12**	-0.32*	-0.09
	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.18)	(0.09)
Voted/would have voted Trump 2020	-0.03	-0.13***	-0.14***	-0.08	-0.06	-0.12**	-0.11**	-0.33**	-0.21**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.16)	(0.08)
Panel C: Vote correlates									
Most people can be trusted	-0.17***	-0.10**	0.09**	0.10**	-0.11**	-0.10**	0.06	-0.48***	0.19**
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.15)	(0.08)
Universalism index	0.02**	-0.00	-0.05***	-0.02**	0.02*	0.01	-0.04***	0.06	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.02)
Neutral Framing Mean (in s.d.)	-0.1	-0.0	0.0	-0.1	-0.1	-0.1	-0.0	-0.4	-0.0
Observations	2146	2147	2144	2145	2141	2153	2151	2136	2138
Adjusted R-Squared	0.13	0.05	0.08	0.07	0.16	0.08	0.07	0.13	0.09

Notes. The sample is restricted to respondents in the 'Positive emotion treatment branch' indicator, 'Negative emotion treatment branch' indicator and Control branch. Independent variables are standardized from a 1–7 scale, where respondents rated the intensity of emotions experienced during the survey. See the notes in Table **??** for details on indices. All regressions control also for an indicator equal to 1 when the voter did not vote or would have not voted for either Trump or Biden. In the regressions, the omitted categories are gender 'male', age '18-29 years old', household income 'low income: below $40,000', education 'below college', voting behavior 'voted/would have voted for Biden in 2020', trust in others 'You can never be too careful when dealing with other people'. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A3: Negative trade perceptions

	(1) Trade is zero sum	(2) Trade causes unemployment	(3) Trade increases inequality	(4) Anti-free trade index
Panel A: Treatment effects				
Positive emotion treatment branch	-0.14***	-0.07	-0.09*	-0.29***
	(0.05)	(0.05)	(0.05)	(0.11)
Negative emotion treatment branch	0.15***	0.16***	0.02	0.33***
	(0.05)	(0.05)	(0.05)	(0.11)
Panel B: Personal Characteristics				
Female	0.05	-0.02	-0.12***	-0.08
	(0.04)	(0.04)	(0.04)	(0.09)
30-49 years old	0.20***	0.02	0.05	0.27*
	(0.07)	(0.07)	(0.08)	(0.15)
50-75 years old	0.35***	0.00	-0.16**	0.20
	(0.07)	(0.07)	(0.07)	(0.14)
Middle income: 40,000-89,999	0.13***	0.03	-0.04	0.13
	(0.05)	(0.05)	(0.05)	(0.11)
High income: 90,000 and above	-0.06	-0.02	-0.04	-0.13
	(0.05)	(0.06)	(0.06)	(0.11)
College and above	-0.03	0.07	0.10*	0.14
	(0.05)	(0.05)	(0.05)	(0.11)
Voted/would have voted Trump 2020	0.27***	0.36***	0.17***	0.80***
	(0.05)	(0.05)	(0.05)	(0.10)
Panel C: Vote correlates				
Most people can be trusted	-0.09**	-0.03	-0.06	-0.18**
	(0.04)	(0.05)	(0.04)	(0.09)
Universalism index	-0.02*	-0.02*	0.01	-0.03
	(0.01)	(0.01)	(0.01)	(0.02)
Control branch Mean (in s.d.)	-0.0	-0.0	0.0	-0.1
Observations	2160	2160	2160	2160
Adjusted R-Squared	0.06	0.04	0.02	0.05

Notes. The sample is restricted to respondents in the 'Positive emotion treatment branch' indicator, 'Negative emotion treatment branch' indicator and Control branch. Independent variables are standardized as z-scores. In the regressions, the omitted categories are gender 'male', age '18-29 years old', household income 'low income: below $40,000', education 'below college', voting behavior 'did not vote/would not have voted Trump in 2020', trust in others 'You can never be too careful when dealing with other people'. See notes Table **??** for details on independent variables.

Table A4: Anti-free trade policy

	(1) Oppose more trade and less barriers	(2) Strong trade ties are not important	(3) Support 60% tariffs on China	(4) Anti-free trade index
Panel A: Treatment effects				
Positive emotion treatment branch	-0.01	-0.01	0.01	-0.01
	(0.05)	(0.05)	(0.05)	(0.09)
Negative emotion treatment branch	0.12**	0.07	-0.00	0.19*
	(0.05)	(0.05)	(0.05)	(0.10)
Panel B: Personal Characteristics				
Female	0.17***	0.05	-0.12***	0.09
	(0.04)	(0.04)	(0.04)	(0.08)
30-49 years old	0.01	0.14**	0.11	0.25**
	(0.07)	(0.06)	(0.07)	(0.12)
50-75 years old	0.12*	0.12**	0.06	0.30***
	(0.06)	(0.05)	(0.07)	(0.11)
Middle income: 40,000-89,999	0.02	-0.07	0.12**	0.07
	(0.05)	(0.05)	(0.05)	(0.10)
High income: 90,000 and above	-0.03	-0.09*	0.17***	0.05
	(0.05)	(0.05)	(0.05)	(0.10)
College and above	0.05	-0.08	0.03	-0.01
	(0.05)	(0.06)	(0.05)	(0.10)
Voted/would have voted Trump 2020	0.33***	0.09**	0.65***	1.08***
	(0.05)	(0.05)	(0.05)	(0.09)
Panel C: Vote correlates				
Most people can be trusted	-0.02	-0.08*	-0.01	-0.11
	(0.04)	(0.04)	(0.04)	(0.08)
Universalism index	-0.03***	-0.00	-0.04***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.02)
Control branch Mean (in s.d.)	-0.1	-0.0	-0.0	-0.1
Observations	2160	2160	2160	2160
Adjusted R-Squared	0.04	0.01	0.14	0.09

Notes. The sample is restricted to respondents in the 'Positive emotion treatment branch' indicator, 'Negative emotion treatment branch' indicator and Control branch. Independent variables are standardized as z-scores. See the notes in Table **??** for details on independent variables and Table A2 for information on regression omitted categories and additional controls.

Table A5: Negative immigration perception

	(1) Unemployed out of 100 U.S.-born	(2) Unemployed out of 100 legal immigrants	(3) Immigrants' poverty due to lack of effort	(4) Immigration threatens economy	(5) Immigration threatens culture	(6) Negative immigration perception index
Panel A: Treatment effects						
Positive emotion treatment branch	-3.49***	-2.67*	-0.00	-0.15***	-0.15***	-0.30***
	(1.18)	(1.46)	(0.05)	(0.05)	(0.05)	(0.10)
Negative emotion treatment branch	1.36	0.20	-0.00	0.00	-0.00	-0.00
	(1.20)	(1.44)	(0.05)	(0.05)	(0.05)	(0.10)
Panel B: Personal Characteristics						
Female	4.69***	1.24	-0.07*	0.04	0.07	0.04
	(1.00)	(1.22)	(0.04)	(0.04)	(0.04)	(0.08)
30-49 years old	-5.13***	-3.23	0.14*	0.15**	0.05	0.33**
	(1.68)	(1.98)	(0.07)	(0.07)	(0.07)	(0.14)
50-75 years old	-15.20***	-8.60***	0.07	0.04	-0.04	0.06
	(1.61)	(1.93)	(0.07)	(0.07)	(0.07)	(0.14)
Middle income: 40,000-89,999	-6.34***	-1.89	0.02	-0.01	-0.09*	-0.09
	(1.20)	(1.44)	(0.05)	(0.05)	(0.05)	(0.10)
High income: 90,000 and above	-10.17***	-4.84***	0.09*	-0.05	0.03	0.08
	(1.27)	(1.56)	(0.05)	(0.05)	(0.06)	(0.11)
College and above	-9.31***	-6.51***	-0.11**	-0.12***	-0.07	-0.30***
	(1.26)	(1.50)	(0.05)	(0.05)	(0.05)	(0.10)
Voted/would have voted Trump 2020	5.29***	6.02***	0.58***	0.78***	0.14***	1.50***
	(1.12)	(1.36)	(0.05)	(0.04)	(0.05)	(0.09)
Panel C: Vote correlates						
Most people can be trusted	-4.37***	-2.18*	-0.11***	-0.16***	0.03	-0.24***
	(1.02)	(1.25)	(0.04)	(0.04)	(0.04)	(0.09)
Universalism index	-0.87***	-0.79**	-0.09***	-0.08***	-0.03**	-0.19***
	(0.26)	(0.31)	(0.01)	(0.01)	(0.01)	(0.02)
Control branch Mean (in s.d.)	32.7	35.7	-0.0	0.0	0.0	0.0
Observations	2159	2158	2160	2160	2160	2160
Adjusted R-Squared	0.19	0.05	0.15	0.22	0.02	0.20

Notes. The sample is restricted to respondents in the 'Positive emotion treatment branch' indicator, 'Negative emotion treatment branch' indicator and Control branch. Independent indicator variables are standardized as z-scores. See the notes in Table **??** for details on independent variables and Table A2 for information on regression omitted categories and additional controls.

Table A6: Anti-immigration policy

	(1) Reduce immigration	(2) Support deportation	(3) Oppose U.S. aid for migration causes	(4) Ideological screening for citizenship	(5) Anti-immigration index
Panel A: Treatment effects					
Positive emotion treatment branch	0.05	-0.03	-0.04	-0.04	-0.07
	(0.05)	(0.04)	(0.05)	(0.05)	(0.10)
Negative emotion treatment branch	0.05	0.02	0.07	0.08	0.22**
	(0.05)	(0.04)	(0.05)	(0.05)	(0.10)
Panel B: Personal Characteristics					
Female	-0.17***	-0.16***	0.04	-0.03	-0.30***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.09)
30-49 years old	-0.18**	0.17**	0.20***	0.05	0.25*
	(0.08)	(0.07)	(0.06)	(0.07)	(0.14)
50-75 years old	-0.51***	0.17***	0.45***	0.04	0.15
	(0.08)	(0.06)	(0.06)	(0.07)	(0.14)
Middle income: 40,000-89,999	-0.03	0.06	0.07	0.05	0.16
	(0.05)	(0.04)	(0.05)	(0.05)	(0.10)
High income: 90,000 and above	0.01	0.08	0.04	-0.07	0.06
	(0.06)	(0.05)	(0.05)	(0.05)	(0.11)
College and above	0.05	-0.05	-0.02	-0.16***	-0.18*
	(0.05)	(0.05)	(0.05)	(0.06)	(0.11)
Voted/would have voted Trump 2020	-0.29***	0.90***	0.55***	0.16***	1.32***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.10)
Panel C: Vote correlates					
Most people can be trusted	0.16***	-0.10***	-0.12***	-0.08*	-0.13
	(0.04)	(0.04)	(0.04)	(0.04)	(0.09)
Universalism index	0.03***	-0.09***	-0.04***	-0.01	-0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Control branch Mean (in s.d.)	0.0	-0.0	-0.0	-0.0	-0.1
Observations	2160	2160	2160	2160	2160
Adjusted R-Squared	0.07	0.29	0.12	0.02	0.14

Notes. The sample is restricted to respondents in the 'Positive emotion treatment branch' indicator, 'Negative emotion treatment branch' indicator and Control branch. Independent indicator variables are standardized as z-scores. See the notes in Table **??** for details on independent variables and Table A2 for information on regression omitted categories and additional controls.

Table A7: Positive redistribution perception

	(1) Poverty due to external circumstances	(2) High earners pay lower tax share	(3) High taxes reduce inequalities	(4) Positive redistribution perception index
Panel A: Treatment effects				
Positive emotion treatment branch	0.01	-0.08	0.07	0.01
	(0.05)	(0.05)	(0.05)	(0.10)
Negative emotion treatment branch	0.11**	0.06	0.06	0.23**
	(0.05)	(0.05)	(0.05)	(0.10)
Panel B: Personal Characteristics				
Female	0.13***	0.01	0.12***	0.26***
	(0.04)	(0.04)	(0.04)	(0.08)
30-49 years old	0.12*	0.04	0.05	0.21
	(0.07)	(0.07)	(0.07)	(0.14)
50-75 years old	0.02	0.26***	0.12*	0.41***
	(0.07)	(0.07)	(0.07)	(0.14)
Middle income: 40,000-89,999	-0.16***	0.04	-0.09**	-0.22**
	(0.05)	(0.05)	(0.05)	(0.10)
High income: 90,000 and above	-0.32***	-0.12**	-0.18***	-0.62***
	(0.05)	(0.06)	(0.05)	(0.11)
College and above	0.10**	-0.06	-0.11**	-0.06
	(0.05)	(0.05)	(0.05)	(0.10)
Voted/would have voted Trump 2020	-0.50***	-0.37***	-0.70***	-1.57***
	(0.05)	(0.05)	(0.05)	(0.09)
Panel C: Vote correlates				
Most people can be trusted	0.02	-0.03	-0.14***	-0.15*
	(0.04)	(0.04)	(0.04)	(0.09)
Universalism index	0.11***	0.07***	0.08***	0.26***
	(0.01)	(0.01)	(0.01)	(0.02)
Control branch Mean (in s.d.)	-0.0	0.0	-0.0	-0.0
Observations	2160	2160	2160	2160
Adjusted R-Squared	0.16	0.07	0.18	0.24

Notes. The sample is restricted to respondents in the 'Positive emotion treatment branch' indicator, 'Negative emotion treatment branch' indicator and Control branch. Independent variables are standardized as z-scores. See the notes in Table **??** for details on independent variables and Table A2 for information on regression omitted categories and additional controls.

Table A8: Anti-redistribution policy

	(1) Gov't should reduce inequality	(2) Support corporate min tax hike	(3) Support top income tax hike	(4) Support price gouging ban	(5) Pro-redistribution index
Panel A: Treatment effects					
Positive emotion treatment branch	0.02	0.05	0.10*	0.07	0.22
	(0.05)	(0.05)	(0.05)	(0.05)	(0.14)
Negative emotion treatment branch	0.07	0.12**	0.07	0.09*	0.35**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.14)
Panel B: Personal Characteristics					
Female	0.06	-0.06	0.01	0.04	0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.12)
30-49 years old	-0.03	-0.04	0.01	0.11	0.02
	(0.07)	(0.07)	(0.07)	(0.07)	(0.19)
50-75 years old	-0.27***	-0.08	0.05	0.12*	-0.21
	(0.07)	(0.07)	(0.07)	(0.07)	(0.19)
Middle income: 40,000-89,999	-0.18***	0.03	-0.02	-0.02	-0.20
	(0.05)	(0.05)	(0.05)	(0.05)	(0.14)
High income: 90,000 and above	-0.24***	-0.06	-0.06	-0.03	-0.38**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.15)
College and above	-0.07	0.15***	0.07	0.00	0.15
	(0.05)	(0.05)	(0.05)	(0.05)	(0.14)
Voted/would have voted Trump 2020	-0.56***	-0.62***	-0.62***	-0.50***	-2.31***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.13)
Panel C: Vote correlates					
Most people can be trusted	-0.03	0.06	0.07	-0.06	0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.12)
Universalism index	0.09***	0.06***	0.06***	0.07***	0.27***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
Control branch Mean (in s.d.)	0.0	-0.0	-0.0	-0.0	-0.1
Observations	2159	2160	2160	2160	2159
Adjusted R-Squared	0.17	0.14	0.13	0.10	0.22

Notes. The sample is restricted to respondents in the 'Positive emotion treatment branch' indicator, 'Negative emotion treatment branch' indicator and Control branch. Independent variables are standardized as z-scores. See the notes in Table **??** for details on independent variables and Table A2 for information on regression omitted categories and additional controls.

Table A9: Pro-populism attitude

	(1) Strong leader is good governance	(2) Experts ruling is bad governance	(3) Democracy is bad governance	(4) Elections are unfair	(5) Politicians serve the rich/powerful	(6) Pro-populism index
Panel A: Treatment effects						
Positive emotion treatment branch	0.04	-0.13**	-0.04	-0.07	-0.05	-0.24*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.13)
Negative emotion treatment branch	0.05	-0.10*	0.04	0.01	0.04	0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.12)
Panel B: Personal Characteristics						
Female	-0.10**	-0.02	0.15***	0.17***	-0.06	0.14
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.10)
30-49 years old	0.07	0.09	-0.03	-0.12	-0.06	-0.05
	(0.08)	(0.07)	(0.08)	(0.08)	(0.07)	(0.18)
50-75 years old	-0.28***	0.27***	-0.17**	-0.14*	-0.12*	-0.44**
	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.17)
Middle income: 40,000-89,999	0.00	0.03	-0.09*	-0.04	-0.01	-0.11
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.12)
High income: 90,000 and above	0.11**	-0.01	-0.04	-0.18***	-0.03	-0.14
	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.13)
College and above	-0.13**	0.05	-0.11*	-0.08	-0.06	-0.32**
	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)	(0.13)
Voted/would have voted Trump 2020	0.10*	0.15***	0.52***	0.73***	0.05	1.54***
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.12)
Panel C: Vote correlates						
Most people can be trusted	0.03	-0.00	-0.06	-0.17***	-0.18***	-0.37***
	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.11)
Universalism index	-0.05***	-0.02**	0.03**	0.00	0.04***	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
Control branch Mean (in s.d.)	-0.0	0.1	0.0	0.0	-0.0	0.1
Observations	2160	2160	2160	2160	2160	2160
Adjusted R-Squared	0.04	0.02	0.07	0.16	0.02	0.11

Notes. The sample is restricted to respondents in the 'Positive emotion treatment branch' indicator, 'Negative emotion treatment branch' indicator and Control branch. Independent variables are standardized as z-scores. See the notes in Table **??** for details on independent variables and Table A2 for information on regression omitted categories and additional controls.

Table A10: Pro-social conservatism

	(1) Believe Metoo has gone too far	(2) Support abortion ban	(3) Support fewer rules for non-lethal firearms	(4) Sign anti-Metoo petition	(5) Sign anti-abortion petition	(6) Sign petition for fewer non-lethal firearm rules
Panel A: Treatment effects						
Positive emotion treatment branch	-0.01	-0.06	-0.03	-0.01	-0.05	-0.01
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Negative emotion treatment branch	-0.00	0.01	0.01	0.04	-0.02	-0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Panel B: Personal Characteristics						
Female	-0.27***	-0.12***	-0.26***	-0.19***	-0.08*	-0.07
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
30-49 years old	-0.02	-0.00	0.16**	0.03	0.03	0.18***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)
50-75 years old	-0.16**	-0.10	-0.16**	-0.16**	-0.12*	0.12*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)
Middle income: 40,000-89,999	0.06	-0.04	-0.01	-0.02	-0.07	0.02
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
High income: 90,000 and above	0.04	-0.02	-0.04	-0.00	0.09	-0.11**
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
College and above	0.01	-0.12**	0.02	-0.01	0.02	0.06
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Voted/would have voted Trump 2020	0.49***	0.72***	0.30***	0.12**	0.53***	0.12**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Panel C: Vote correlates						
Most people can be trusted	0.01	0.03	0.03	-0.01	0.00	-0.08*
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
Universalism index	-0.07***	-0.06***	-0.03***	-0.05***	-0.04***	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Control branch Mean (in s.d.)	-0.0	0.0	-0.0	-0.0	0.0	0.0
Observations	2160	2160	2160	2160	2160	2160
Adjusted R-Squared	0.12	0.16	0.07	0.04	0.09	0.01

Notes. The sample is restricted to respondents in the 'Positive emotion treatment branch' indicator, 'Negative emotion treatment branch' indicator and Control branch. Independent variables are standardized as z-scores. See the notes in Table **??** for details on independent variables and Table A2 for information on regression omitted categories and additional controls.

A.3 Experiment 2: Anger versus Fear - Individual component

Table A11: Effects of the treatments on emotions

	(1) Anger	(2) Fear	(3) Disgust	(4) Sadness	(5) Joy	(6) Tranquility	(7) Surprise	(8) Negative emotion index	(9) Positive emotion index
Panel A: Treatment effects									
Positive emotion treatment branch	-0.41***	-0.40***	-0.50***	-0.31***	0.76***	0.90***	-0.32***	-1.62***	1.66***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.12)	(0.07)
Fear treatment branch	0.57***	1.19***	0.25***	1.29***	-0.88***	-0.78***	-0.10**	3.29***	-1.66***
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.14)	(0.07)
Anger treatment branch	1.25***	0.54***	1.22***	1.19***	-0.73***	-0.66***	0.42***	4.20***	-1.39***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.13)	(0.07)
Panel B: Personal Characteristics									
Female	0.04	0.13***	0.01	0.09***	-0.13***	-0.06*	-0.07**	0.26***	-0.19***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.09)	(0.05)
30-49 years old	0.01	0.07*	0.10**	0.05	-0.01	0.05	0.03	0.23*	0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.13)	(0.07)
50-69 years old	0.07	-0.01	0.13***	0.01	-0.18***	0.02	-0.15***	0.19	-0.16**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.13)	(0.08)
College Degree	-0.05	-0.07**	-0.07**	-0.00	-0.06*	-0.00	-0.12***	-0.20*	-0.06
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.11)	(0.06)
Middle income: 40,000-89,999	-0.04	-0.04	-0.01	0.01	-0.08*	-0.06	-0.04	-0.07	-0.14**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.13)	(0.07)
High income: 90,000 and above	-0.16***	-0.14***	-0.14***	-0.09**	-0.10**	-0.12***	-0.17***	-0.51***	-0.23***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.13)	(0.07)
Trump	-0.18***	-0.22***	-0.10***	-0.21***	0.14***	0.02	0.06	-0.71***	0.17***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.10)	(0.06)
No Video	-0.35	-0.33	-0.28	-0.52	0.26	0.17	0.01	-1.48	0.42
Observations	3270	3278	3278	3287	3271	3273	3271	3241	3254
Adjusted R-Squared	0.38	0.32	0.38	0.45	0.37	0.39	0.09	0.45	0.45

Notes. The table displays the effects of video treatments conditional on socio-demographic characteristics. Omitted categories are: no video treatment, male (for gender), 18–29 years old (for age), no college (for education), income below 40,000 (for income), voted for Harris (for vote in 2024 elections). Independent variables are standardized from a 1–7 scale. The'Negative emotion index' measures respondents' negative emotional responses during the survey. It is constructed as the sum of the z-scores of the emotional indicators for sadness, fear, anger and disgust. The 'Positive emotion index' measures respondents' positive emotional responses during the survey. It is constructed as the sum of the z-scores of the emotional indicators for joy and tranquility. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A12: Effects on general attitudes toward climate change

	(1) CC is man made[1]	(2) CC side effect of econ growth[2]	(3) Slowdown economy to reduce CC[3]	(4) Climate general attitudes index
Panel A: Treatment effects				
Positive emotion treatment branch	0.06	0.06	0.06	0.20**
	(0.05)	(0.04)	(0.04)	(0.09)
Fear treatment branch	0.04	-0.02	0.05	0.03
	(0.05)	(0.05)	(0.05)	(0.10)
Anger treatment branch	0.19***	-0.05	0.17***	0.33***
	(0.05)	(0.05)	(0.05)	(0.09)
Panel B: Personal Characteristics				
Female	0.04	-0.06*	0.03	0.04
	(0.04)	(0.04)	(0.03)	(0.07)
30-49 years old	-0.05	-0.05	-0.10**	-0.19**
	(0.05)	(0.05)	(0.05)	(0.09)
50-69 years old	-0.20***	-0.01	-0.29***	-0.50***
	(0.05)	(0.05)	(0.05)	(0.10)
College Degree	0.08*	0.06	0.02	0.14*
	(0.04)	(0.04)	(0.04)	(0.08)
Middle income: 40,000-89,999	0.05	0.10**	-0.09*	0.06
	(0.05)	(0.05)	(0.05)	(0.10)
High income: 90,000 and above	0.09*	0.18***	-0.12**	0.16*
	(0.05)	(0.05)	(0.05)	(0.10)
Trump	-0.83***	-0.27***	-0.32***	-1.42***
	(0.04)	(0.04)	(0.04)	(0.08)
No video	-0.14	-0.03	-0.08	-0.21
Observations	3119	3318	3318	3115
Adjusted R-Squared	0.14	0.02	0.04	0.12

Standard errors in parentheses

1. Believe that climate change is mainly caused by human activity

2. Support that the environmental crisis is an unfortunate side effect of positive

3. Support that it is necessary to slow down U.S. economic growth to alleviate CC

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes. The table displays second-stage effects of video treatments conditional socio-demographic characteristics. Omitted categories are: no video treatment, male (for gender), 18–29 years old (for age), no college (for education), income below 40,000 (for income), voted for Harris (for vote in 2024 elections). Dependent variables are standardized to z-scores.

Table A13: Effects on climate policy views 1/2

	(1) Join Paris Agreement[1]	(2) CC policy in inflation act[2]	(3) More e-vehicles policy[3]	(4) Oppose fossil fuels policy[4]
Panel A: Treatment effects				
Positive emotion treatment branch	0.05	0.01	0.07*	0.00
	(0.04)	(0.04)	(0.04)	(0.04)
Fear treatment branch	0.01	-0.03	0.01	0.04
	(0.05)	(0.05)	(0.05)	(0.05)
Anger treatment branch	0.09**	0.03	0.08*	0.03
	(0.04)	(0.05)	(0.04)	(0.04)
Panel B: Personal Characteristics				
Female	-0.07**	-0.07**	-0.18***	-0.06*
	(0.03)	(0.03)	(0.03)	(0.03)
30-49 years old	-0.02	0.07	0.01	-0.10**
	(0.04)	(0.05)	(0.05)	(0.05)
50-69 years old	-0.08	0.03	-0.20***	-0.16***
	(0.05)	(0.05)	(0.05)	(0.05)
College Degree	0.17***	0.07*	0.10***	0.10***
	(0.04)	(0.04)	(0.04)	(0.04)
Middle income: 40,000-89,999	0.19***	0.13***	0.10**	0.08*
	(0.05)	(0.05)	(0.05)	(0.05)
High income: 90,000 and above	0.23***	0.18***	0.20***	0.07
	(0.05)	(0.05)	(0.05)	(0.05)
Trump	-0.96***	-0.65***	-0.77***	-0.81***
	(0.03)	(0.04)	(0.04)	(0.04)
No video	-0.06	-0.04	-0.09	-0.05
Observations	3320	3320	3319	3319
Adjusted R-Squared	0.21	0.10	0.14	0.14

Standard errors in parentheses

1. Support for the U.S. participating to Paris Climate Agreement

2. Support for tax incentives for renewable energy projects

3. Support for a legislation to increase the proportion of electric cars sold

4. Oppose policy to expand fossil fuels in the U.S.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes. The table displays second-stage effects of video treatments conditional socio-demographic characteristics. Omitted categories are: no video treatment, male (for gender), 18–29 years old (for age), no college (for education), income below 50k (for income), employed (for employment status), voted for other candidates or did not vote (for vote in 2024 elections). Dependent variables are standardized to z-scores.

Table A14: Effects on climate policy views 2/2

	(1) Support for costly renewables[1]	(2) Pay more for renewables[2]	(3) Support car ban[3]	(4) Support carbon tax[4]	(5) Climate policy views index
Panel A: Treatment effects					
Positive emotion treatment branch	0.08*	0.07	0.07*	-0.06	0.29
	(0.04)	(0.04)	(0.04)	(0.04)	(0.20)
Fear treatment branch	0.03	0.05	0.06	0.09*	0.25
	(0.05)	(0.05)	(0.05)	(0.05)	(0.23)
Anger treatment branch	0.06	0.13***	0.11**	0.08	0.62***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.22)
Panel B: Personal Characteristics					
Female	-0.04	0.00	-0.06*	-0.09**	-0.57***
	(0.03)	(0.03)	(0.04)	(0.03)	(0.17)
30-49 years old	0.15***	-0.00	-0.02	-0.00	0.09
	(0.05)	(0.05)	(0.05)	(0.05)	(0.22)
50-69 years old	0.10**	-0.10**	-0.12**	-0.12**	-0.65***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.24)
College Degree	0.06	0.02	0.09**	0.04	0.66***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.19)
Middle income: 40,000-89,999	0.11**	0.00	-0.01	0.06	0.65***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.23)
High income: 90,000 and above	0.21***	0.09*	0.06	0.05	1.09***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.24)
Trump	-0.68***	-0.60***	-0.42***	-0.52***	-5.41***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.18)
No video	-0.09	-0.08	-0.09	-0.05	-0.54
Observations	3320	3318	3321	3320	3310
Adjusted R-Squared	0.11	0.08	0.04	0.07	0.24

Standard errors in parentheses

1. Require electric utilities to produce from renewable energy, even if it costs extra for the household

2. Pay more to get your electricity from renewable energy sources

3. Support a ban on combustion-engine cars

4. Support a carbon tax with cash transfers

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes. The table displays second-stage effects of video treatments conditional socio-demographic characteristics. Omitted categories are: no video treatment, male (for gender), 18–29 years old (for age), no college (for education), income below 50k (for income), employed (for employment status), voted for other candidates or did not vote (for vote in 2024 elections). Dependent variables are standardized to z-scores.

Table A15: Effects on preferences for redistributive climate policies

	(1)	(2)	(3)
	Support carbon tax on rich[1]	Support for minorities hit by CC[2]	Redistributive climate policy index
Panel A: Treatment effects			
Positive emotion treatment branch	0.00	0.06	0.06
	(0.04)	(0.04)	(0.07)
Fear treatment branch	0.03	0.06	0.09
	(0.05)	(0.05)	(0.08)
Anger treatment branch	0.11**	0.08*	0.18**
	(0.05)	(0.05)	(0.07)
Panel B: Personal Characteristics			
Female	-0.08**	0.03	-0.05
	(0.03)	(0.03)	(0.05)
30-49 years old	-0.12**	-0.01	-0.13*
	(0.05)	(0.05)	(0.07)
50-69 years old	-0.32***	-0.17***	-0.49***
	(0.05)	(0.05)	(0.08)
College Degree	0.06	-0.02	0.04
	(0.04)	(0.04)	(0.06)
Middle income: 40,000-89,999	0.04	0.09*	0.13*
	(0.05)	(0.05)	(0.08)
High income: 90,000 and above	0.01	0.07	0.07
	(0.05)	(0.05)	(0.08)
Trump	-0.62***	-0.74***	-1.36***
	(0.04)	(0.04)	(0.06)
No video	-0.05	-0.05	-0.10
Observations	3320	3319	3318
Adjusted R-Squared	0.09	0.11	0.15

Standard errors in parentheses

1. Support a progressive carbon tax for high-income people only

2. Increase funding to minorities that are disproportionately harmed by pollution

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes. The table displays second-stage effects of video treatments conditional socio-demographic characteristics. Omitted categories are: no video treatment, male (for gender), 18–29 years old (for age), no college (for education), income below 50k (for income), employed (for employment status), voted for other candidates or did not vote (for vote in 2024 elections). Dependent variables are standardized to z-scores.

Table A16: Effects on pro-climate individual behaviors

	(1) Reduce meat[1]	(2) Reduce flights[2]	(3) Everyone reduce flights[3]	(4) Private action index
Panel A: Treatment effects				
Positive emotion treatment branch	0.08*	0.04	0.07	0.11
	(0.04)	(0.04)	(0.04)	(0.07)
Fear treatment branch	0.02	0.10**	0.17***	0.13
	(0.05)	(0.05)	(0.05)	(0.08)
Anger treatment branch	0.10**	0.10**	0.11**	0.20***
	(0.05)	(0.05)	(0.05)	(0.08)
Panel B: Personal Characteristics				
Female	0.18***	0.08**	0.07**	0.26***
	(0.04)	(0.04)	(0.04)	(0.06)
30-49 years old	0.07	-0.01	0.16***	0.06
	(0.05)	(0.05)	(0.05)	(0.07)
50-69 years old	-0.01	-0.06	0.31***	-0.07
	(0.05)	(0.05)	(0.05)	(0.08)
College Degree	0.10***	-0.13***	-0.00	-0.03
	(0.04)	(0.04)	(0.04)	(0.06)
Middle income: 40,000-89,999	-0.01	-0.06	0.02	-0.06
	(0.05)	(0.05)	(0.05)	(0.07)
High income: 90,000 and above	0.08*	-0.26***	-0.06	-0.18**
	(0.05)	(0.05)	(0.05)	(0.08)
Trump	-0.39***	-0.38***	-0.41***	-0.77***
	(0.04)	(0.04)	(0.04)	(0.06)
No video	-0.07	-0.04	-0.10	-0.12
Observations	3321	3319	3319	3319
Adjusted R-Squared	0.05	0.06	0.05	0.06

Standard errors in parentheses

1. Willing to reduce meat consumption
2. Willing to reduce the number of flights taken
3. Everyone should reduce their number of flights

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes. The table displays second-stage effects of video treatments conditional socio-demographic characteristics. Omitted categories are: no video treatment, male (for gender), 18–29 years old (for age), no college (for education), income below 50k (for income), employed (for employment status), voted for other candidates or did not vote (for vote in 2024 elections). Dependent variables are standardized to z-scores.

A.4 Robustness

A.4.1 Positive and negative emotions

Table A17: Effects of the treatments on emotions

	(1) Anger	(2) Fear	(3) Joy	(4) Tranquility	(5) Outrage	(6) Sadness	(7) Surprise	(8) Negative emotion index	(9) Positive emotion index
Positive video only treatment branch	-0.10**	-0.04	0.11**	0.29***	-0.08*	-0.12**	-0.03	-0.34**	0.41***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.17)	(0.09)
Negative framing only treatment branch	0.11**	-0.02	-0.06	-0.04	0.11**	-0.04	-0.04	0.17	-0.10
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.17)	(0.08)
Panel B: Personal Characteristics									
Female	-0.01	0.03	-0.23***	-0.15***	-0.04	-0.02	-0.13***	-0.04	-0.37***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.14)	(0.07)
30-49 years old	0.07	0.07	-0.05	-0.07	0.15**	0.14**	-0.07	0.45**	-0.13
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.23)	(0.11)
50-75 years old	-0.06	-0.15**	-0.32***	-0.11*	-0.00	-0.05	-0.37***	-0.26	-0.44***
	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.21)	(0.11)
Middle income: 40,000-89,999	-0.09*	-0.14***	-0.05	-0.09*	-0.09*	-0.18***	-0.11**	-0.51***	-0.15*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.17)	(0.09)
High income: 90,000 and above	-0.24***	-0.21***	-0.14***	-0.08	-0.19***	-0.30***	-0.14**	-0.92***	-0.23**
	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.18)	(0.10)
College and above	-0.01	-0.05	-0.12**	0.06	-0.03	-0.03	-0.14***	-0.13	-0.06
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.17)	(0.09)
Voted/would have voted Trump 2020	-0.05	-0.13***	-0.13***	-0.04	-0.10**	-0.11**	-0.16***	-0.40***	-0.18**
	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.15)	(0.08)
Panel C: Vote correlates									
Most people can be trusted	-0.18***	-0.15***	0.11**	0.13***	-0.14***	-0.15***	0.07	-0.63***	0.25***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.14)	(0.08)
Universalism index	0.01	-0.00	-0.05***	-0.00	-0.01	0.00	-0.05***	0.01	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)
Neutral Framing Mean (in s.d.)	-0.1	-0.0	0.0	-0.1	-0.1	-0.1	-0.0	-0.4	-0.0
Observations	2313	2310	2310	2316	2311	2323	2322	2301	2304
Adjusted R-Squared	0.03	0.03	0.05	0.03	0.03	0.03	0.04	0.04	0.05

Notes. The sample is restricted to respondents in the 'Positive Video only treatment branch' indicator, 'Negative Framing only treatment branch' indicator, and Control branch. Independent variables are standardized from a 1–7 scale, where respondents rated the intensity of emotions experienced during the survey. See the notes in Table **??** for details on indices and in Table A2 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure A2: Effects of the treatments on indices

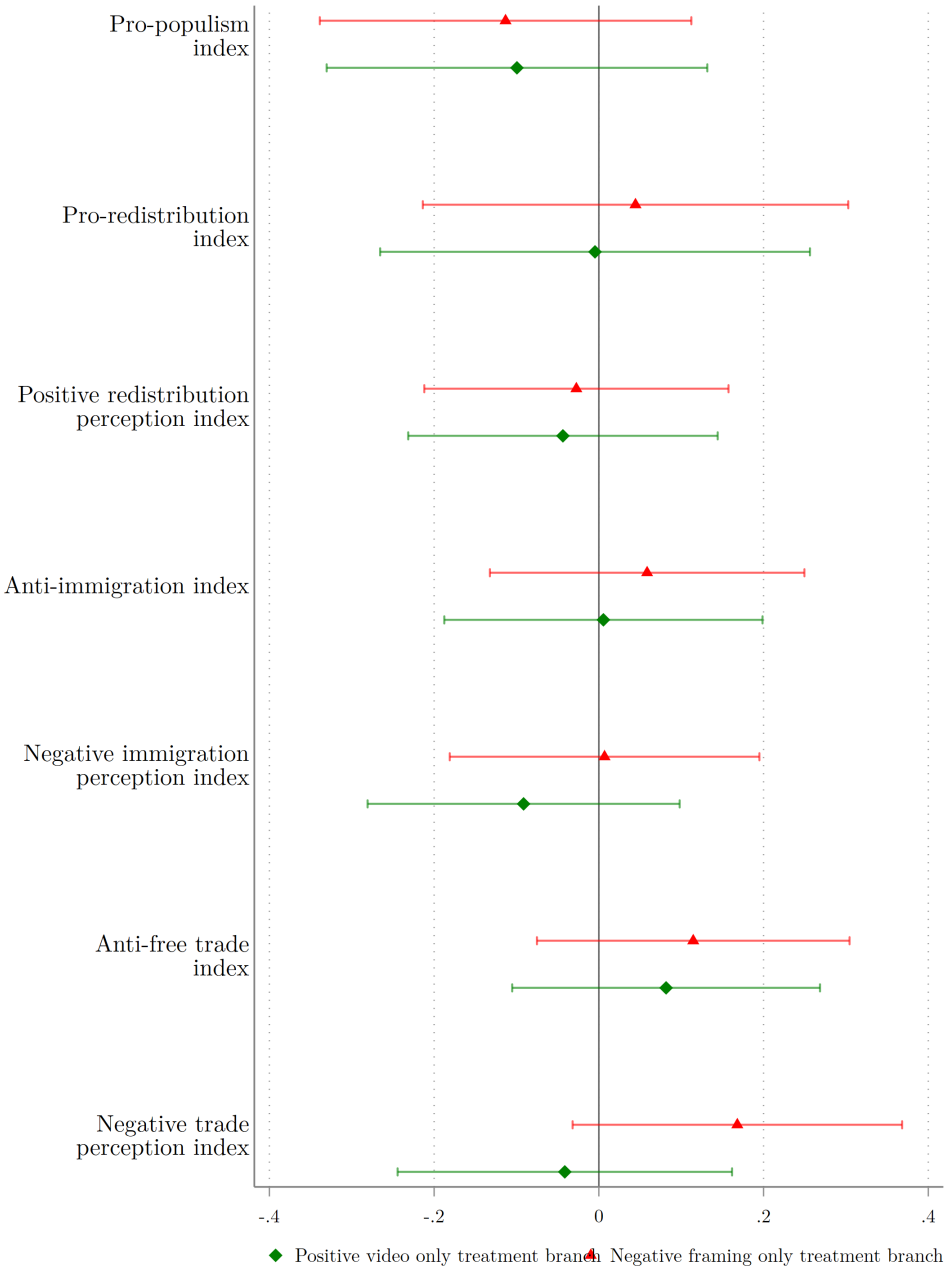


Table A18: All indices

	(1) Negative trade perception index	(2) Anti-free trade index	(3) Negative immigration perception index	(4) Anti-immigration index	(5) Positive redistribution perception index	(6) Pro-redistribution index	(7) Pro-populism index
Positive video only treatment branch	-0.04	0.08	-0.09	0.01	-0.04	-0.00	-0.10
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.13)	(0.12)
Negative framing only treatment branch	0.17*	0.11	0.01	0.06	-0.03	0.04	-0.11
	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)	(0.13)	(0.12)
Panel B: Personal Characteristics							
Female	-0.18**	0.03	-0.10	-0.36***	0.20**	0.03	0.13
	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.11)	(0.10)
30-49 years old	0.08	0.03	0.23*	0.13	0.17	0.29	-0.05
	(0.14)	(0.12)	(0.13)	(0.13)	(0.13)	(0.19)	(0.16)
50-75 years old	-0.03	0.11	0.01	0.08	0.49***	-0.02	-0.39***
	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.18)	(0.15)
Middle income: 40,000-89,999	-0.10	-0.11	0.02	-0.01	-0.23**	-0.17	-0.08
	(0.10)	(0.10)	(0.09)	(0.10)	(0.09)	(0.13)	(0.12)
High income: 90,000 and above	-0.22*	-0.08	0.10	0.06	-0.69***	-0.38**	-0.21*
	(0.12)	(0.11)	(0.11)	(0.11)	(0.10)	(0.15)	(0.12)
College and above	-0.06	0.14	-0.21**	-0.12	-0.09	-0.14	-0.20
	(0.11)	(0.10)	(0.10)	(0.10)	(0.10)	(0.14)	(0.12)
Voted/would have voted Trump 2020	0.72***	1.30***	1.44***	1.29***	-1.74***	-2.35***	1.57***
	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)	(0.12)	(0.11)
Panel C: Vote correlates							
Most people can be trusted	-0.30***	-0.03	-0.31***	-0.28***	-0.19**	0.35***	-0.29***
	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.11)	(0.10)
Universalism index	-0.03	-0.11***	-0.21***	-0.10***	0.26***	0.26***	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Control branch Mean (in s.d.)	-0.1	-0.1	0.0	-0.1	-0.0	-0.1	0.1
Observations	2332	2332	2332	2332	2332	2330	2332
Adjusted R-Squared	0.04	0.12	0.20	0.13	0.28	0.23	0.11

Notes. The sample is restricted to respondents in the 'Positive Video only treatment branch' indicator, 'Negative Framing only treatment branch' indicator, and Control branch. See Table A2 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A19: Negative trade perceptions

	(1) Trade is zero sum	(2) Trade causes unemployment	(3) Trade increases inequality	(4) Anti-free trade index
Positive video only treatment branch	-0.03	-0.04	0.02	-0.04
	(0.05)	(0.05)	(0.05)	(0.10)
Negative framing only treatment branch	0.11**	0.03	0.03	0.17*
	(0.05)	(0.05)	(0.05)	(0.10)
Panel B: Personal Characteristics				
Female	0.06	-0.09**	-0.16***	-0.18**
	(0.04)	(0.04)	(0.04)	(0.09)
30-49 years old	0.04	0.13*	-0.09	0.08
	(0.07)	(0.07)	(0.07)	(0.14)
50-75 years old	0.22***	0.10	-0.35***	-0.03
	(0.06)	(0.06)	(0.07)	(0.13)
Middle income: 40,000-89,999	0.01	-0.01	-0.09*	-0.10
	(0.05)	(0.05)	(0.05)	(0.10)
High income: 90,000 and above	-0.12**	-0.00	-0.10*	-0.22*
	(0.06)	(0.06)	(0.06)	(0.12)
College and above	-0.01	-0.05	-0.00	-0.06
	(0.05)	(0.05)	(0.05)	(0.11)
Voted/would have voted Trump 2020	0.32***	0.34***	0.06	0.72***
	(0.05)	(0.05)	(0.05)	(0.10)
Panel C: Vote correlates				
Most people can be trusted	-0.13***	-0.13***	-0.04	-0.30***
	(0.04)	(0.04)	(0.04)	(0.09)
Universalism index	-0.02**	-0.02*	0.01	-0.03
	(0.01)	(0.01)	(0.01)	(0.02)
Control branch Mean (in s.d.)	-0.0	-0.0	0.0	-0.1
Observations	2332	2332	2332	2332
Adjusted R-Squared	0.05	0.04	0.03	0.04

Notes. The sample is restricted to respondents in the 'Positive Video only treatment branch' indicator, 'Negative Framing only treatment branch' indicator, and Control branch. Independent variables are standardized as z-scores. See the notes in Table A2 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A20: Anti-free trade policy

	(1) Oppose more trade and less barriers	(2) Strong trade ties are not important	(3) Support 60% tariffs on China	(4) Anti-free trade index
Positive video only treatment branch	0.07	0.04	0.03	0.13
	(0.05)	(0.05)	(0.05)	(0.09)
Negative framing only treatment branch	0.12**	-0.00	-0.00	0.12
	(0.05)	(0.05)	(0.05)	(0.09)
Panel B: Personal Characteristics				
Female	0.11***	-0.05	-0.17***	-0.10
	(0.04)	(0.04)	(0.04)	(0.08)
30-49 years old	0.07	0.01	-0.06	0.01
	(0.06)	(0.06)	(0.07)	(0.11)
50-75 years old	0.15**	0.09	-0.09	0.15
	(0.06)	(0.06)	(0.06)	(0.11)
Middle income: 40,000-89,999	-0.08	-0.05	0.01	-0.11
	(0.05)	(0.05)	(0.05)	(0.10)
High income: 90,000 and above	-0.07	-0.02	0.11**	0.02
	(0.06)	(0.06)	(0.05)	(0.11)
College and above	0.08	0.00	0.08*	0.17*
	(0.05)	(0.05)	(0.05)	(0.10)
Voted/would have voted Trump 2020	0.46***	0.16***	0.59***	1.22***
	(0.05)	(0.05)	(0.04)	(0.09)
Panel C: Vote correlates				
Most people can be trusted	0.02	-0.08**	0.01	-0.05
	(0.04)	(0.04)	(0.04)	(0.08)
Universalism index	-0.02**	-0.01	-0.06***	-0.09***
	(0.01)	(0.01)	(0.01)	(0.02)
Control branch Mean (in s.d.)	-0.1	-0.0	-0.0	-0.1
Observations	2332	2332	2332	2332
Adjusted R-Squared	0.06	0.01	0.13	0.11

Notes. The sample is restricted to respondents in the 'Positive Video only treatment branch' indicator, 'Negative Framing only treatment branch' indicator, and Control branch. Independent variables are standardized as z-scores. See the notes in Table A2 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A21: Negative immigration perception

	(1) Unemployed out of 100 U.S.-born	(2) Unemployed out of 100 legal immigrants	(3) Immigrants' poverty due to lack of effort	(4) Immigration threatens economy	(5) Immigration threatens culture	(6) Negative immigration perception index
Positive video only treatment branch	-0.79	-0.98	-0.05	-0.03	-0.01	-0.09
	(1.15)	(1.40)	(0.05)	(0.05)	(0.05)	(0.10)
Negative framing only treatment branch	-0.16	-0.65	0.00	-0.04	0.04	0.01
	(1.16)	(1.41)	(0.05)	(0.04)	(0.05)	(0.10)
Panel B: Personal Characteristics						
Female	7.48***	3.19***	-0.08*	-0.02	-0.01	-0.10
	(0.95)	(1.17)	(0.04)	(0.04)	(0.04)	(0.08)
30-49 years old	-1.57	-1.87	0.19***	-0.01	0.06	0.23*
	(1.56)	(1.86)	(0.06)	(0.06)	(0.07)	(0.13)
50-75 years old	-12.99***	-7.71***	0.12**	-0.10*	-0.01	0.01
	(1.46)	(1.75)	(0.06)	(0.06)	(0.06)	(0.12)
Middle income: 40,000-89,999	-6.59***	-2.05	0.08*	-0.01	-0.05	0.02
	(1.13)	(1.36)	(0.05)	(0.04)	(0.05)	(0.09)
High income: 90,000 and above	-10.31***	-5.30***	0.07	0.02	0.01	0.10
	(1.24)	(1.56)	(0.05)	(0.05)	(0.06)	(0.11)
College and above	-6.91***	-2.02	-0.10**	-0.07*	-0.04	-0.21**
	(1.18)	(1.44)	(0.05)	(0.04)	(0.05)	(0.10)
Voted/would have voted Trump 2020	3.86***	2.53*	0.63***	0.71***	0.10**	1.44***
	(1.04)	(1.32)	(0.04)	(0.04)	(0.05)	(0.09)
Panel C: Vote correlates						
Most people can be trusted	-5.77***	-3.96***	-0.13***	-0.22***	0.04	-0.31***
	(0.98)	(1.22)	(0.04)	(0.04)	(0.05)	(0.08)
Universalism index	-1.30***	-1.47***	-0.08***	-0.09***	-0.03***	-0.21***
	(0.24)	(0.29)	(0.01)	(0.01)	(0.01)	(0.02)
Control branch Mean (in s.d.)	32.7	35.7	-0.0	0.0	0.0	0.0
Observations	2331	2330	2332	2332	2332	2332
Adjusted R-Squared	0.19	0.04	0.17	0.21	0.01	0.20

Notes. The sample is restricted to respondents in the 'Positive Video only treatment branch' indicator, 'Negative Framing only treatment branch' indicator, and Control branch. Independent indicator variables are standardized as z-scores. See Table A2 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A22: Anti-immigration policy

	(1) Reduce immigration	(2) Support deportation	(3) Oppose U.S. aid for migration causes	(4) Ideological screening for citizenship	(5) Anti-immigration index
Positive video only treatment branch	-0.01	0.00	0.00	0.02	0.01
	(0.05)	(0.04)	(0.05)	(0.05)	(0.10)
Negative framing only treatment branch	-0.03	0.03	0.00	0.06	0.06
	(0.05)	(0.04)	(0.05)	(0.05)	(0.10)
Panel B: Personal Characteristics					
Female	-0.16***	-0.15***	0.01	-0.05	-0.36***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.08)
30-49 years old	-0.21***	0.09	0.17***	0.08	0.13
	(0.07)	(0.06)	(0.06)	(0.06)	(0.13)
50-75 years old	-0.54***	0.09	0.41***	0.12*	0.08
	(0.07)	(0.06)	(0.05)	(0.06)	(0.12)
Middle income: 40,000-89,999	-0.08*	0.06	0.07	-0.06	-0.01
	(0.05)	(0.04)	(0.05)	(0.05)	(0.10)
High income: 90,000 and above	-0.03	0.15***	0.05	-0.10*	0.06
	(0.05)	(0.05)	(0.05)	(0.05)	(0.11)
College and above	0.02	-0.05	0.01	-0.09	-0.12
	(0.05)	(0.04)	(0.05)	(0.06)	(0.10)
Voted/would have voted Trump 2020	-0.30***	0.91***	0.52***	0.16***	1.29***
	(0.04)	(0.04)	(0.05)	(0.05)	(0.09)
Panel C: Vote correlates					
Most people can be trusted	0.14***	-0.09**	-0.19***	-0.14***	-0.28***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.08)
Universalism index	0.03***	-0.08***	-0.03***	-0.01	-0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Control branch Mean (in s.d.)	0.0	-0.0	-0.0	-0.0	-0.1
Observations	2332	2332	2332	2332	2332
Adjusted R-Squared	0.08	0.29	0.11	0.02	0.13

Notes. The sample is restricted to respondents in the 'Positive Video only treatment branch' indicator, 'Negative Framing only treatment branch' indicator, and Control branch. Independent indicator variables are standardized as z-scores. See Table A2 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A23: Positive redistribution perception

	(1) Poverty due to external circumstances	(2) High earners pay lower tax share	(3) High taxes reduce inequalities	(4) Positive redistribution perception index
Positive video only treatment branch	0.03	-0.07	-0.00	-0.04
	(0.05)	(0.05)	(0.05)	(0.10)
Negative framing only treatment branch	-0.03	-0.04	0.04	-0.03
	(0.05)	(0.05)	(0.04)	(0.09)
Panel B: Personal Characteristics				
Female	0.14***	-0.02	0.09**	0.20**
	(0.04)	(0.04)	(0.04)	(0.08)
30-49 years old	0.04	0.03	0.09	0.17
	(0.06)	(0.07)	(0.07)	(0.13)
50-75 years old	-0.02	0.30***	0.21***	0.49***
	(0.06)	(0.06)	(0.06)	(0.12)
Middle income: 40,000-89,999	-0.09**	-0.07	-0.07*	-0.23**
	(0.05)	(0.05)	(0.04)	(0.09)
High income: 90,000 and above	-0.20***	-0.21***	-0.28***	-0.69***
	(0.05)	(0.05)	(0.05)	(0.10)
College and above	-0.01	0.04	-0.12**	-0.09
	(0.05)	(0.05)	(0.05)	(0.10)
Voted/would have voted Trump 2020	-0.59***	-0.38***	-0.78***	-1.74***
	(0.04)	(0.04)	(0.04)	(0.09)
Panel C: Vote correlates				
Most people can be trusted	-0.03	-0.05	-0.11***	-0.19**
	(0.04)	(0.04)	(0.04)	(0.08)
Universalism index	0.10***	0.07***	0.08***	0.26***
	(0.01)	(0.01)	(0.01)	(0.02)
Control branch Mean (in s.d.)	-0.0	0.0	-0.0	-0.0
Observations	2332	2332	2332	2332
Adjusted R-Squared	0.19	0.08	0.21	0.28

Notes. The sample is restricted to respondents in the 'Positive Video only treatment branch' indicator, 'Negative Framing only treatment branch' indicator, and Control branch. Independent variables are standardized as z-scores. See Table A2 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A24: Anti-redistribution policy

	(1) Gov't should reduce inequality	(2) Support corporate min tax hike	(3) Support top income tax hike	(4) Support price gouging ban	(5) Pro-redistribution index
Positive video only treatment branch	-0.07	-0.00	-0.02	0.09*	-0.00
	(0.05)	(0.05)	(0.05)	(0.05)	(0.13)
Negative framing only treatment branch	-0.00	0.04	-0.01	0.02	0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.13)
Panel B: Personal Characteristics					
Female	0.02	-0.08**	-0.01	0.09**	0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.11)
30-49 years old	-0.05	0.09	0.11	0.16**	0.29
	(0.06)	(0.07)	(0.07)	(0.07)	(0.19)
50-75 years old	-0.29***	0.02	0.11*	0.15**	-0.02
	(0.06)	(0.06)	(0.06)	(0.07)	(0.18)
Middle income: 40,000-89,999	-0.18***	0.01	-0.00	0.00	-0.17
	(0.05)	(0.05)	(0.05)	(0.05)	(0.13)
High income: 90,000 and above	-0.30***	-0.02	-0.02	-0.05	-0.38**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.15)
College and above	-0.09**	-0.00	-0.03	-0.02	-0.14
	(0.05)	(0.05)	(0.05)	(0.05)	(0.14)
Voted/would have voted Trump 2020	-0.56***	-0.69***	-0.57***	-0.52***	-2.35***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.12)
Panel C: Vote correlates					
Most people can be trusted	0.03	0.15***	0.15***	0.03	0.35***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.11)
Universalism index	0.08***	0.06***	0.07***	0.05***	0.26***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
Control branch Mean (in s.d.)	0.0	-0.0	-0.0	-0.0	-0.1
Observations	2330	2332	2332	2332	2330
Adjusted R-Squared	0.17	0.16	0.13	0.10	0.23

Notes. The sample is restricted to respondents in the 'Positive Video only treatment branch' indicator, 'Negative Framing only treatment branch' indicator, and Control branch. Independent variables are standardized as z-scores. See Table A4 for information on regression omitted categories and additional controls. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A25: Pro-populism attitude

	(1) Strong leader is good governance	(2) Experts ruling is bad governance	(3) Democracy is bad governance	(4) Elections are unfair	(5) Politicians serve the rich/powerful	(6) Pro-populism index
Positive video only treatment branch	-0.02	-0.09*	-0.01	-0.00	0.03	-0.10
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.12)
Negative framing only treatment branch	-0.00	-0.11**	-0.02	-0.01	0.04	-0.11
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.12)
Panel B: Personal Characteristics						
Female	-0.08*	-0.02	0.08**	0.20***	-0.05	0.13
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.10)
30-49 years old	-0.03	0.07	0.11	-0.05	-0.15**	-0.05
	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.16)
50-75 years old	-0.38***	0.34***	-0.06	-0.15**	-0.14**	-0.39***
	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)	(0.15)
Middle income: 40,000-89,999	0.00	-0.00	-0.00	-0.05	-0.03	-0.08
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.12)
High income: 90,000 and above	0.05	-0.08	-0.01	-0.14***	-0.03	-0.21*
	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.12)
College and above	-0.06	0.06	-0.21***	0.03	-0.01	-0.20
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.12)
Voted/would have voted Trump 2020	0.08	0.20***	0.49***	0.78***	0.02	1.57***
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.11)
Panel C: Vote correlates						
Most people can be trusted	0.10**	0.02	-0.04	-0.23***	-0.14***	-0.29***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.10)
Universalism index	-0.04***	-0.01	0.02*	0.00	0.06***	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Control branch Mean (in s.d.)	-0.0	0.1	0.0	0.0	-0.0	0.1
Observations	2332	2332	2332	2332	2332	2332
Adjusted R-Squared	0.04	0.04	0.07	0.17	0.02	0.11

Notes. The sample is restricted to respondents in the 'Positive Video only treatment branch' indicator, 'Negative Framing only treatment branch' indicator, and Control branch. Independent variables are standardized as z-scores. See Table A2 for information on regression omitted categories and additional controls. For the treatment coefficients we show the p-value from the baseline regression (*Model p-value*) and the Romano-Wolf step-down adjusted p-values robust to multiple hypothesis testing (*Romano-Wolf p-value*) with 5000 repetitions. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A26: Pro-social conservatism

	(1) Believe Metoo has gone too far	(2) Support abortion ban	(3) Support fewer rules for non-lethal firearms	(4) Sign anti-Metoo petition	(5) Sign anti-abortion petition	(6) Sign petition for fewer non-lethal firearm rules
Positive video only treatment branch	-0.01	-0.07	0.05	0.03	-0.07	0.03
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Negative framing only treatment branch	0.02	-0.09**	-0.00	0.02	-0.07	-0.03
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Panel B: Personal Characteristics						
Female	-0.29***	-0.09**	-0.27***	-0.20***	-0.05	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
30-49 years old	-0.11*	0.01	-0.01	0.02	0.06	0.15**
	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
50-75 years old	-0.22***	-0.12**	-0.32***	-0.22***	-0.17***	0.02
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Middle income: 40,000-89,999	0.08	0.03	-0.04	0.05	-0.02	-0.06
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
High income: 90,000 and above	0.06	0.01	-0.08	0.02	0.06	-0.18***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
College and above	0.03	-0.06	-0.04	-0.06	-0.02	-0.02
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Voted/would have voted Trump 2020	0.45***	0.72***	0.27***	0.14***	0.53***	0.05
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Panel C: Vote correlates						
Most people can be trusted	0.02	0.06	0.13***	0.09**	0.11***	-0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Universalism index	-0.07***	-0.07***	-0.05***	-0.04***	-0.06***	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Control branch Mean (in s.d.)	-0.0	0.0	-0.0	-0.0	0.0	0.0
Observations	2332	2332	2332	2332	2332	2332
Adjusted R-Squared	0.11	0.18	0.08	0.04	0.11	0.01

Notes. The sample is restricted to respondents in the 'Positive Video only treatment branch' indicator, 'Negative Framing only treatment branch' indicator, and Control branch. Independent variables are standardized as z-scores. See Table A2 for information on regression omitted categories and additional controls.*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

A.5 Large language model and emotional content in textual data

We use a large language model (LLMs) to analyze emotional content in policy-related textual data (political speeches and tweets). We apply GPT-4o-mini to a randomly selected sample comprising 100,000 tweets and 50,000 segments extracted from political speeches, classifying each along three principal dimensions: cognition versus affect, specific emotional category, and primary topic. The precise prompt formulations are detailed below.

Cognition versus affect

You are an AI assistant tasked with classifying the given sentence / tweet.

Rules: - Do not generate, infer, or suggest any responses outside the list. - Your response must be exactly **one** of the provided answers. - Do **not** provide explanations, justifications, or additional context. - If the answer is unclear or ambiguous, default to **"unsure"**.

Task: **Question:** Is the following sentence / tweet cognitive (appeal to logic, facts, and rationality) or affective (appeal to feelings, values, and emotions) ?

Sentence: """ + document["text"] + """

Potential Answers: - cognitive - affective - unsure

Your response should be only one of these words.

Emotional category

You are an AI assistant that must only classify the given sentence / tweet based on the provided list of emotions.

Rules: - Do not generate, infer, or suggest any responses outside the list. - Your response must be exactly **one** of the provided answers. - Do **not** provide explanations, justifications, or additional context. - If the emotion is unclear or ambiguous, default to **"no emotion"**.

Task: **Question:** What is the main emotion conveyed in the following sentence / tweet?

Sentence: """ + document["text"] + """

Potential Answers: - sadness - fear - anger - disgust - joy - hope - gratitude - pride - no emotion

Your response should be only one of these words.

Primary topic

You are an AI assistant that must only classify the given sentence / tweet based on the provided list of topics.

Rules

- Do not generate, infer, or suggest any responses outside the list.

- Your response must be exactly **one** of the provided answers.

- Do **not** provide explanations, justifications, or additional context.

- If the emotion is unclear or ambiguous, default to **"no emotion"**.

Task:

Question: What is the main topic conveyed in the following sentence / tweet?

Sentence: """ + document["text"] + """

Potential Answers: - trade - immigration - tax and inequality - democracy - gender equality - gun control - abortion - other topic

Your response should be only one of these words.

Category Definitions::

- Trade: Discusses free trade, tariffs, trade policy, domestic industry impact, trade alliances, or trade relations (e.g., U.S.-China tariffs).

- Immigration: Covers perceptions of immigration, policy preferences, deportation, pathways to citizenship, or immigration's impact on employment and society.

- Tax and Inequality: Addresses wealth distribution, taxation policies, poverty causes, government intervention, or corporate taxation.

- Democracy: Examines governance, election integrity, trust in democracy, authoritarianism, or perceptions of politicians.

- Gender equality: Encompasses issues like the MeToo movement, diversity, equity and inclusion

- Gun control: Discusses the regulation of firearms, gun ownership rights, the impact of mass shootings, and debates over Second Amendment rights versus gun violence prevention.

- Abortion: Explores legal and ethical debates surrounding abortion and women's reproductive rights.

- Other Topic: If the sentence does not clearly fit into any of the above categories, classify it as "other topic."