Emotions and Policy Views*

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[*INCOMPLETE DRAFT – COMMENTS VERY WELCOME!*]

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, Guriev, 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'

[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".

dataset includes 679,760 tweets from the 762 users who most frequently retweeted the official party accounts' tweets. These tweets, spanning from 2013 to November 2024, contain keywords related to trade, immigration, taxes and redistribution, democracy and governance, and societal issues. We complement this analysis with official speeches delivered by Trump, Biden, and Harris during the 2024 and with a dataset of 3.7 million tweets about climate change to contextualize public discourse on environmental issues. 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, anger expressed about climate change doubles between 2013 and 2023, while at the same time, the overall level of fear has not significantly changed. 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 37% more retweets than neutral (non-emotional) tweets. 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

2.1 Observational data

2.1.1 Twitter data

We construct five distinct Twitter-based datasets.

The first two datasets focus on citizen discourse by analyzing tweets from individual user accounts. We infer each user's political affiliation based on their interactions with political content, enabling us to explore the broader public's political perspectives and affiliations. These two datasets specifically include a random sample of Twitter users and a partisan sample. The third dataset centers on tweets discussing climate change, in alignment with topics explored in Survey B. Finally, the fourth and fifth datasets examine the political landscape through tweets from official party accounts and congress members, respectively. These datasets provide insights into the communication strategies and messaging employed by political parties and legislators.

Random sample of Twitter users. This dataset consists of a random sample representing approximately 0.02% of all tweets posted on Twitter, collected from four distinct 5-second intervals per day between 2010 and 2025 (approximately 960,000 tweets in total). These tweets were filtered to include at least one 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. To assign a political leaning to each user, we follow the methodology proposed by Mosleh and Rand, 2022.[2]

Partisan citizens sample. We select the 762 users who most frequently retweeted the official party accounts' tweets. 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.[3] Our dataset is composed of 3.7 millions tweets from 1.5 million distinct users.

[2] We thank Mohsen Mosleh for providing the partisan scores used for each user in our dataset.

[3] 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.

Official party tweets. We extracted all the tweets and retweets from the main official accounts of each party. These are, for the Republican Party, @GOP, @HouseGOP, @SenateGOP and for the Democratic Party, @TheDemocrats, @HouseDemocrats and @SenateDems. Table 1 shows a breakdown of the data by source. Our database is comprised of 395,272 tweets sent between January 2013 and November 2024.[4]

Table 1: 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

Congressional tweets. We rely on the dataset constructed by Algan, Renault, et al., 2025. The authors collected a random sample of tweets posted by U.S. Congress members from 2006 onward ($\approx 25\%$), identifying tweets from 1,108 unique congresspersons (out of the 1,439 who served between 2006 and 2024), totaling approximately 700,000 tweets.

2.1.2 Political speech data

Congressional floor speeches. We further analyze the floor speeches delivered by members of Congress using the dataset compiled by Gauthier et al., 2025, which covers the period from 1994 to 2024. This dataset is constructed using the congressional-record parser developed by Judd et al., 2017,[5] which downloads the HTML files of the official Congressional Record from the U.S. Congress website and extracts both the full text and associated metadata. The dataset retains all speeches in their original form without any textual modification. The dataset comprises 1,796,583 individual turns[6] across 15 congressional sessions.

Campaign speech. 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.[7]

[4] We excluded 7,313 tweets from the @TheDemocrats account that consisted of the same automatically generated message sent to multiple users (e.g., `https://x.com/TheDemocrats/status/1314709281611018240`). As the only variation was the recipient's name, we removed these duplicates to prevent distortion in the emotional distribution—specifically, to avoid overrepresenting a single emotional tone due to mass duplication.

[5] `https://github.com/unitedstates/congressional-record`.

[6] In the context of the Congressional Record or floor speeches in the U.S. Congress, a turn typically refers to an instance when a Member of Congress is given the floor to speak during debate or proceedings. It is often one continuous block of speech, and spans several paragraphs or sentences.

[7] 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.

2.1.3 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.6.

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 predict emotions, distinguish affect from cognition, and identify topics within the dataset.

2.2 Experimental data

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.

2.2.1 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 2 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 2: Sample Representativeness

	Survey A	Survey B	US Population
Targeted characteristics			
Gender			
Male (%)	43	49	50
Female (%)	57	51	50
Age			
18-29 years old (%)	13	23	22
30-39 years old (%)	14	18	19
40-49 years old (%)	19	20	17
50-59 years old (%)	22	20	17
60-75 years old (%)	33	19	24
Annual Household Income			
0-19,999 (%)	15	11	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	11	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 (%)	36	23	30
Survey A: Voted in 2020			
Yes (%)	79	-	66
No (%)	21	-	34
Survey A: Voted whom in 2020 (% of all 18+ voters)			
Biden (%)	56	-	51
Trump (%)	41	-	47
Others (%)	2	-	2
Prefer not to say/Don't know (%)	2	-	0
Survey B: Voted in 2024 (Survey B)			
Yes (%)	-	84	64
No (%)	-	16	36
Survey B: Voted whom in 2024 (% of all 18+ voters)			
Harris (%)	-	52	50
Trump (%)	-	42	48
Others (%)	-	3	2
Prefer not to say/Don't know (%)	-	2	0
Observations	3,704	5,390	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 Figure A1 for the full distribution of survey durations). Furthermore, we included attention-check questions to filter out inattentive respondents. The representative samples (as reported in Table 2) were obtained after excluding participants who were screend out, exceeded quota limits, abandoned the survey before completion, failed the attention or technical checks, or did not fully watch the treatment video. In total, for Survey A, 39% of all respondents who initially began the survey were ultimately excluded from Survey A and B. Appendix Table A1 details the attrition process at each stage. We also test for differential attrition in Appendix Table A27 (Survey A) and Appendix Table A29 (Survey B). We find correlations between certain socio-demographic characteristics and various forms of attrition; however, the overall differences in attrition rates remain small.

2.2.2 The Surveys

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

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 2.2.3. 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.

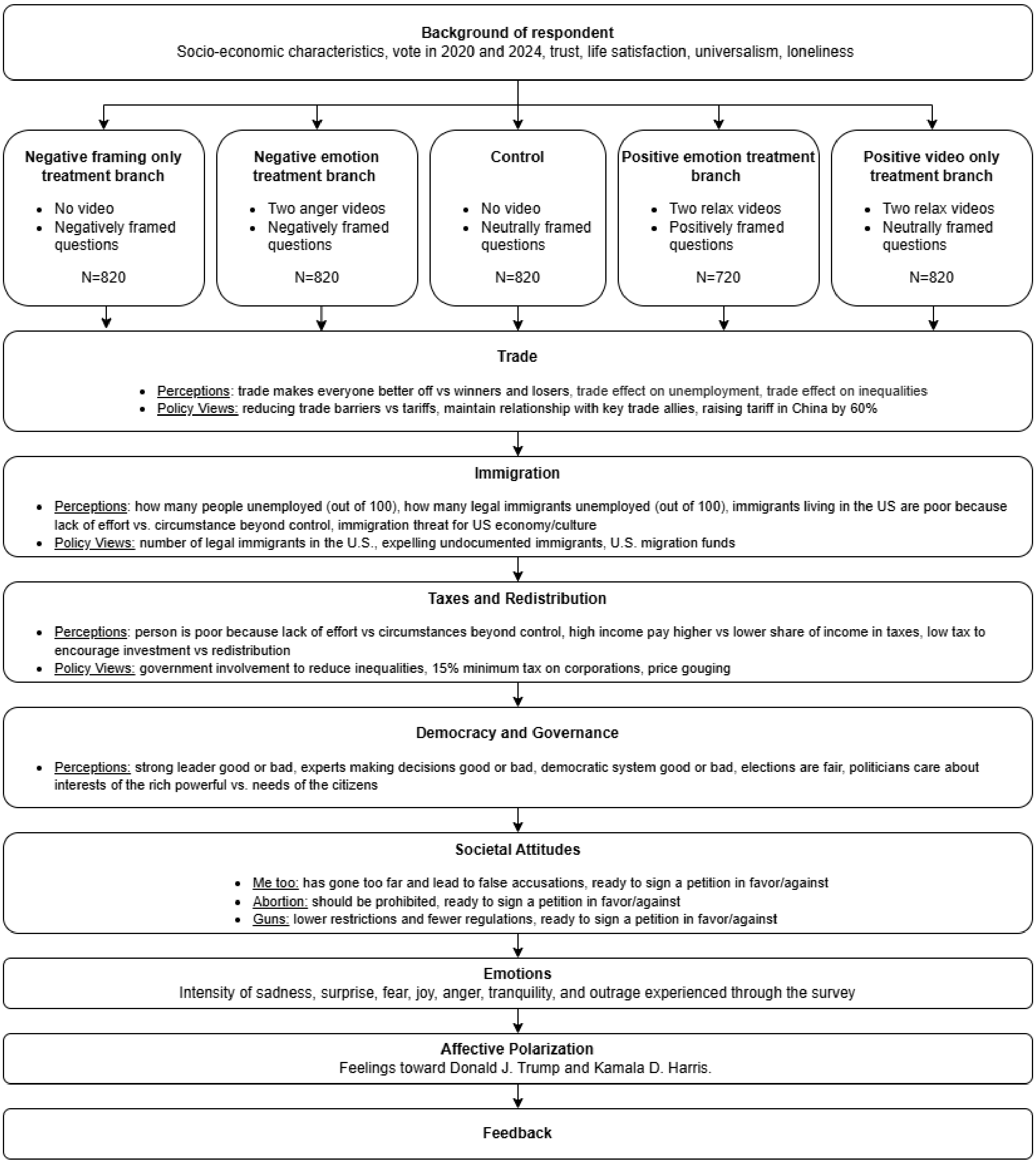
Societal Attitudes We gauge agreement with statements on prominent social issues including the MeToo movement, abortion restrictions, and firearm regulations. For each issue, respondents are also asked to indicate whether they would sign a petition supporting or opposing the position.

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.

   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.

Appendix Table A28 shows that our treatment assignment is balanced across socio-demographic characteristics as well as political affiliation, trust and universalism.

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 2.2.3.

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.

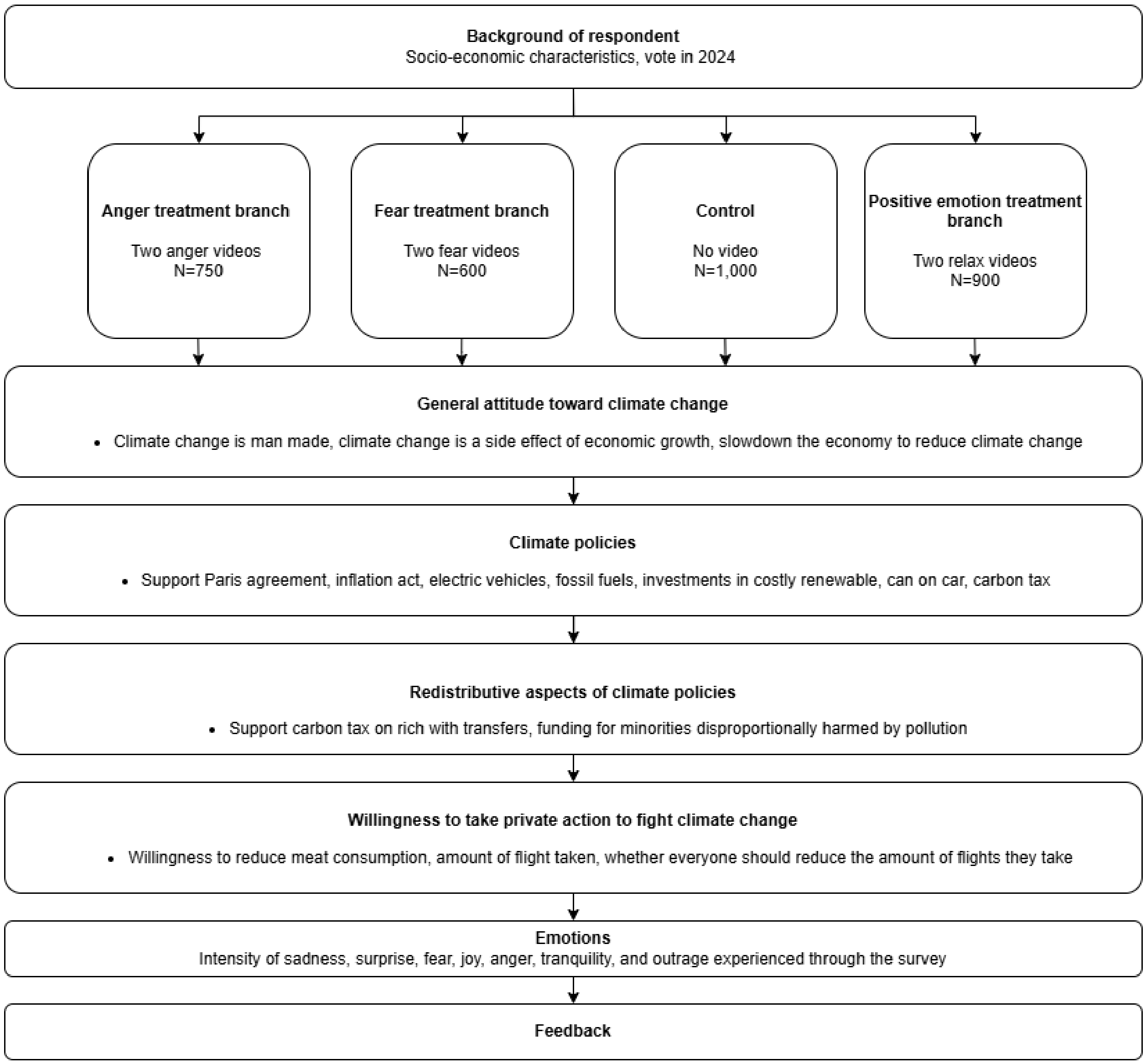
Redistributive Aspects of Climate Policies. Preferences for redistributive climate policies are assessed by measuring respondents' support for a redistributive carbon tax and increased assistance to minorities disproportionately harmed by pollution.

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 2.2.3.

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 2.2.3.

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.

Appendix Table A30 shows that our treatment assignment is balanced across socio-demographic characteristics as well as political affiliation.

2.2.3 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.

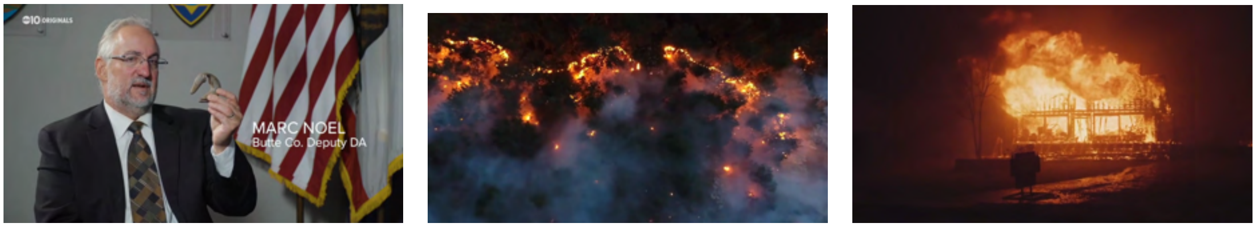
The negative treatment similarly comprises two videos. The first video emphasizes government corruption and corporate negligence by focusing on a wildfire caused by PG&E's failure to maintain aging electrical equipment, resulting in 84 corporate homicide charges. It vividly illustrates the resulting 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

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

3.1 Emotional Expressions of Citizens : Analyzing Tweets on policy issues

Distribution of emotions by topic. Figure 6 presents the distribution of emotions expressed in tweets across the various policy topics covered in Survey A, contrasting a random Twitter user sample (panel 6a) with a partisan sample (panel 6b). Strikingly, anger emerges as the dominant emotion across all policy issues in both samples, highlighting its pervasive role in citizens' discourse. Abortion, democracy, and immigration consistently evoke the highest levels of anger in both user samples. Conversely, trade appears to elicit relatively lower levels of anger. Partisan users generally exhibit a more diverse emotional palette compared to random users, reflecting deeper emotional engagement linked to partisan identities.

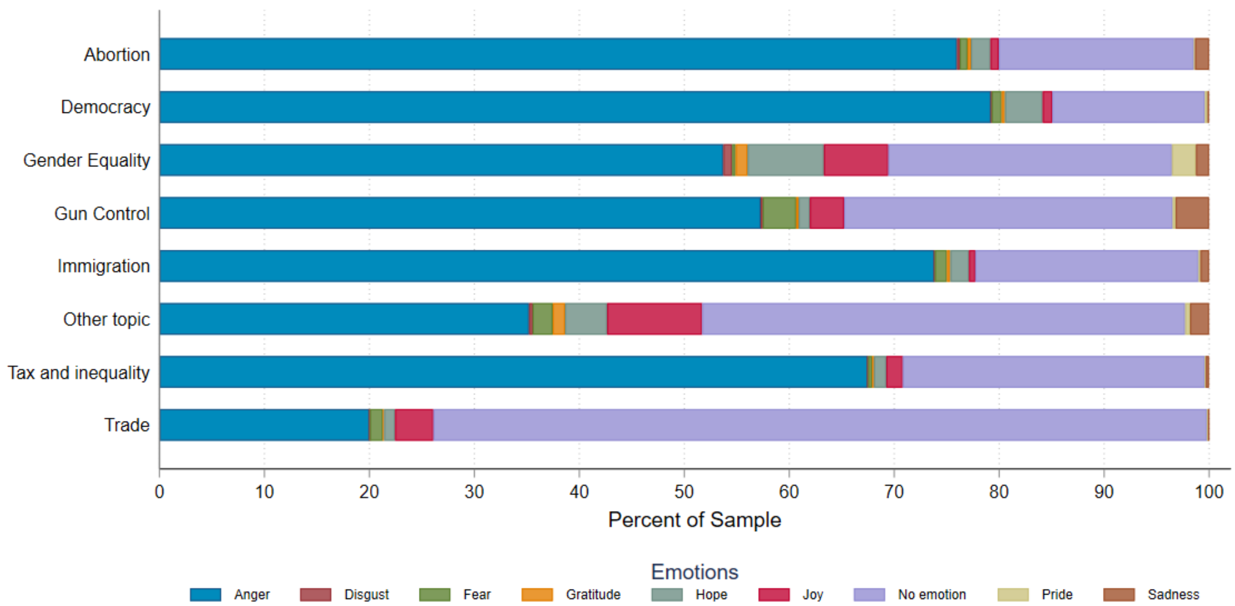
Evolution of emotions. Figure 7 illustrates the evolution of emotional expressions in citizens' tweets about the policy issues detailed previously in Figure 6.[8] The most striking result is the sharp and sustained increase in the share of tweets expressing anger, rising by approximately 40 percentage points in both the random and partisan samples over the observed period. Concurrently, the proportion of tweets without any emotional content has substantially declined, falling from around 60% to approximately 30% in the random sample, and from roughly 58% to below 20% in the partisan sample. In contrast, the prevalence of other emotions has remained largely stable. Positive emotions consistently account for less than 10% of tweets in both samples throughout the entire period.

Figure 8 illustrates the evolution of emotions and their nature in discussions on the key policy issue covered in Survey B, namely, climate change. While this topic was mostly unemotional at the beginning of the period, anger expressed about climate change doubles between 2013 and 2023, a result that is consistent

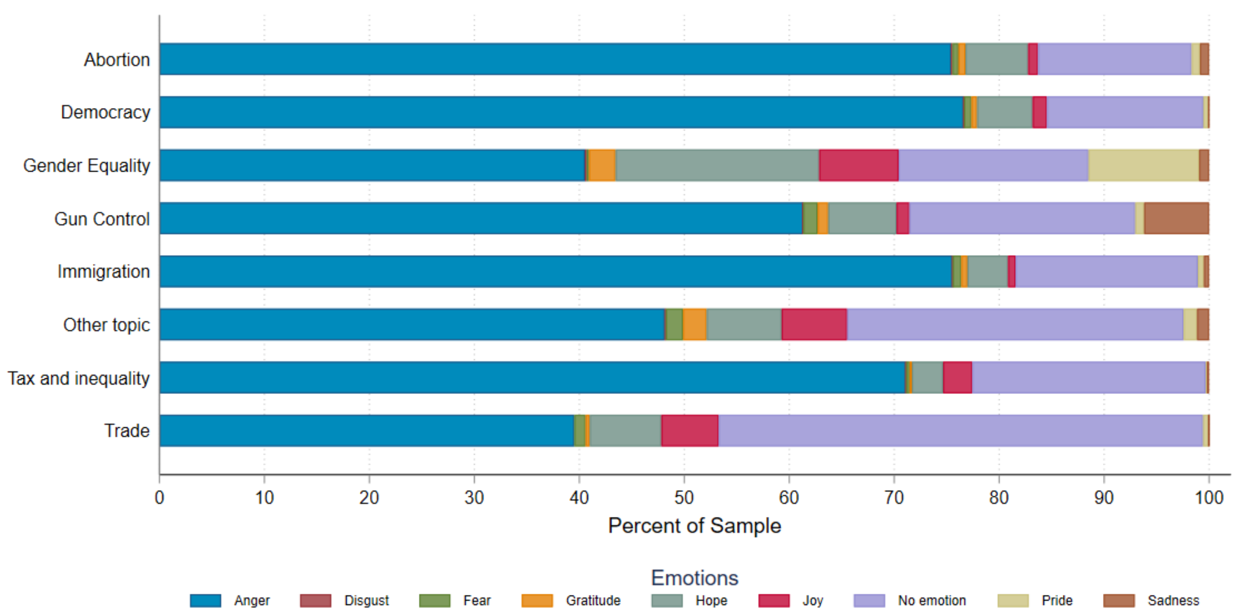
[8]Except the category "Other topic" that is excluded in Figure 7.

Figure 6: Emotional content of citizens' tweets on policy issues

(a) Random twitter users sample



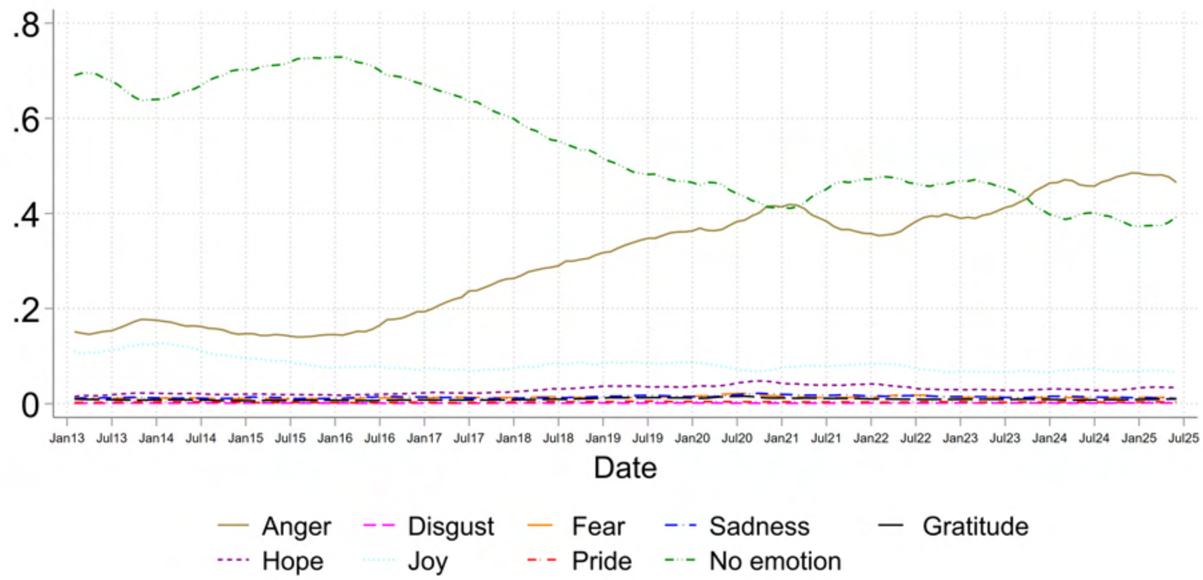
(b) Partisan citizens sample



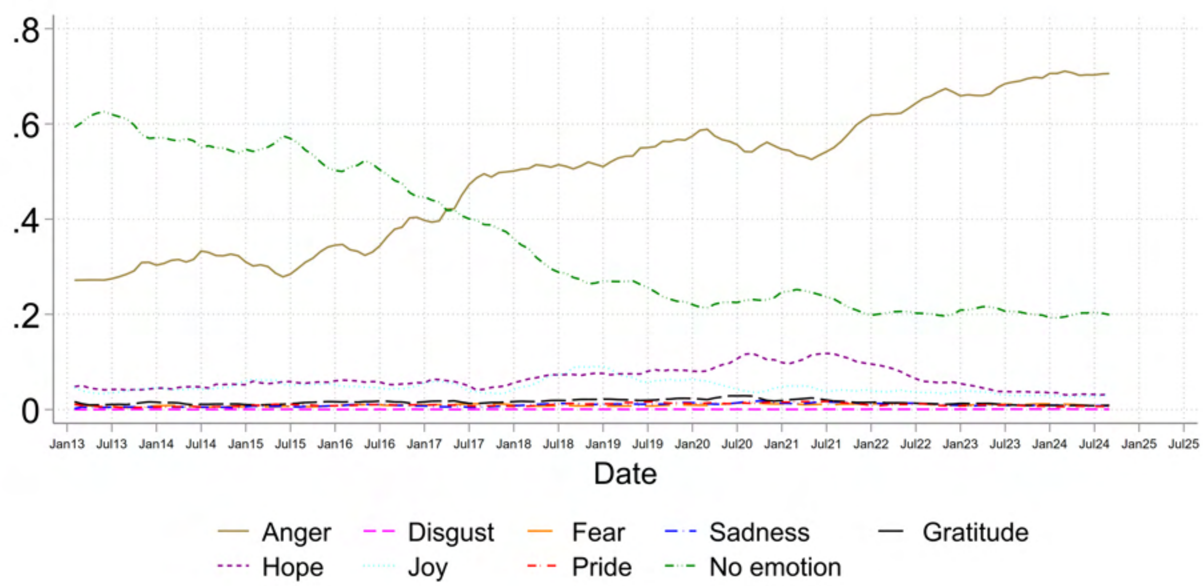
Notes. The figure shows the share of tweets by emotion for each policy topic for the period 2013-2025. The numerator represents the number of tweets by X users that express a given emotion within a specific topic, while the denominator is the total number of tweets by X users on that topic.

Figure 7: Evolution of Emotional Content in Citizens' Tweets

(a) Random twitter users sample

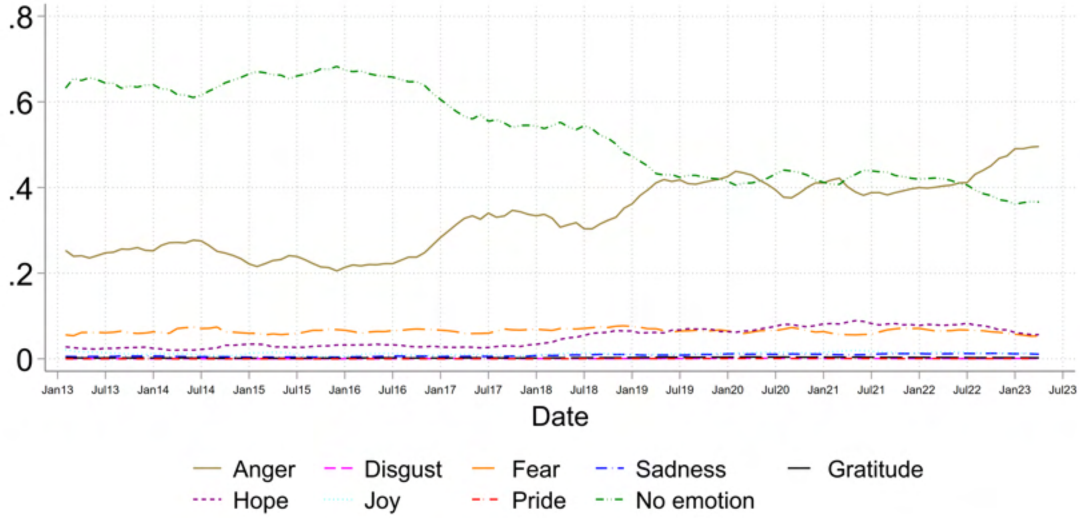


(b) Partisan citizens sample



Notes. The figure shows, for each month from January 2013 to June 2025, the share of tweets classified under each emotional tone. The numerator represents the number of tweets by X users in a given month that are classified in a specific emotion category, while the denominator is the total number of tweets by X users in that month. For readability, the graph displays a 6-month moving average of monthly percentages. The sample is restricted to tweets by citizens or partisan users whose primary topic is one of the following: 'abortion', 'democracy', 'gender equality', 'gun control', 'immigration', 'tax and inequality', or 'trade'. The category 'other topic' is excluded.

Figure 8: Evolution of Emotional Content in Tweets on Climate Change



Notes. The figure shows, for each month from January 2013 to April 2023, the share of tweets classified under each emotional tone for climate change-related tweets. The numerator represents the number of tweets by X users in a given month that are classified in a specific emotion category, while the denominator is the total number of tweets by X users in that month. For readability, the graph displays a 6-month moving average of monthly percentages. The sample is restricted to tweets about climate change.

with what we observe on the other policy issues presented above. At the same time, the overall level of fear about climate change has not significantly changed. The rise in anger 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.

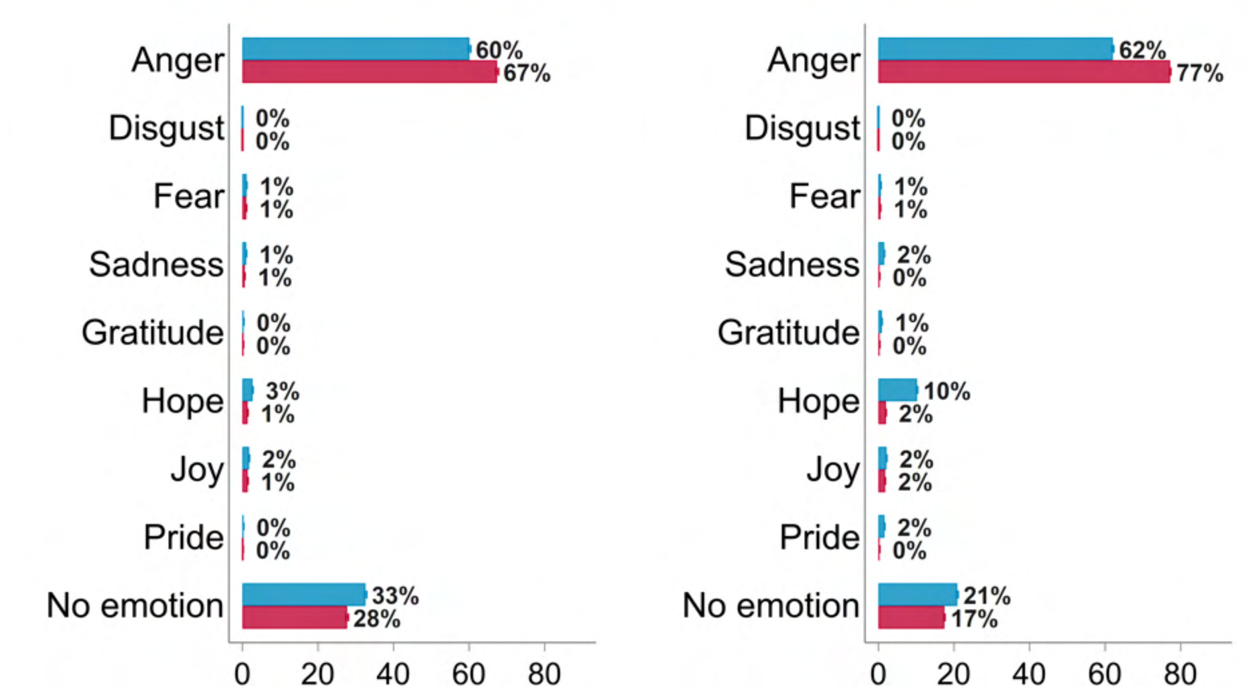
3.2 Emotional Expressions of Citizens by Political Affiliation

Distribution of emotions by political affiliation. Figure 9 presents the distribution of tweets by emotional category, separately for users affiliated with each party. As in Figure 6, we restrict the sample to tweets whose primary topic is one of the policy issues covered in Survey A. In the random Twitter users sample, only 28 % of tweets by Republican-affiliated users and 33 % of tweets by Democratic-affiliated users are classified as having no detectable emotion. These shares fall to 17 % and 21 % , respectively, in the partisan sample. Across both samples, anger is by far the most common emotion. In the random sample, 67 % of emotionally-charged tweets by Republicans express anger, compared to 60 % among Democrats; these figures rise to 77 % and 62 % in the partisan sample. Other emotions are relatively rare: disgust, fear, sadness, gratitude, joy, and pride each account for less than 2 % of tweets in both groups. The only notable exception is hope among Democratic partisans, which appears in 10% of their tweets.

Evolution of emotions by political affiliation. Finally, Figure 10 illustrates the evolution of anger—the most prevalent emotion—among Democrat- and Republican-affiliated Twitter users. Panel 10a shows that, in the random-user sample, anger sharply increases among both groups starting around 2015–2016, rising

Figure 9: Emotional content of citizens' tweets by political affiliation

(a) Random twitter users sample (b) Partisan citizens sample

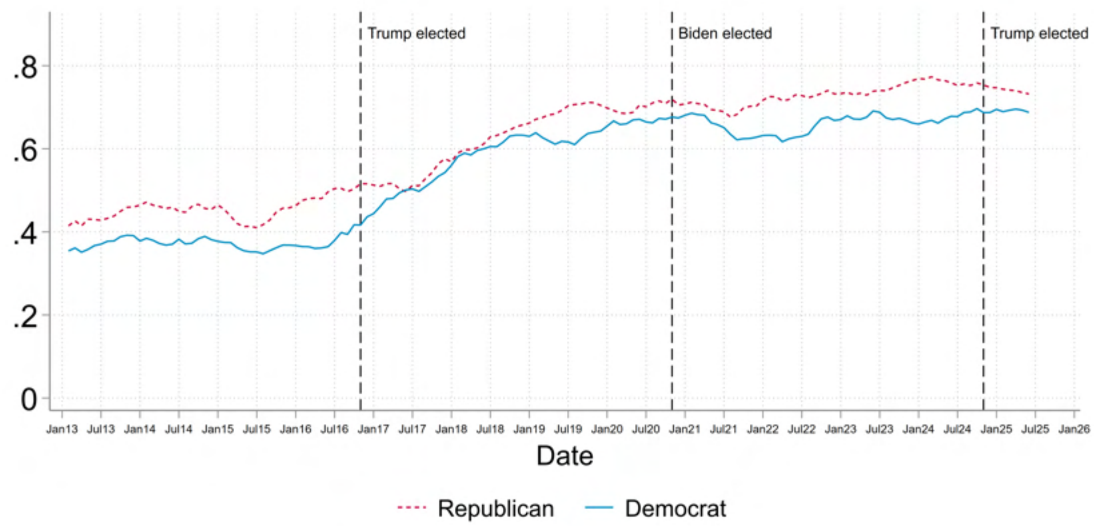


Notes. The figure shows, for each emotion, the share of tweets classified in a given emotional category by political affiliation. The numerator represents the number of tweets by X users within a given political affiliation classified in that emotion category, while the denominator is the total number 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'. The category 'other topic' is excluded. Appendix Figure A2 shows the partisan citizens sample panel disaggregated for each policy topic.

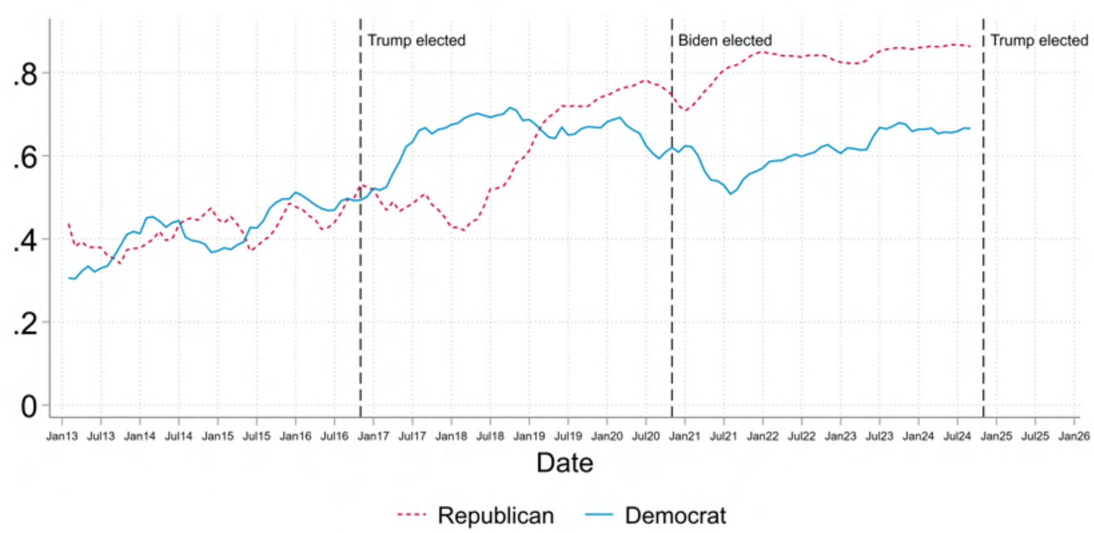
from approximately 40% to nearly 70%. Panel 10b presents the partisan-user sample, which exhibits more pronounced differences across parties. Among Democratic partisans, anger increases significantly following Trump's election in November 2016. Subsequently, anger declines among Democrats when Biden is elected in November 2024 but increases markedly among Republicans, reflecting clear partisan dynamics in emotional expression tied directly to political outcomes. This pattern strongly suggests that the LLM used to classify emotions effectively captures meaningful variations in political sentiment over time.

Figure 10: Evolution of Anger in Citizens' Tweets by Political Affiliation

(a) Random twitter users sample



(b) Partisan citizens sample



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. For readability, the graph displays a 6-month moving average of monthly percentages. The sample is restricted to citizens' tweets whose primary topic is either 'abortion', 'democracy', 'gender equality', 'gun control', 'immigration', 'tax and inequality' or 'trade'. The category 'other topic' is excluded. Appendix Figure A3 shows the partisan citizens sample for others emotions.

4 The Supply Side of Emotions: The Rise of Emotional Political Rhetoric

4.1 Emotional Expressions of Political Communication: Analyzing Tweets and Speeches

Distribution of emotions by topic. Figure 11 analyzes the distribution of emotional expressions across various policy topics in political communications, including official party tweets (panel 11a), congressional tweets (panel 11b), congressional floor speeches (panel 11c), and campaign speeches (panel 11d). A striking observation is the alignment between the emotional content (”supply”) from political actors and the emotional responses (”demand”) expressed by citizens, as shown previously. Indeed, anger is consistently the most prominent emotion in political rhetoric across all forms of communication, mirroring citizen sentiment. Furthermore, anger is particularly prevalent in discussions surrounding abortion and immigration across all four types of political communication. These findings suggest that political and citizen discourses mutually reinforce emotional narratives, contributing to heightened emotional intensity in public debates on policy issues.

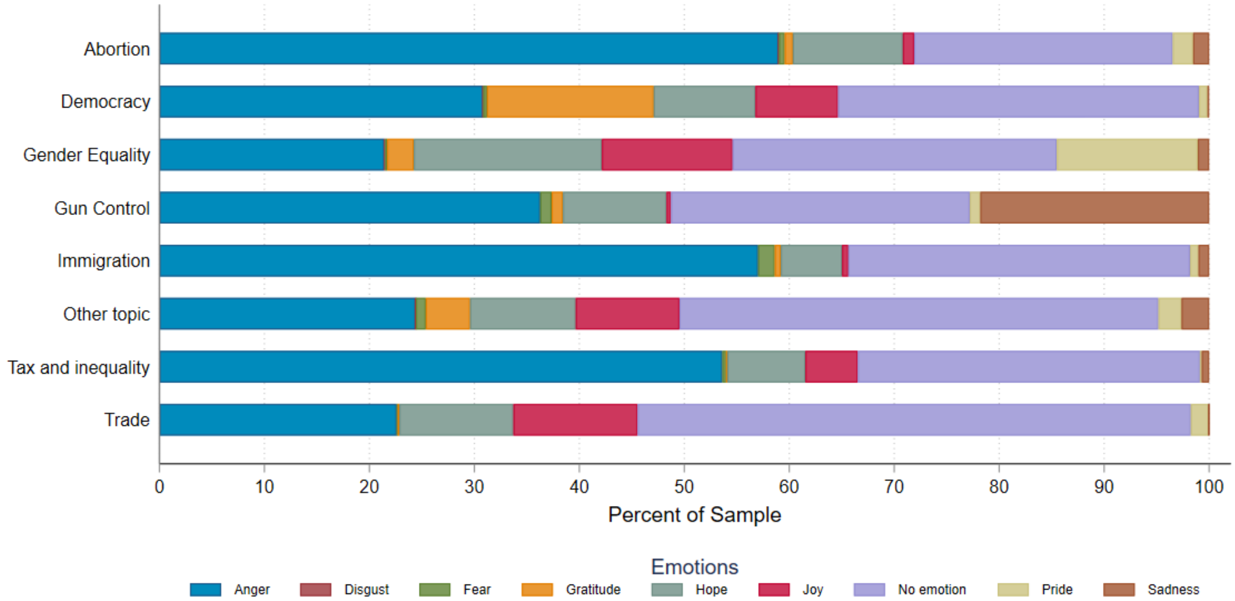
Yet, a notable difference from citizens' tweets is that, despite the overall dominance of anger, political discourse frequently incorporates expressions of hope. This likely reflects strategic rhetorical choices during critical moments, such as election campaigns, when politicians aim to mobilize and inspire voters. Furthermore, certain emotions exhibit clear topic-specific patterns: notably, about 20% of political communications on gun control consistently express sadness across all samples.

Evolution of emotions. Figure 12 illustrates the evolution of emotional content in political communication across three distinct samples: official tweets from political parties (panel 12a), tweets from congress members (panel 12b), and congressional floor speeches (panel 12c). Consistent with the patterns observed among citizen tweets, the proportion of political communications devoid of emotional content significantly declined over the decade, falling from approximately 55% in 2014 to around 30% in 2024 in panel 12a. This reduction is more pronounced in congress members' tweets (panel 12b), while somewhat more muted in their floor speeches (panel 12c), suggesting strategic differences in emotional communication online versus offline.

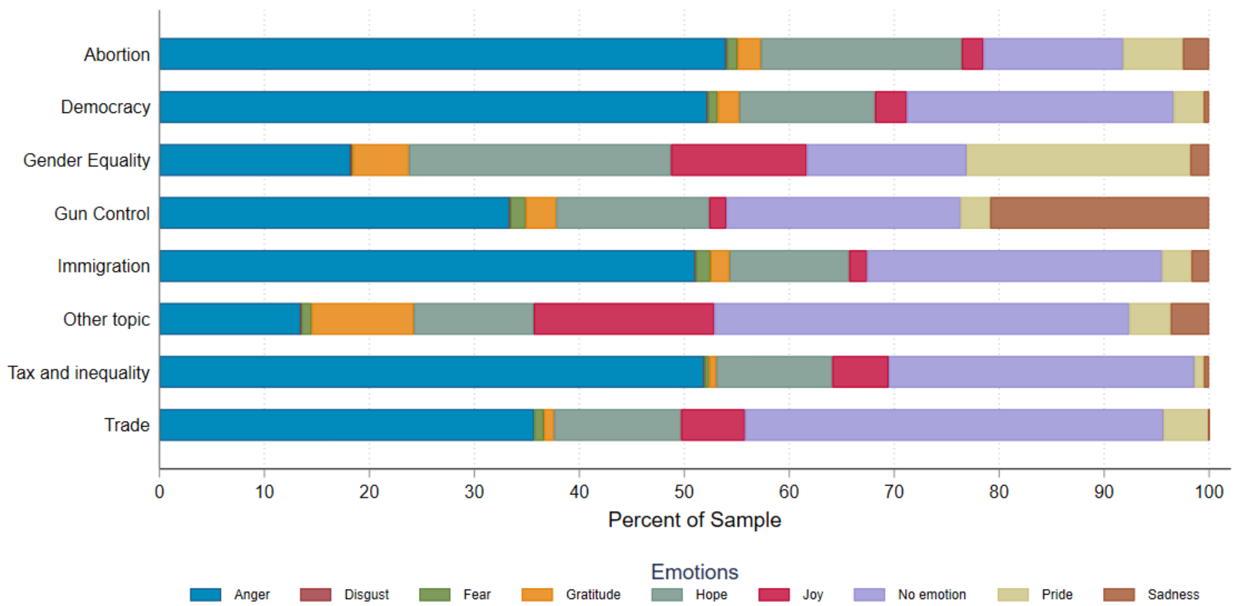
Simultaneously, expressions of anger steadily increased across all samples, underscoring the growing emotional intensity of political discourse. Specifically, anger in official party tweets rose markedly from about 35% in early 2014 to nearly 60% by 2024 (panel 12a. Similarly, congress members' tweets saw anger increase substantially, from roughly 30% to above 50% in the same period (panel 12b). Although floor speeches display a lower overall level of anger remaining below 40% over the period (panel 12c) , they still exhibit a clear upward trajectory. These patterns indicate a convergence toward increasingly emotionally charged political messaging, particularly in online platforms where emotional rhetoric appears especially amplified.

Figure 11: Emotional content of political communications on policy issues

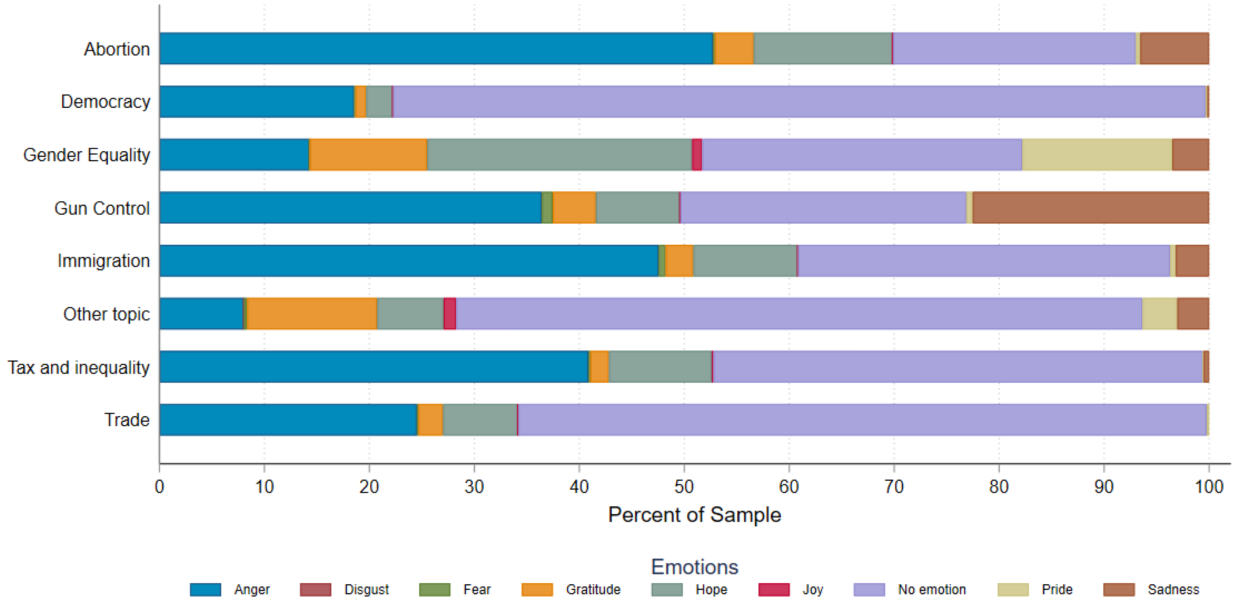
(a) Official Tweets



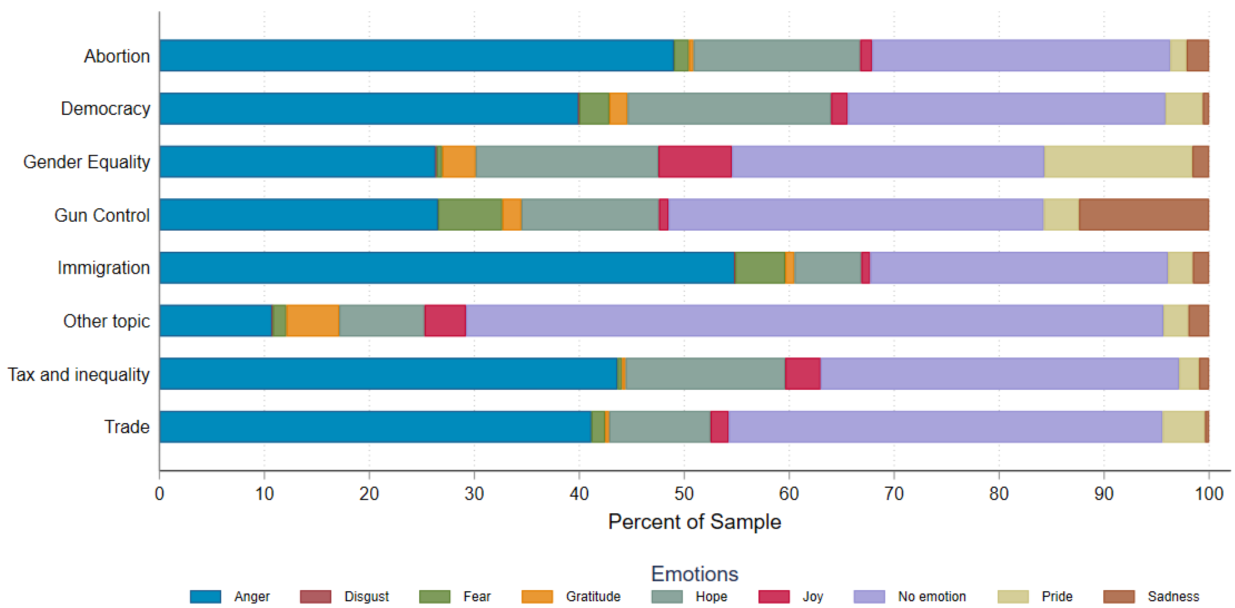
(b) Congressional tweets



(c) Congressional floor speeches



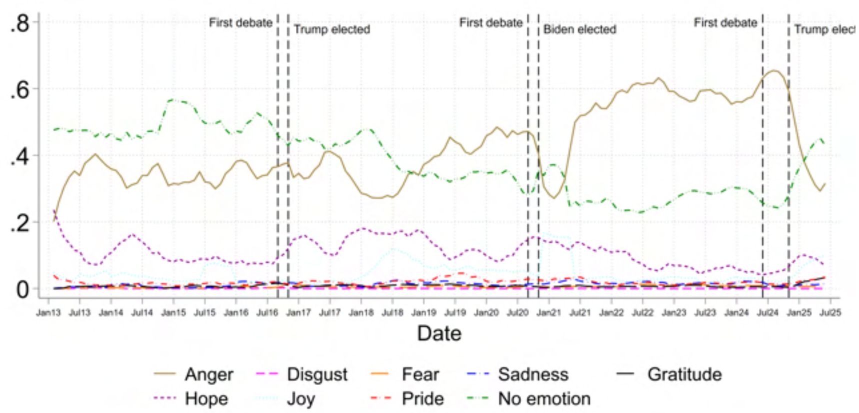
(d) Campaign speeches



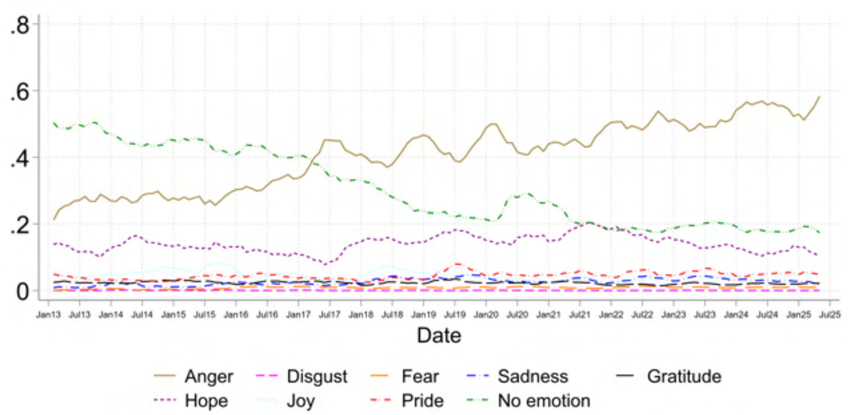
Notes. The figure shows the share of tweets or speech segments by emotion for each policy topic for the period 2013-2025. The numerator represents the number of tweets or speech segments that express a given emotion within a specific topic, while the denominator is the total number of tweets or speech segments on that topic.

Figure 12: Evolution of Emotional Content in Political Communication

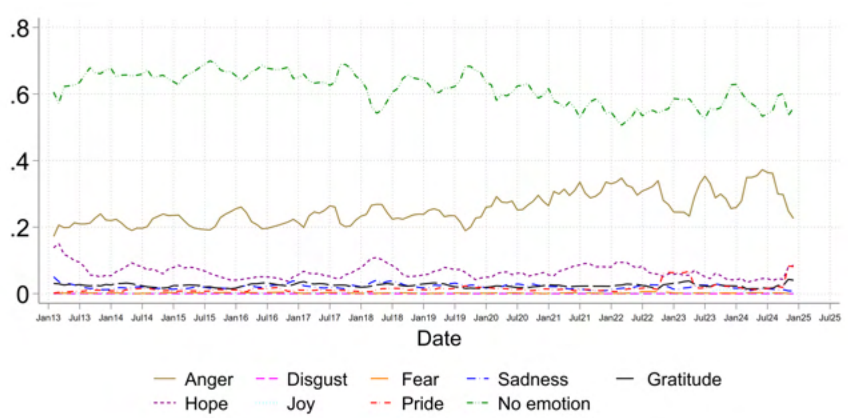
(a) Official Tweets



(b) Congressional Tweets



(c) Congressional Floor Speeches



Notes. The figure shows, for each month from January 2013 to June 2025, the share of tweets classified under each emotional tone. The numerator represents the number of tweets by X users in a given month that are classified in a specific emotion category, while the denominator is the total number of tweets by X users in that month. For readability, the graph displays a 6-month moving average of monthly percentages. The sample is restricted to tweets by citizens or partisan users whose primary topic is one of the following: 'abortion', 'democracy', 'gender equality', 'gun control', 'immigration', 'tax and inequality', or 'trade. The category 'other topic' is excluded. We didn't include the graph with campaign speeches given the short time coverage (2023-2024).

4.2 Emotional Expressions of Political Communication by Political Affiliation

Distribution of emotions by political affiliation. We next examine the emotional content of political communication by party affiliation across all four samples in Figure 13. Once again, the overall pattern closely mirrors that observed in citizen tweets and remains consistent across communication formats. Panel 13a shows that 38% of Democratic Party official tweets and 36% of Republican Party official tweets are classified as non-emotional. This share decreases slightly in congressional tweets and campaign speeches (panels 13b and 13d), and increases significantly in congressional floor speeches (panel 13c), where around 60% of all messages are classified as non-emotional for both parties.

There are also notable differences in the types of emotions expressed by each party. Across all samples, anger emerges as the dominant emotion, but more likely so in Republican communication. For instance, in campaign speeches (panel 13d), 61% of Republican statements express anger, compared to just 32% among Democrats. In contrast, Democratic communication is more likely to contain positive emotions—particularly hope and joy. In official party tweets (panel 13a), 14% of Democratic tweets express hope and 9% express joy, compared to 6% and 5% respectively among Republicans. The contrast is most striking in campaign speeches (panel 13d), where 29% of Democratic statements express hope—more than three times the share observed for Republicans (9%). This consistent divergence in emotional tone underscores distinct rhetorical strategies across parties, with Republican communication leaning more heavily on negative affect, and Democratic messaging incorporating a more positive appeals.

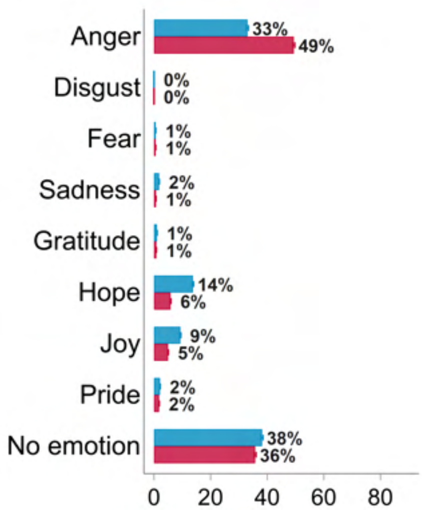
Evolution of emotions by political affiliation. Figure 14 disaggregates the evolution of anger by party affiliation across the three samples. Two main patterns emerge. First, anger expressions consistently align with shifts in executive power: during Trump's presidency (2016–2020), Democrats exhibited a higher share of anger messages across all samples, while this pattern reversed under the Biden administration (2020–2024), with Republicans displaying greater levels of anger. This finding echoes Gennaro and Ash, 2022, who document heightened emotionality among the opposition party.

Second, changes in presidential leadership serve as key inflection points in the expression of anger among the party losing executive power. Democratic anger rose markedly following Trump's election in 2016, while Republican anger remained relatively stable—or even declined in the case of official tweets (panel 14a). A similar pattern is observed following Biden's election in 2020, with a surge in Republican anger and a decline in Democratic anger in the same panel. Note that within presidential terms, we observe further fluctuations. Republican anger began to decline in congressional floor speeches (panel 14c) after the party regained control of the House in 2022, though it remained consistently higher than Democratic anger throughout Biden's term.

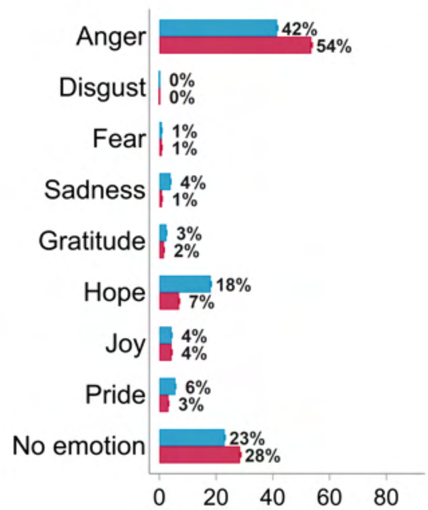
These patterns closely mirror the trends observed among partisan citizens (Figure 10b), once again suggesting a strong alignment between citizens' emotional expressions (demand side) and political communication (supply side). The consistency of these dynamics across both groups reinforces the validity of the anger classification, as it reliably tracks major political events and shifts in partisan status.

Figure 13: Emotional content of political communications by political affiliation

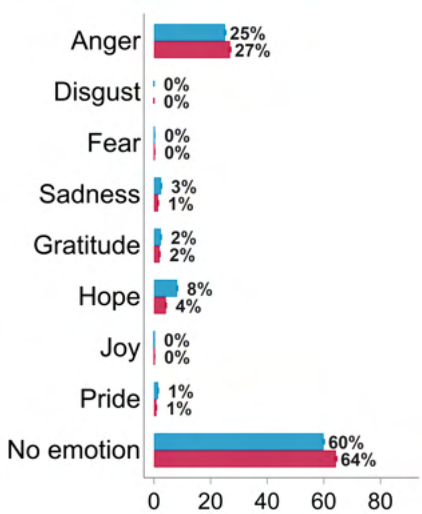
(a) Official Tweets



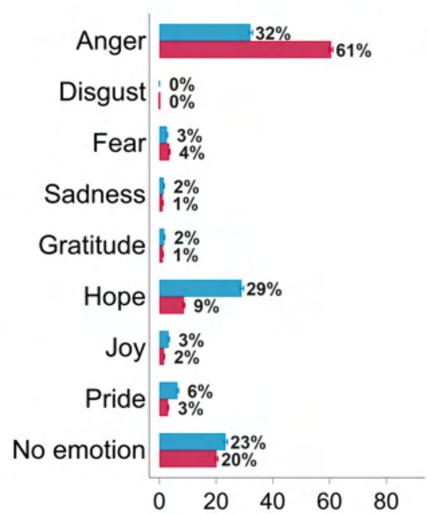
(b) Congressional Tweets



(c) Congressional Floor Speeches



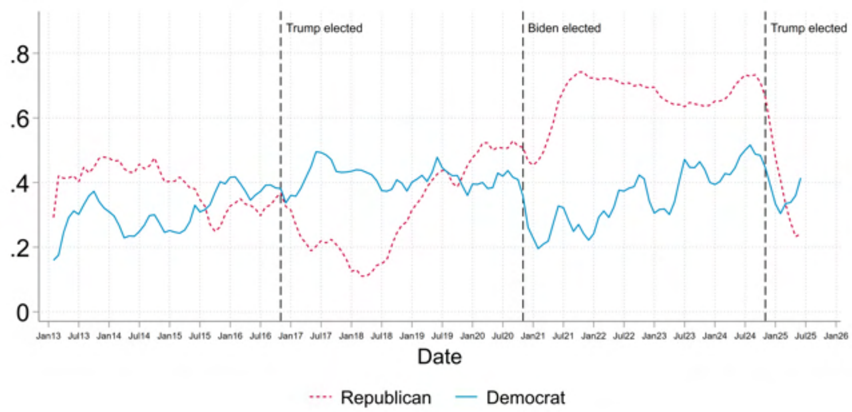
(d) Campaign Speeches



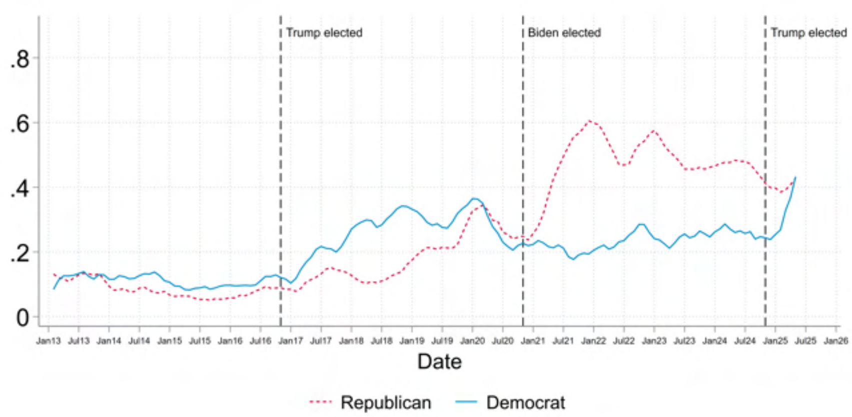
Notes. The figure shows, for each emotion, the share of tweets or speeches' segment classified in that emotional category for Democrat and Republican leaning. The numerator represents the number of tweets or segments classified in that emotion category, while the denominator is the total number of tweets or segments with a Democrat or Republican leaning. The sample is restricted to tweets whose primary topic is either 'abortion', 'democracy', 'gender equality', 'gun control', 'immigration', 'tax and inequality' or 'trade'. The category 'other topic' is excluded.

Figure 14: Evolution of Anger in Political Communication by Political Affiliation

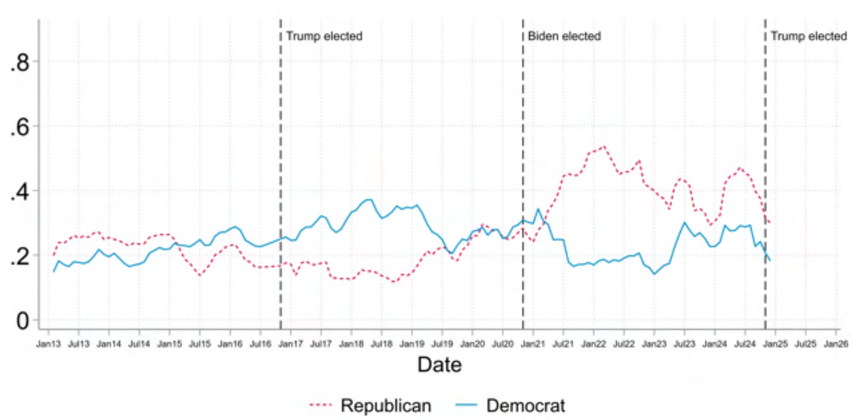
(a) Official Tweets



(b) Congressional Tweets



(c) Congressional Floor Speeches



Notes. The figure shows, for each year, the share of tweets or speech segments classified as anger by political affiliation. The numerator represents the number of tweets or speech segments within a given political affiliation in which the predominant emotional tone is anger, while the denominator is the total number of tweets or speech segments 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'. The category 'other topic' is excluded. We didn't include the graph with campaign speeches given the short time coverage (2023-2024).

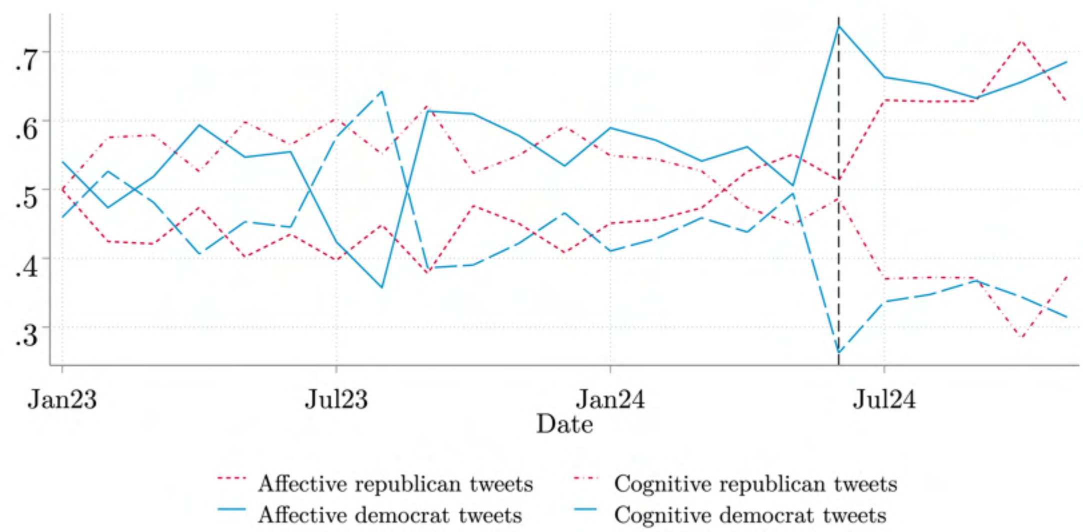
4.3 The strategic supply of emotions by political parties

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 15). Notably, this increase in emotionality appears similar across both parties, suggesting a strategic shift in communication tactics as the election approached.

FIGURE 15: 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 using both open-ended and closed-ended questions. 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 5.3, 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

5.1.1 Priming Open-Ended Questions

Part of the treatments involve asking respondents open-ended questions about their views on trade, immigration, taxation and redistribution, and democracy. These questions were framed in a priming way – either positively, neutrally, or negatively. It is interesting to briefly consider the answers to these questions to get a sense of which specific issues make people angry or optimistic about a policy.

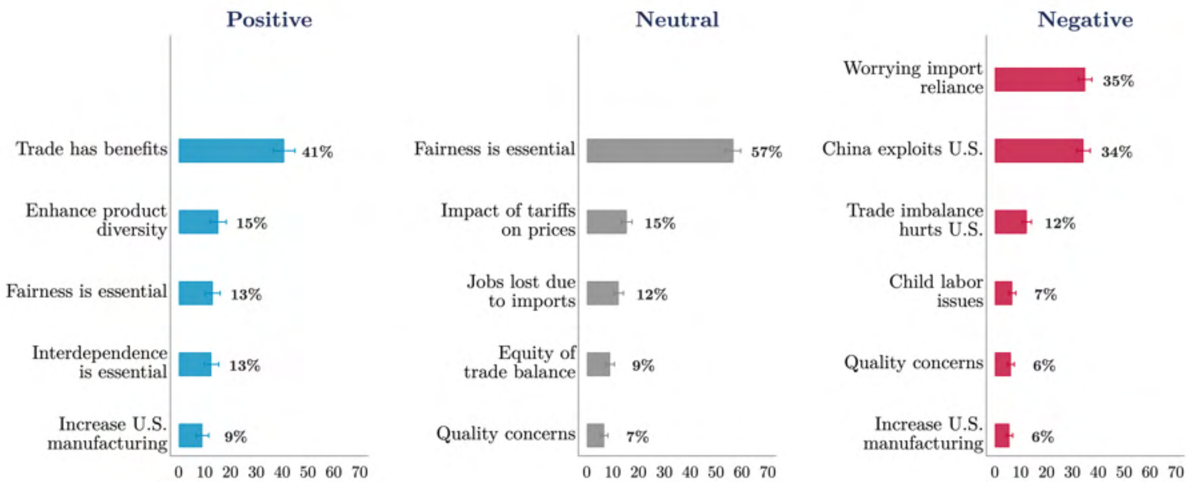
Thoughts about trade When asked the positively framed question, 41% of classifiable responses conveyed optimism regarding the gains from trade. By contrast, 57% of responses to the neutral prompt emphasized the importance of fairness. The predominant themes prompted by the negatively framed question were concerns about reliance on foreign goods (35%) and perceptions that China takes advantage of the U.S. (34%).

Secondary themes further illustrate the effects of framing. Positive framing led respondents to mention that trade facilitates access to diverse products (15%), the importance of fair trade agreements (13%), and global interdependence (13%). Under neutral framing, responses often noted that tariffs raise prices (15%) but, interestingly, also that jobs are lost due to imports (12%). Negative framing prompted mentions of trade imbalances harming the U.S. economy (12%).

Together, these results demonstrate that positive framing encourages respondents to express optimism about trade and highlight its benefits; neutral framing brings forth mixed concerns; and negative framing evokes anxiety over the consequences of trade.

Thoughts about immigration Under positive framing, 34% of respondents expressed concern that illegal immigration is a growing issue that requires control; neutral framing elicited calls to stop illegal immigration in 35% of responses, while 31% of those responding to negatively framed prompts mentioned a fear of criminals entering the country. Interestingly, and in contrast to trade, the most frequently mentioned theme regarding immigration is similar across framings—but differs in how strongly it emphasizes the urgency of immigration control.

Figure 16: Classification of open-ended questions on trade by framing



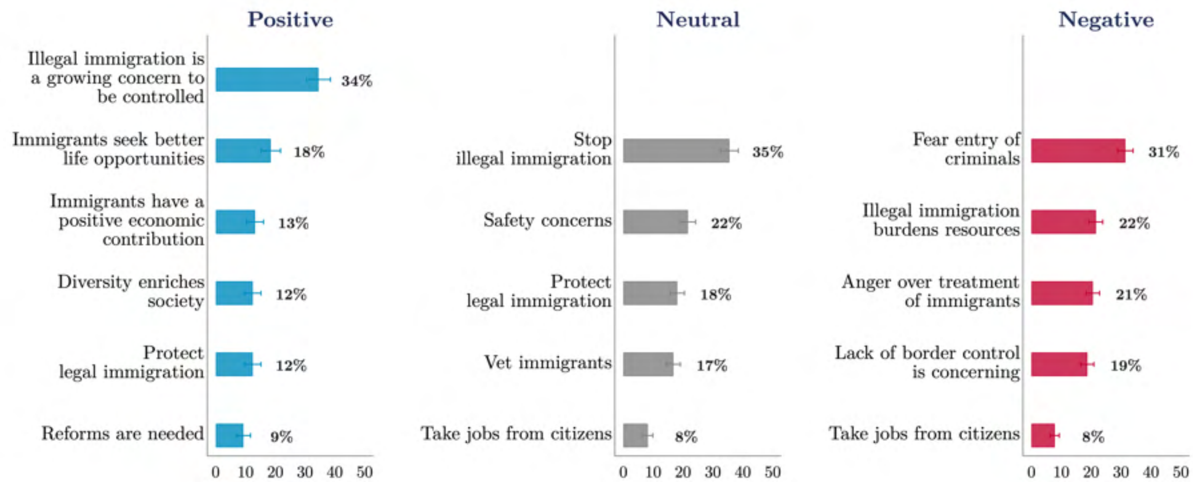
Notes. This figure displays the classification of respondents' answers into the five or six most popular topics. Frequency shares sum to 100% within each framing (positive, neutral, and negative) and are conditional on responses that were successfully classified. The share of unclassified responses over the total is 46% for the positive framing, 42% for the negative framing, and 47% for the neutral framing. The classification is fully unsupervised and it is obtained using GPT. Confidence intervals are displayed at the 90% significance level.

Other themes also emerged. Positive framing elicited reflections on the idea that immigrants seek better opportunities (18%), contribute positively to the economy (13%), and enriches the culture and society (12%). Neutral framing brought out concerns about burdens on safety (22%), that legal immigration should be easier (18%), and that immigrants should be vetted before entry (17%). Under negative framing, 22% of responses mention the burden on resources created by illegal immigration, 19% raised concerns over a lack of border control, while 17% mentioned anger or frustration regarding how immigrants are treated. These secondary thoughts show that positive framing is associated with integrative views toward immigration, whereas neutral and negative framings more often emphasized control, security, and competition over resources.

Thoughts about taxation and redistribution Open-ended answers are dominated by concerns about inequality. 35% of responses prompted by the positive framing expressed not much optimism about wealth distribution. 59% of responses to the neutral prompt identified income inequality as a major concern, and 42% of negatively framed responses highlighted that the rich get richer while the poor get poorer. As with immigration, the most frequently cited theme is similar across all three framings; however, its prevalence varies significantly, with the neutral framing far more likely to elicit explicit concerns about inequality. This variation underscores the importance of examining the secondary themes prompted by the question.

Positive framing also prompted mentions of growing awareness of inequality that leads to change (26%), of success coming with hark work (18%), and of opportunities for upward mobility (17%). Neutral framing led 17% of respondents to mention that everyone should have equal opportunities, and 11% to propose that taxes on the wealthy should increase. Negative framing prompted respondents to express that income inequality limits opportunities for upward mobility (26%), highlighted discontent with tax loopholes for the rich (20%) and with corporations prioritizing profits over employee welfare (8%). Digging into the less frequent theme mentioned, positive framing invites greater focus on mobility and fairness, while negative framing draws out

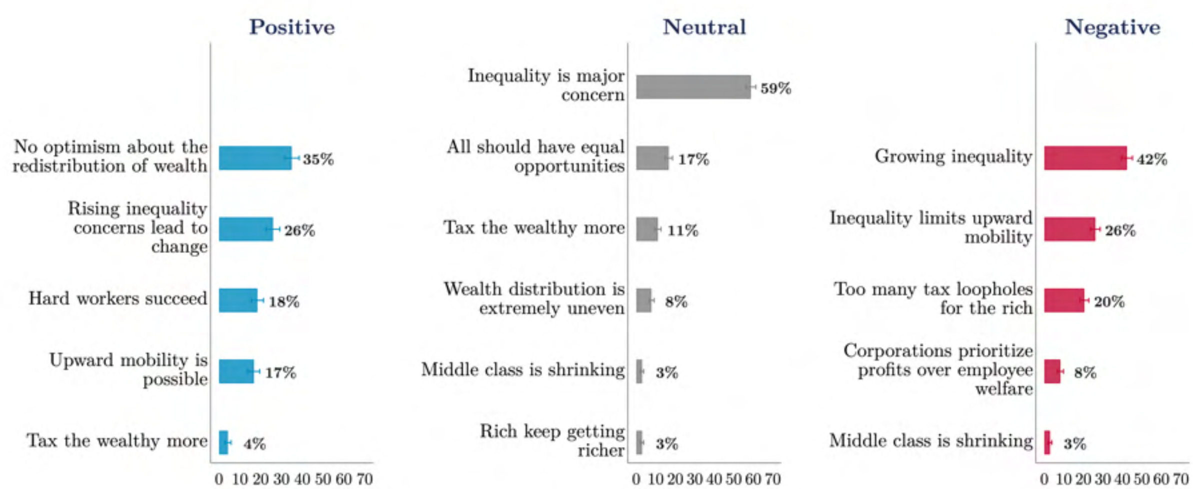
Figure 17: Classification of open-ended questions on immigration by framing



Notes. This figure displays the classification of respondents' answers into the five or six most popular topics. Frequency shares sum to 100% within each framing (positive, neutral, and negative) and are conditional on responses that were successfully classified. The share of unclassified responses over the total is 45% for the positive framing, 44% for the negative framing, and 55% for the neutral framing. The classification is fully unsupervised and it is obtained using GPT. Confidence intervals are displayed at the 90% significance level.

more system-critical narratives.

Figure 18: Classification of open-ended questions on taxation and redistribution by framing



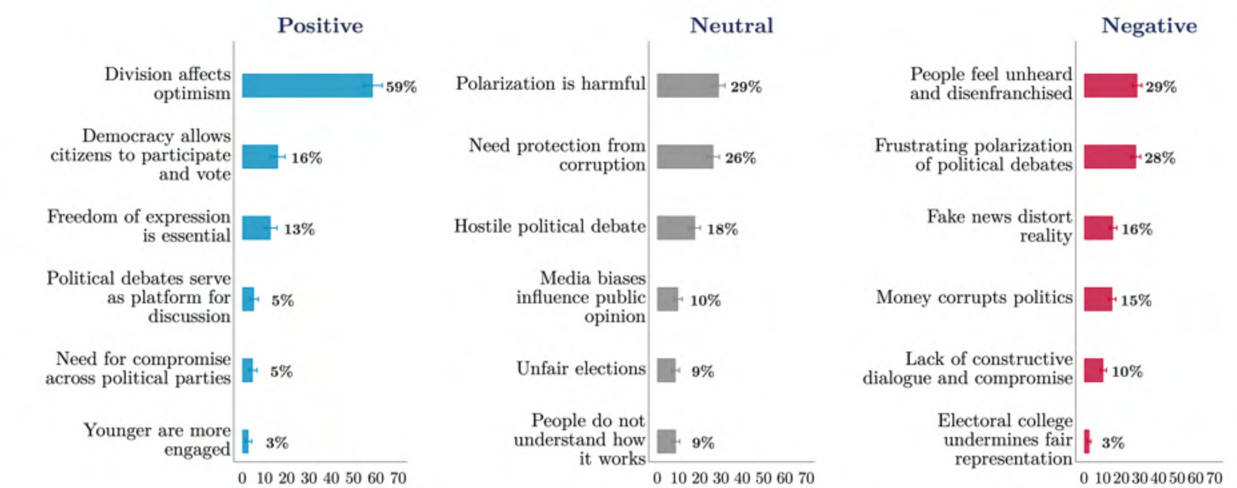
Notes. This figure displays the classification of respondents' answers into the five or six most popular topics. Frequency shares sum to 100% within each framing (positive, neutral, and negative) and are conditional on responses that were successfully classified. The share of unclassified responses over the total is 30% for the positive framing, 44% for the negative framing, and 34% for the neutral framing. The classification is fully unsupervised and it is obtained using GPT. Confidence intervals are displayed at the 90% significance level.

Thoughts about democracy and governance When asked about democracy and governance, respondents expressed concern about polarization and lack or representation. 59% of responses to the positively framed question stated that division in the country affects optimism about democracy, while 29% of responses to both neutral and negative framings cited political polarization and a sense of being unheard or disenfranchised.

Beyond this most cited theme, positive framing emphasized the role of democracy in enabling citizens' participation (16%) and the importance of free speech (13%). Neutral framing highlighted the need to protect democracy from corruption (26%) and a lack of respect in political debates (18%). Under negative framing, 28% of responses pointed to frustration with polarized political debates, and 16% mentioned the spread of misinformation.

These patterns suggest that while concerns about democratic erosion are shared across framings, positive framing encourages affirmation of democratic ideals, whereas neutral and negative framings elicit concerns about representation and trust.

FIGURE 19: CLASSIFICATION OF OPEN-ENDED QUESTIONS ON DEMOCRACY AND GOVERNANCE BY FRAMING



Notes. This figure displays the classification of respondents' answers into the five or six most popular topics. Frequency shares sum to 100% within each framing (positive, neutral, and negative) and are conditional on responses that were successfully classified. The share of unclassified responses over the total is 47% for the positive framing, 41% for the negative framing, and 57% for the neutral framing. The classification is fully unsupervised and it is obtained using GPT. Confidence intervals are displayed at the 90% significance level.

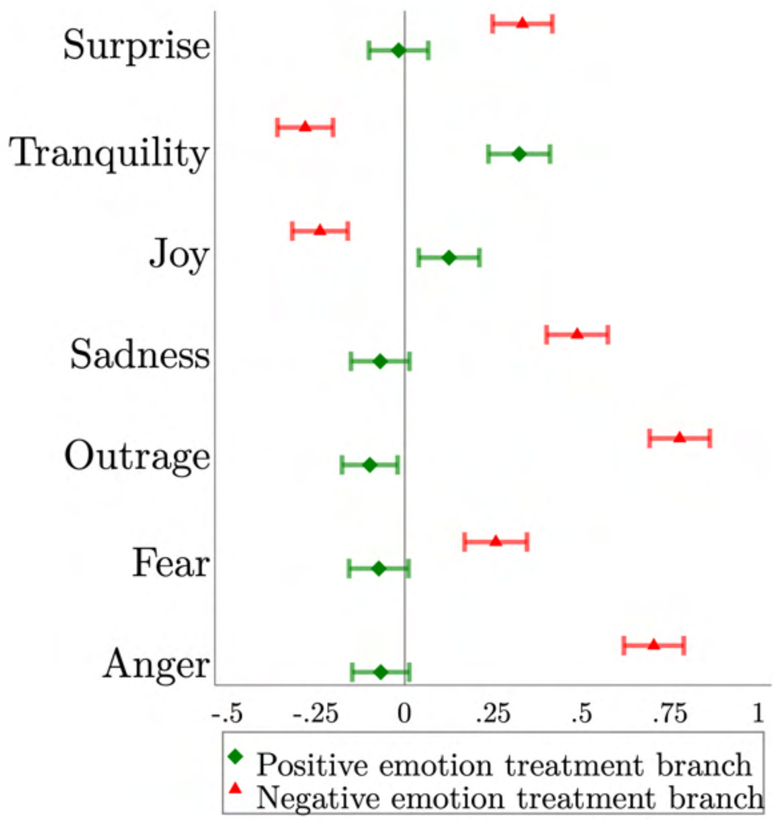
Open-ended responses about the topics we study reveal thus a wide range of perspectives, with clear variation across framing conditions.

5.2 Close-Ended questions

Second, after respondents were asked an open-ended question framed either positively, neutrally, or negatively, they were presented with a series of close-ended questions probing their views on trade, immigration, taxation and redistribution, and democracy.

Effects of the treatments on emotions. Figure 20 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.

Figure 20: 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.

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 21 depicts the effects of the treatments on perceptions and policy views for trade, immigration, redistribution, and democracy.[9] 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.3 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

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

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 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.

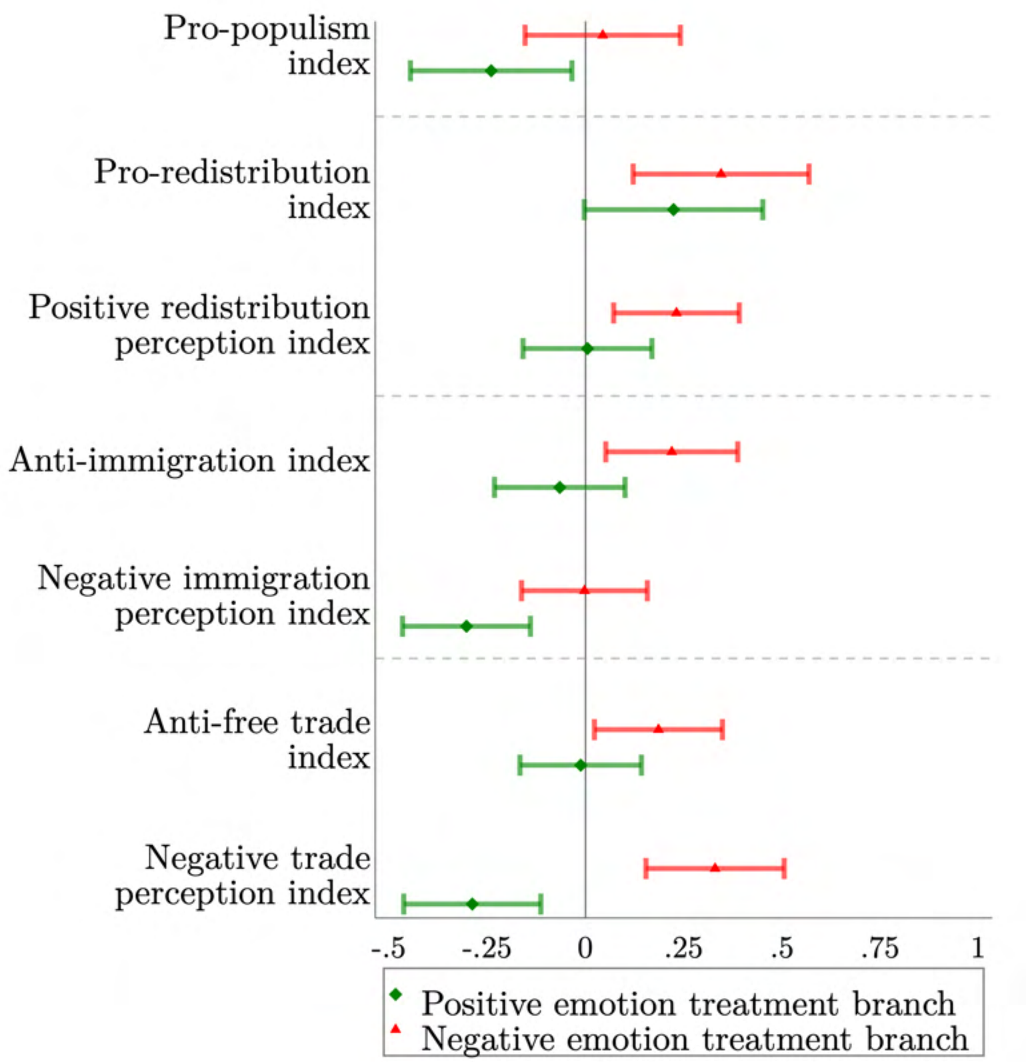
Similarly, Appendix Table A5 illustrates that the positive emotion treatment diminishes negative perceptions toward immigration, by an effect equivalent to 16% of the Harris-Trump voter gap, primarily because positively treated respondents are less likely to view immigration as a threat to the economy or cultural integrity.[10] 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.

[10] 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 21: 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.3 displays one table per index, presenting the variables composing each index. Confidence intervals are displayed at a 90% significance level.

5.3 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 22 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.

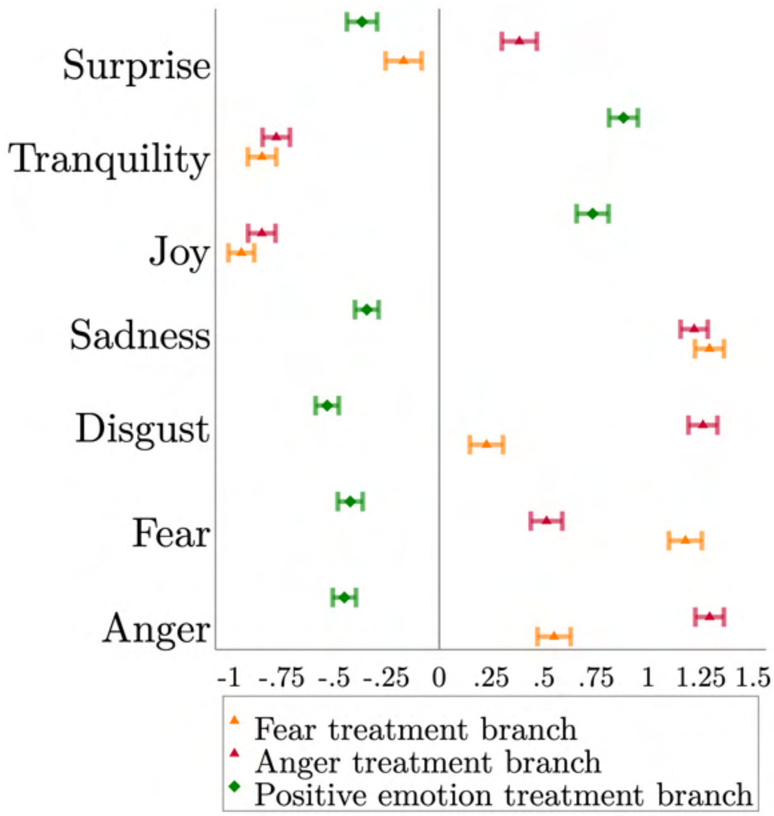
Effects on policy views. Figure 23 illustrates the effects of the anger and fear treatments on attitudes and policy preferences regarding climate change. Survey questions have been grouped into four distinct indices: general attitudes toward climate change, policy views on climate change, preferences 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.4 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.

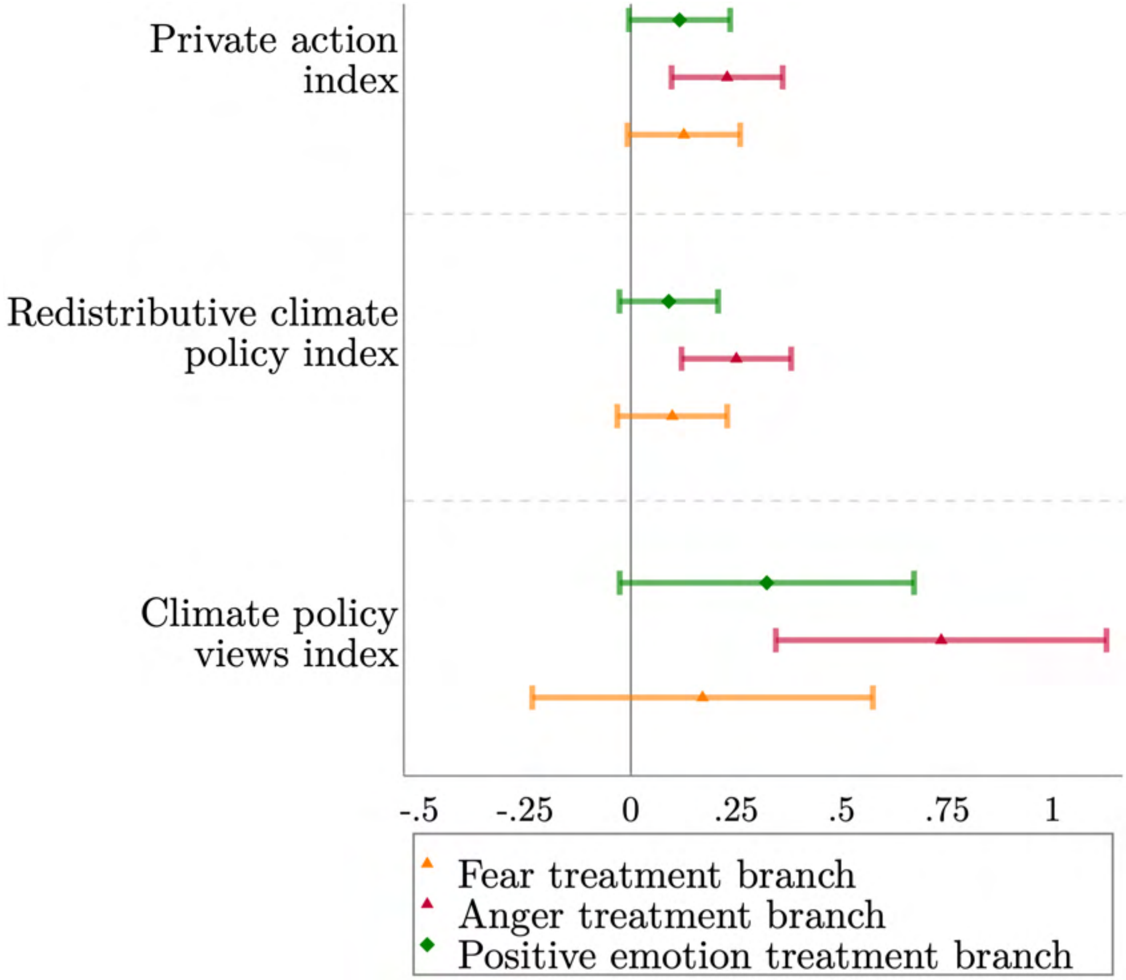
These findings highlight the need to distinguish the role different negative emotions: while fear and anger are both typically categorized as negative emotions, anger substantially shapes climate-related attitudes and policy views, whereas fear does not. Furthermore, positive emotions do not systematically produce effects opposite to those elicited by negative emotions.

Figure 22: 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 23: 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.4 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

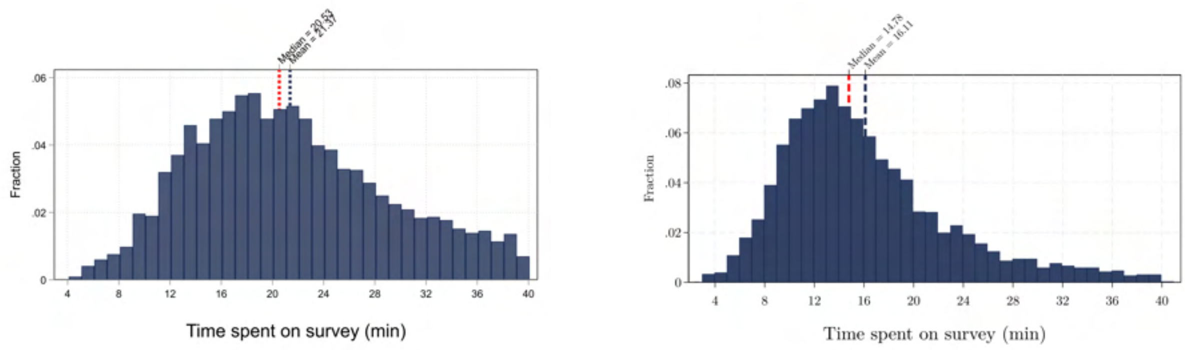
Table A1: Sample evolution

	Survey A		Survey B	
Survey Completion	**N**	**%**	**N**	**%**
Respondents who started the survey	9714	-	9904	-
Screened out (consent, age)	408	-	159	-
Respondents over quota or abandoning the survey	3566	-	940	-
Initial sample	5740	100 %	8805	100 %
Respondents failing 1st Attention Check	1147	20%	558	6%
Respondents failing 2nd Attention Check	325	6%	-	-
Respondents failing Video Technical Check	59	1%	772	9%
Completes	4209	73%	7475	85%
Respondents not watching full video	149	3%	1338	15%
Respondents failing video qualitative check	-	-	528	6%
Inattentive respondents manually dropped	322	6%	219	2%
Final Sample	3,738	65%	5390	61%

Notes. ‘Screened-out’ includes respondents who did not provide consent to participate, were younger than 18 or older than 75, or were not residing in the US at the time of the survey. ‘Respondents over quota or abandoning the survey’ includes those who could not complete the survey because their quota group was full, as well as those who voluntarily dropped out. ‘Respondents failing 1st Attention Check’ includes those who answered the first attention check question incorrectly. ‘Respondents failing 2nd Attention Check’ includes those who answered the second attention check question incorrectly. ‘Respondents failing Video Technical Check’ includes those unable to view the full video due to technical issues; this check applied only to the initial anger and relax video treatments, not the booster video. ‘Respondents not watching the full video’ includes those who spent less time on the video page than the actual duration of the video, excluding respondents already removed for inattentiveness. ‘Respondents failing the Video Qualitative Check’ includes those unable to correctly identify the video’s content from a set of 3–4 closed-ended options, excluding those already removed for inattentiveness or for not watching the full video. Finally, ‘Inattentive respondents manually excluded’ includes those removed for providing poor-quality, inconsistent, or repetitive responses to open-ended questions.

Figure A1: Distribution of time spent in the survey

Survey A **Survey B**



A.1.2 Details on framed questions.

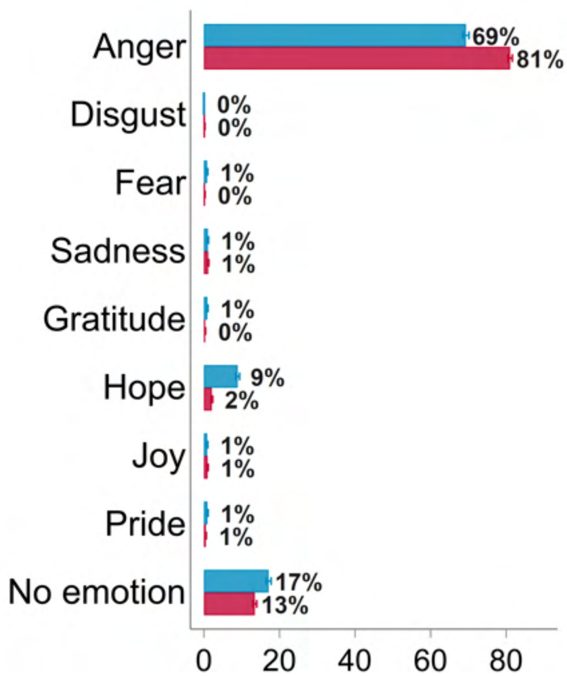
The exact wording of the framed policy open-ended questions is as follows:

- 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?

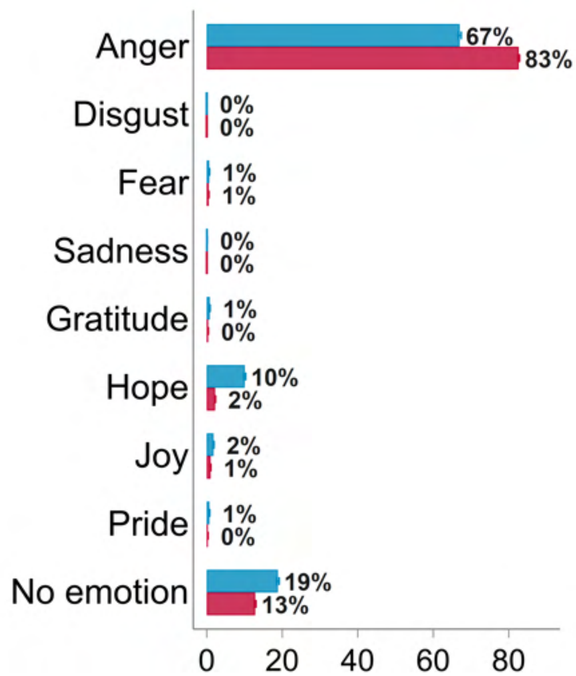
A.2 Demand

Figure A2: Partisan citizens' tweets on policy issues: emotions by political affiliation and topic

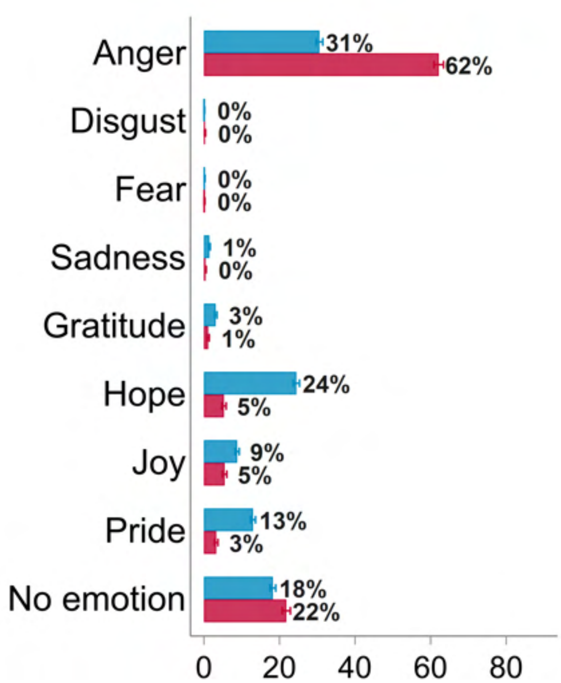
(a) Abortion



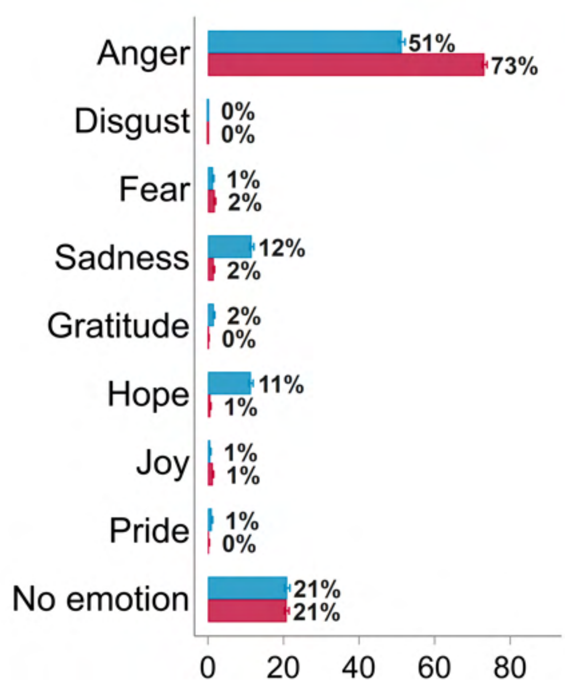
(b) Democracy



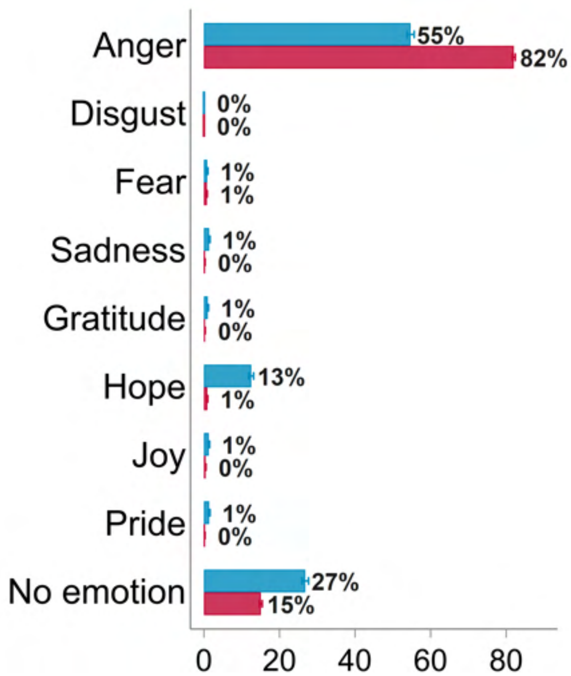
(c) Gender Equality



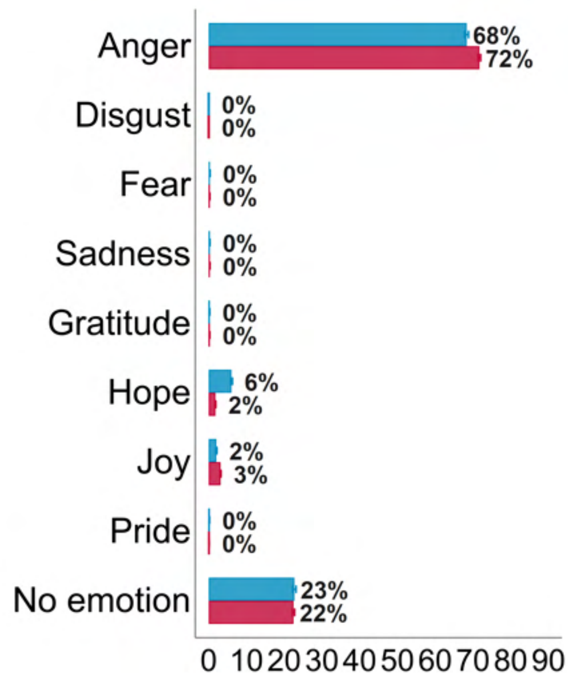
(d) Gun Control



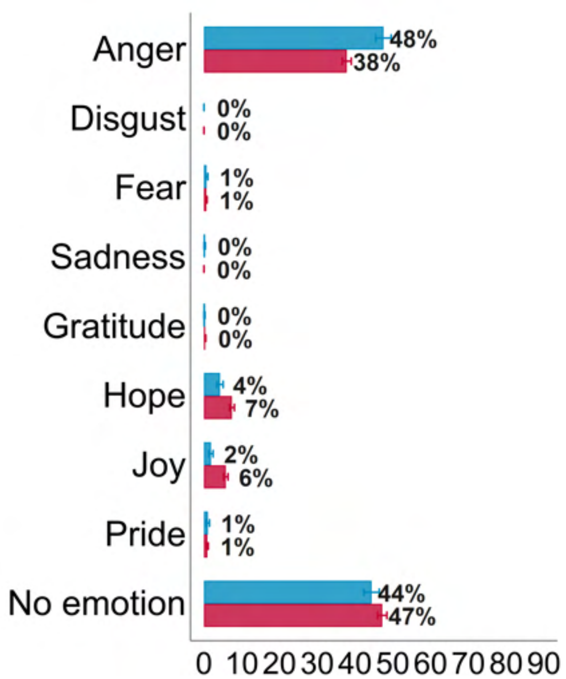
(e) Immigration



(f) Tax and inequality



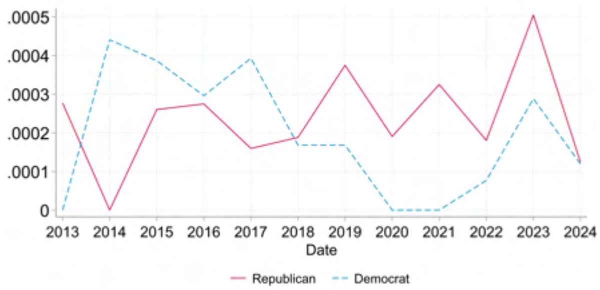
(g) Trade



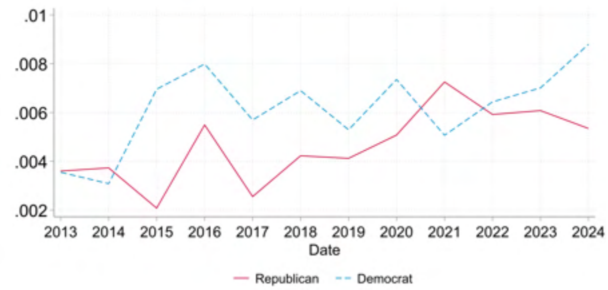
Notes.

Figure A3: Evolution in Partisans' Tweets by Emotions: Democrats versus Republicans

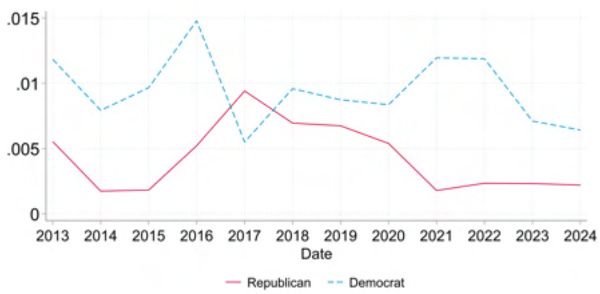
(a) Disgust



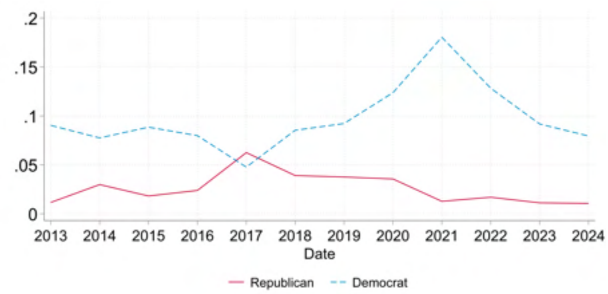
(b) Fear



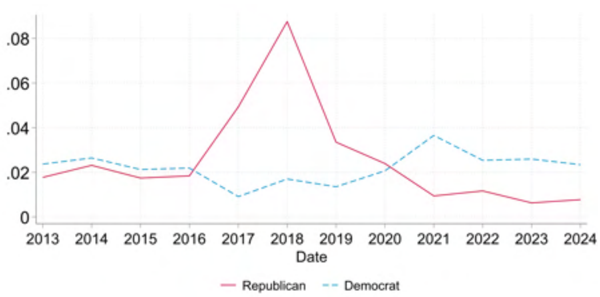
(c) Gratitude



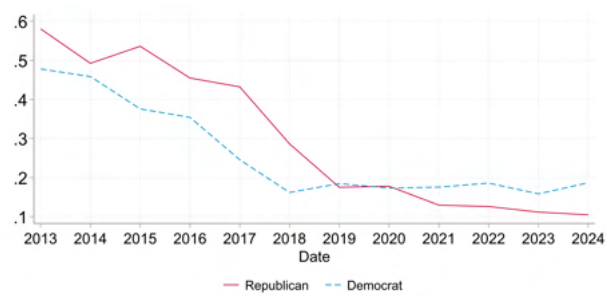
(g) Hope



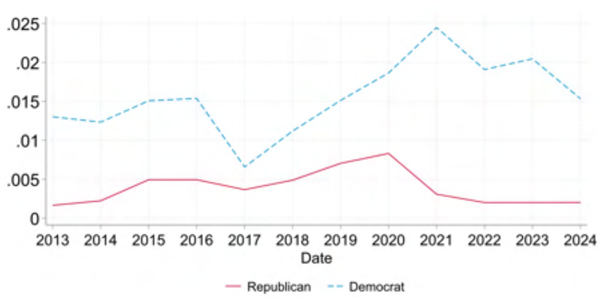
(h) Joy



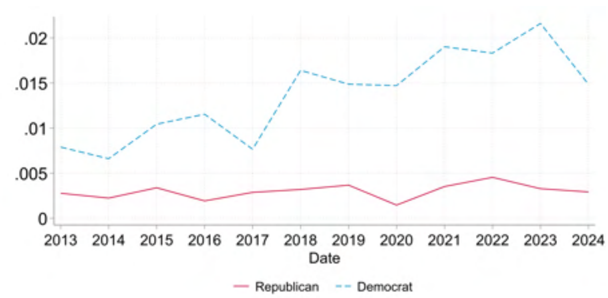
(i) No emotion



(p) Pride



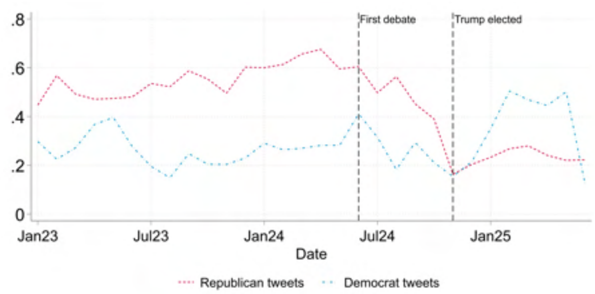
(q) Sadness



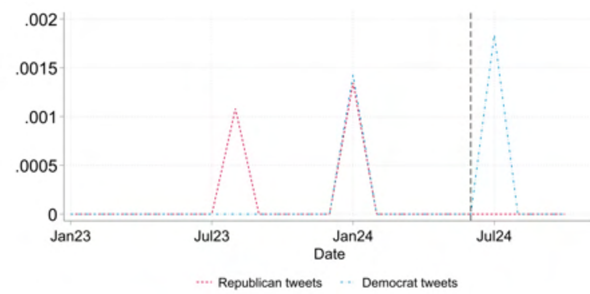
Notes.

Figure A4: Emotions around the election, by political affiliation

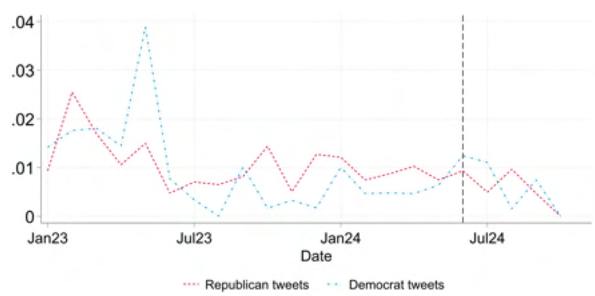
(a) Anger



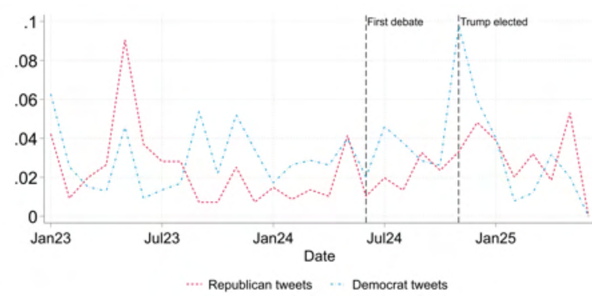
(b) Disgust



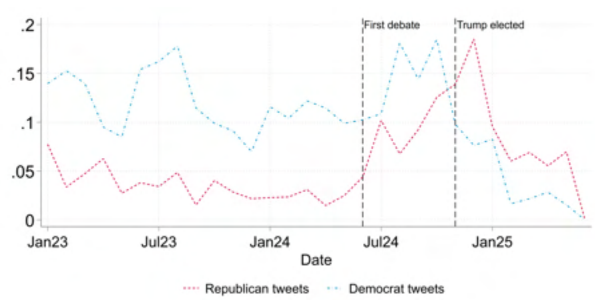
(c) Fear



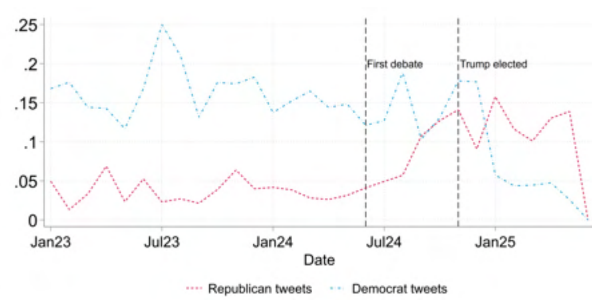
(d) Gratitude



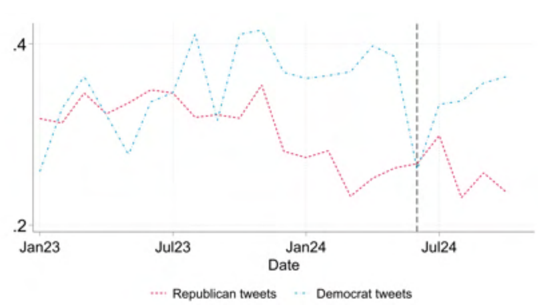
(h) Hope



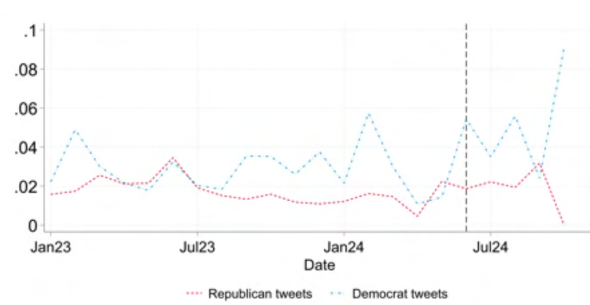
(i) Joy



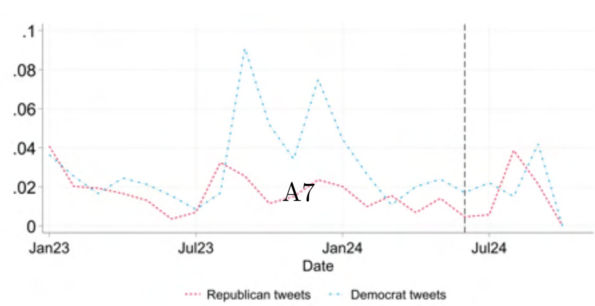
(j) No emotion



(q) Pride



(r) Sadness



A.3 Survey A: 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									
Gender: 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)
Age: 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)
Age: 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)
Highest education level: some 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. 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) Negative trade perception 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				
Gender: Female	0.05	-0.02	-0.12***	-0.08
	(0.04)	(0.04)	(0.04)	(0.09)
Age: 30-49 years old	0.20***	0.02	0.05	0.27*
	(0.07)	(0.07)	(0.08)	(0.15)
Age: 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)
Highest education level: some 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'.

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				
Gender: Female	0.17***	0.05	-0.12***	0.09
	(0.04)	(0.04)	(0.04)	(0.08)
Age: 30-49 years old	0.01	0.14**	0.11	0.25**
	(0.07)	(0.06)	(0.07)	(0.12)
Age: 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)
Highest education level: some 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 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						
Gender: 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)
Age: 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)
Age: 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)
Highest education level: some 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 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					
Gender: Female	-0.17***	-0.16***	0.04	-0.03	-0.30***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.09)
Age: 30-49 years old	-0.18**	0.17**	0.20***	0.05	0.25*
	(0.08)	(0.07)	(0.06)	(0.07)	(0.14)
Age: 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)
Highest education level: some 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 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				
Gender: Female	0.13***	0.01	0.12***	0.26***
	(0.04)	(0.04)	(0.04)	(0.08)
Age: 30-49 years old	0.12*	0.04	0.05	0.21
	(0.07)	(0.07)	(0.07)	(0.14)
Age: 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)
Highest education level: some 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 A2 for information on regression omitted categories and additional controls.

Table A8: Pro-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					
Gender: Female	0.06	-0.06	0.01	0.04	0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.12)
Age: 30-49 years old	-0.03	-0.04	0.01	0.11	0.02
	(0.07)	(0.07)	(0.07)	(0.07)	(0.19)
Age: 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)
Highest education level: some 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 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						
Gender: 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)
Age: 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)
Age: 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)
Highest education level: some 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 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						
Gender: 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)
Age: 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)
Age: 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)
Highest education level: some 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 A2 for information on regression omitted categories and additional controls.

A.4 Survey B: 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	-0.45***	-0.43***	-0.54***	-0.35***	0.73***	0.88***	-0.37***	-1.76***	1.61***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)	(0.12)	(0.07)
Fear treatment branch	0.55***	1.18***	0.23***	1.29***	-0.95***	-0.85***	-0.17***	3.22***	-1.79***
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.14)	(0.07)
Anger treatment branch	1.29***	0.51***	1.26***	1.22***	-0.85***	-0.78***	0.38***	4.29***	-1.62***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.14)	(0.07)
Panel B: Personal Characteristics									
Female	0.05*	0.14***	0.02	0.10***	-0.12***	-0.05	-0.06	0.32***	-0.17***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.10)	(0.05)
30-49 years old	0.01	0.06	0.10**	0.03	-0.01	0.06	0.03	0.20	0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.13)	(0.07)
50-69 years old	0.06	-0.03	0.13***	-0.02	-0.16***	0.05	-0.15***	0.15	-0.11
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.14)	(0.08)
College Degree	-0.04	-0.07*	-0.07**	0.00	-0.07*	-0.03	-0.13***	-0.19*	-0.09
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.11)	(0.06)
Middle income: 40,000-89,999	-0.03	-0.05	-0.02	-0.00	-0.09**	-0.07*	-0.04	-0.09	-0.16**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.13)	(0.07)
High income: 90,000 and above	-0.14***	-0.16***	-0.12***	-0.09**	-0.10**	-0.12***	-0.16***	-0.50***	-0.22***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.13)	(0.07)
Trump	-0.17***	-0.21***	-0.09***	-0.20***	0.14***	0.01	0.05	-0.67***	0.15**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.11)	(0.06)
No Video	-0.34	-0.32	-0.27	-0.51	0.31	0.21	0.06	-1.44	0.52
Observations	2953	2957	2959	2967	2951	2956	2952	2928	2938
Adjusted R-Squared	0.40	0.33	0.40	0.48	0.40	0.42	0.09	0.47	0.49

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	0.09*	0.10**	0.06	0.26***
	(0.05)	(0.05)	(0.04)	(0.09)
Fear treatment branch	0.06	-0.03	0.06	0.05
	(0.05)	(0.05)	(0.05)	(0.10)
Anger treatment branch	0.21***	-0.05	0.20***	0.38***
	(0.05)	(0.05)	(0.05)	(0.10)
Panel B: Personal Characteristics				
Female	0.07*	-0.07*	0.04	0.07
	(0.04)	(0.04)	(0.04)	(0.07)
30-49 years old	-0.04	-0.03	-0.11**	-0.17*
	(0.05)	(0.05)	(0.05)	(0.10)
50-69 years old	-0.19***	0.01	-0.31***	-0.49***
	(0.05)	(0.05)	(0.05)	(0.10)
College Degree	0.09**	0.07	0.02	0.16*
	(0.04)	(0.04)	(0.04)	(0.08)
Middle income: 40,000-89,999	0.02	0.09*	-0.11**	0.01
	(0.05)	(0.05)	(0.05)	(0.10)
High income: 90,000 and above	0.07	0.16***	-0.13**	0.11
	(0.05)	(0.05)	(0.05)	(0.10)
Trump	-0.84***	-0.27***	-0.33***	-1.44***
	(0.04)	(0.04)	(0.04)	(0.08)
No video	-0.17	-0.03	-0.08	-0.25
Observations	2825	2992	2992	2821
Adjusted R-Squared	0.15	0.02	0.05	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	0.07	0.04	0.07	-0.02
	(0.04)	(0.05)	(0.04)	(0.04)
Fear treatment branch	0.01	-0.02	-0.02	0.04
	(0.05)	(0.05)	(0.05)	(0.05)
Anger treatment branch	0.12***	0.07	0.08*	0.04
	(0.05)	(0.05)	(0.05)	(0.05)
Panel B: Personal Characteristics				
Female	-0.06*	-0.05	-0.17***	-0.07*
	(0.03)	(0.04)	(0.04)	(0.04)
30-49 years old	-0.02	0.05	0.01	-0.11**
	(0.05)	(0.05)	(0.05)	(0.05)
50-69 years old	-0.08	0.02	-0.19***	-0.17***
	(0.05)	(0.05)	(0.05)	(0.05)
College Degree	0.17***	0.06	0.10**	0.11***
	(0.04)	(0.04)	(0.04)	(0.04)
Middle income: 40,000-89,999	0.16***	0.13**	0.11**	0.08*
	(0.05)	(0.05)	(0.05)	(0.05)
High income: 90,000 and above	0.21***	0.18***	0.20***	0.08
	(0.05)	(0.05)	(0.05)	(0.05)
Trump	-0.97***	-0.67***	-0.77***	-0.84***
	(0.04)	(0.04)	(0.04)	(0.04)
No video	-0.10	-0.08	-0.10	-0.05
Observations	2995	2994	2993	2993
Adjusted R-Squared	0.21	0.10	0.14	0.15

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	0.10**	0.06	0.07	-0.07*	0.32
	(0.04)	(0.05)	(0.05)	(0.04)	(0.21)
Fear treatment branch	0.03	0.03	0.03	0.07	0.17
	(0.05)	(0.05)	(0.05)	(0.05)	(0.24)
Anger treatment branch	0.08*	0.12**	0.10**	0.09*	0.72***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.24)
Panel B: Personal Characteristics					
Female	-0.03	0.01	-0.06*	-0.10***	-0.54***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.17)
30-49 years old	0.15***	0.03	-0.05	-0.00	0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.24)
50-69 years old	0.10*	-0.07	-0.14***	-0.14***	-0.65***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.25)
College Degree	0.05	-0.00	0.09**	0.04	0.61***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.20)
Middle income: 40,000-89,999	0.10*	-0.03	-0.01	0.03	0.56**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.24)
High income: 90,000 and above	0.21***	0.10**	0.07	0.03	1.09***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.25)
Trump	-0.67***	-0.60***	-0.44***	-0.52***	-5.47***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.19)
No video	-0.10	-0.08	-0.08	-0.05	-0.64
Observations	2994	2992	2995	2994	2985
Adjusted R-Squared	0.11	0.08	0.05	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) Support carbon tax on rich[1]	(2) Support for minorities hit by CC[2]	(3) Redistributive climate policy index[3]
Panel A: Treatment effects			
Positive emotion treatment branch	-0.01	0.09**	0.09
	(0.04)	(0.04)	(0.07)
Fear treatment branch	0.02	0.08	0.10
	(0.05)	(0.05)	(0.08)
Anger treatment branch	0.14***	0.11**	0.25***
	(0.05)	(0.05)	(0.08)
Panel B: Personal Characteristics			
Female	-0.07*	0.04	-0.02
	(0.04)	(0.04)	(0.06)
30-49 years old	-0.12**	-0.04	-0.16**
	(0.05)	(0.05)	(0.08)
50-69 years old	-0.34***	-0.19***	-0.53***
	(0.05)	(0.05)	(0.08)
College Degree	0.04	-0.03	0.01
	(0.04)	(0.04)	(0.07)
Middle income: 40,000-89,999	0.06	0.07	0.12
	(0.05)	(0.05)	(0.08)
High income: 90,000 and above	0.02	0.05	0.06
	(0.05)	(0.05)	(0.08)
Trump	-0.62***	-0.75***	-1.37***
	(0.04)	(0.04)	(0.06)
No video	-0.06	-0.08	-0.13
Observations	2995	2993	2993
Adjusted R-Squared	0.09	0.12	0.16

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

3. Redistribution index

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

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	0.07	0.04	0.08*	0.12
	(0.05)	(0.05)	(0.05)	(0.07)
Fear treatment branch	0.02	0.10**	0.16***	0.13
	(0.05)	(0.05)	(0.05)	(0.08)
Anger treatment branch	0.11**	0.12**	0.13***	0.23***
	(0.05)	(0.05)	(0.05)	(0.08)
Panel B: Personal Characteristics				
Female	0.18***	0.10***	0.09**	0.28***
	(0.04)	(0.04)	(0.04)	(0.06)
30-49 years old	0.07	-0.00	0.19***	0.07
	(0.05)	(0.05)	(0.05)	(0.08)
50-69 years old	-0.01	-0.05	0.34***	-0.07
	(0.05)	(0.05)	(0.05)	(0.08)
College Degree	0.10**	-0.15***	0.00	-0.05
	(0.04)	(0.04)	(0.04)	(0.06)
Middle income: 40,000-89,999	0.01	-0.07	0.03	-0.06
	(0.05)	(0.05)	(0.05)	(0.08)
High income: 90,000 and above	0.11**	-0.27***	-0.07	-0.16**
	(0.05)	(0.05)	(0.05)	(0.08)
Trump	-0.40***	-0.37***	-0.42***	-0.77***
	(0.04)	(0.04)	(0.04)	(0.06)
No video	-0.08	-0.05	-0.12	-0.13
Observations	2995	2994	2994	2994
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.5 Robustness

A.5.1 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									
Gender: 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)
Age: 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)
Age: 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)
Highest education level: some 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 A5: Effects of the treatments on indices

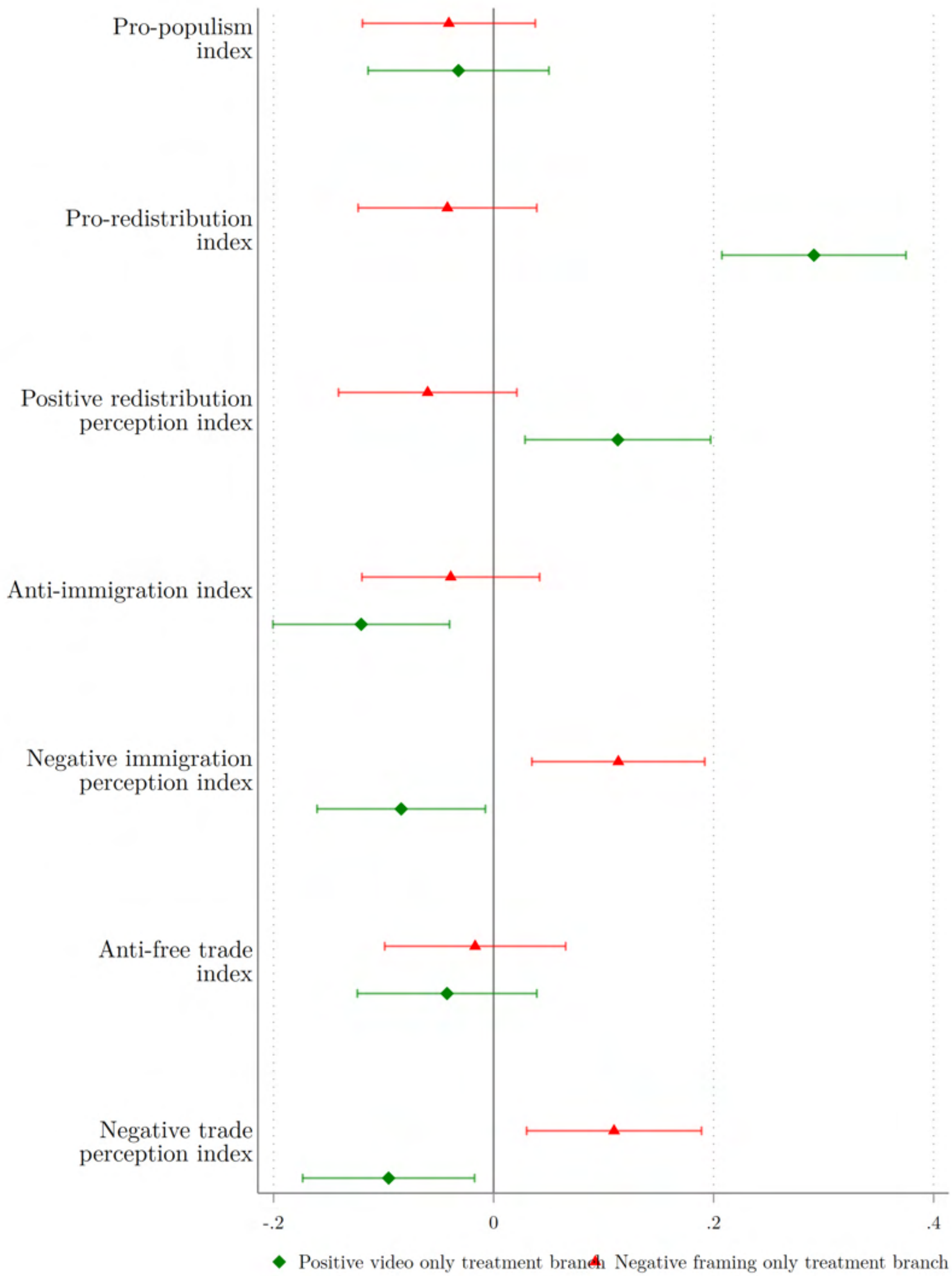


Table A18: All indices

	(1) Negative trade perception index	(2) Anti-free trade index	(3) Negative immigration perception index	(4) Anti-immigration index	(5) Negative redistribution perception index	(6) Anti-redistribution index	(7) Pro-populism index
Positive video only treatment branch	-0.04	0.13	-0.09	0.01	-0.04	-0.00	-0.10
	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)	(0.13)	(0.12)
Negative framing only treatment branch	0.17*	0.12	0.01	0.06	-0.03	0.04	-0.11
	(0.10)	(0.09)	(0.10)	(0.10)	(0.09)	(0.13)	(0.12)
Panel B: Personal Characteristics							
Gender: Female	-0.18**	-0.10	-0.10	-0.36***	0.20**	0.03	0.13
	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.11)	(0.10)
Age: 30-49 years old	0.08	0.01	0.23*	0.13	0.17	0.29	-0.05
	(0.14)	(0.11)	(0.13)	(0.13)	(0.13)	(0.19)	(0.16)
Age: 50-75 years old	-0.03	0.15	0.01	0.08	0.49***	-0.02	-0.39***
	(0.13)	(0.11)	(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*	0.02	0.10	0.06	-0.69***	-0.38**	-0.21*
	(0.12)	(0.11)	(0.11)	(0.11)	(0.10)	(0.15)	(0.12)
Highest education level: some college and above	-0.06	0.17*	-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***	1.22***	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***	-0.05	-0.31***	-0.28***	-0.19**	0.35***	-0.29***
	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.11)	(0.10)
Universalism index	-0.03	-0.09***	-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	0.11	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				
Gender: Female	0.06	-0.09**	-0.16***	-0.18**
	(0.04)	(0.04)	(0.04)	(0.09)
Age: 30-49 years old	0.04	0.13*	-0.09	0.08
	(0.07)	(0.07)	(0.07)	(0.14)
Age: 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)
Highest education level: some 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				
Gender: Female	0.11***	-0.05	-0.17***	-0.10
	(0.04)	(0.04)	(0.04)	(0.08)
Age: 30-49 years old	0.07	0.01	-0.06	0.01
	(0.06)	(0.06)	(0.07)	(0.11)
Age: 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)
Highest education level: some 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						
Gender: 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)
Age: 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)
Age: 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)
Highest education level: some 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					
Gender: Female	-0.16***	-0.15***	0.01	-0.05	-0.36***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.08)
Age: 30-49 years old	-0.21***	0.09	0.17***	0.08	0.13
	(0.07)	(0.06)	(0.06)	(0.06)	(0.13)
Age: 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)
Highest education level: some 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				
Gender: Female	0.14***	-0.02	0.09**	0.20**
	(0.04)	(0.04)	(0.04)	(0.08)
Age: 30-49 years old	0.04	0.03	0.09	0.17
	(0.06)	(0.07)	(0.07)	(0.13)
Age: 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)
Highest education level: some 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					
Gender: Female	0.02	-0.08**	-0.01	0.09**	0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.11)
Age: 30-49 years old	-0.05	0.09	0.11	0.16**	0.29
	(0.06)	(0.07)	(0.07)	(0.07)	(0.19)
Age: 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)
Highest education level: some 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						
Gender: 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)
Age: 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)
Age: 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)
Highest education level: some 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						
Gender: 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)
Age: 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)
Age: 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)
Highest education level: some 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.6 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.”

A.7 Attrition analysis

A.7.1 Survey A

Table A27: Attrition Analysis

	Abandoned before completion	Abandoned before completion	Failed Attention or Video Checks	Did not watch entire video	Manually dropped because inattentive
	(1)	(2)	(3)	(4)	(5)
Panel A: Targeted Demographics					
Gender: Female	0.045***	0.033***	-0.010	-0.003	-0.009
	(0.007)	(0.006)	(0.012)	(0.004)	(0.006)
Age: 30-49 years old	0.006	0.004	0.025	-0.029***	-0.018*
	(0.012)	(0.010)	(0.018)	(0.008)	(0.010)
Age: 50-75 years old	-0.004	-0.000	-0.087***	-0.041***	-0.027***
	(0.012)	(0.010)	(0.018)	(0.008)	(0.010)
Middle income: 40,000-89,999	-0.033***	-0.021***	-0.060***	0.001	-0.008
	(0.009)	(0.008)	(0.013)	(0.005)	(0.007)
High income: 90,000 and above	-0.042***	-0.028***	-0.065***	0.002	-0.019**
	(0.010)	(0.009)	(0.015)	(0.006)	(0.007)
Race: African American/Black	0.010	-0.011	0.132***	-0.001	0.002
	(0.011)	(0.010)	(0.018)	(0.006)	(0.009)
Race: Hispanic/Latino	0.024*	0.003	0.035	-0.006	0.012
	(0.014)	(0.013)	(0.022)	(0.007)	(0.012)
Race: Asian/Asian American	0.008	-0.013	0.009	-0.002	0.036**
	(0.018)	(0.014)	(0.027)	(0.012)	(0.018)
Race: Mixed/Others	0.073***	0.055**	-0.087***	-0.001	-0.006
	(0.027)	(0.025)	(0.029)	(0.013)	(0.017)
US area: Midwest	0.002	0.000	-0.049***	-0.013**	0.008
	(0.012)	(0.010)	(0.018)	(0.006)	(0.009)
US area: South	-0.003	0.007	-0.030*	-0.009	0.005
	(0.010)	(0.009)	(0.016)	(0.006)	(0.008)
US area: West	-0.014	-0.002	-0.075***	-0.001	0.019**
	(0.012)	(0.010)	(0.018)	(0.007)	(0.009)
Panel B: Non-Targeted Socio-Demographics					
Born in the US		0.002	-0.007	-0.004	-0.005
		(0.013)	(0.024)	(0.010)	(0.013)
Highest education level: some college and above		-0.012	-0.087***	0.004	-0.020***
		(0.008)	(0.013)	(0.005)	(0.007)
Liberal/conservative spectrum: Moderate		0.000	-0.008	0.005	0.016**
		(0.008)	(0.014)	(0.005)	(0.007)
Liberal/conservative spectrum: Very conservative/Conservative		0.007	-0.054***	-0.002	0.011
		(0.010)	(0.019)	(0.006)	(0.009)
Voted/would have voted Trump 2020		-0.017**	0.065***	0.007	-0.007
		(0.008)	(0.015)	(0.005)	(0.008)
Most people can be trusted		-0.022***	0.087***	-0.002	-0.015***
		(0.006)	(0.012)	(0.004)	(0.006)
Universalism index		-0.001	-0.010***	0.001	-0.003**
		(0.002)	(0.003)	(0.001)	(0.001)
Observations	6372	6109	6109	6109	6109
Adjusted R-Squared	0.011	0.012	0.069	0.007	0.009

Notes. The table reports the results of regressions where the dependent variables are indicator variables for different types of attrition or exclusion. Specifically, the dependent variable equals 1 if the respondent: (1) dropped out voluntarily after completing the questions on targeted demographic characteristics; (2) dropped out voluntarily after answering additional demographic and social questions; (3) was excluded for failing at least one attention check, being unable to view the full video due to technical issues, or being unable to correctly identify the video's content from a set of 3–4 closed-ended options; (4) was excluded for spending less time on the video page than the video's actual duration; or (5) was excluded for providing poor-quality, inconsistent, or repetitive responses to open-ended questions. Respondents who did not provide consent to participate, were younger than 18 or older than 75, or were not residing in the US at the time of the survey and respondents who could not complete the survey because their quota group was full are excluded from the analysis. Moreover, in column (1), 205 respondents who dropped out before answering the targeted demographic questions are excluded from the analysis. In column (2), 394 respondents who dropped out before answering the additional demographic and social questions are excluded. In the regressions, the omitted categories are gender 'male', age '18-29 years old', household income 'low income: below $40,000', race/ethnicity 'white', US region 'Northeast', liberal/conservative position 'Very liberal/liberal', 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'. All regressions control also for respondents who did not vote or voted/would have voted for others in 2020. Robust standard errors are in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A28: Balance Analysis

	Positive emotion treatment branch	Negative emotion treatment branch	Positive video only treatment branch	Negative framing only treatment branch
	(1)	(2)	(3)	(4)
Gender: Female	0.013	-0.020	0.024*	-0.018
	(0.014)	(0.013)	(0.014)	(0.015)
Age: 30-49 years old	0.063***	0.042**	0.003	-0.055**
	(0.021)	(0.020)	(0.023)	(0.025)
Age: 50-75 years old	0.031	0.057***	0.014	-0.042*
	(0.021)	(0.019)	(0.023)	(0.025)
Middle income: 40,000-89,999	-0.019	-0.026*	0.008	0.037**
	(0.016)	(0.015)	(0.017)	(0.017)
High income: 90,000 and above	-0.020	-0.022	-0.010	0.015
	(0.019)	(0.017)	(0.019)	(0.019)
Race: African American/Black	-0.033	0.022	-0.034	0.009
	(0.021)	(0.021)	(0.022)	(0.024)
Race: Hispanic/Latino	-0.027	0.017	-0.022	0.045
	(0.025)	(0.024)	(0.026)	(0.029)
Race: Asian/Asian American	-0.054*	-0.006	-0.002	0.042
	(0.030)	(0.029)	(0.036)	(0.039)
Race: Mixed/Others	-0.094***	0.041	0.006	0.019
	(0.029)	(0.039)	(0.040)	(0.042)
US area: Midwest	0.005	-0.020	-0.031	0.027
	(0.021)	(0.020)	(0.022)	(0.023)
US area: South	0.016	-0.010	-0.022	0.011
	(0.018)	(0.018)	(0.020)	(0.020)
US area: West	-0.009	0.012	-0.033	0.033
	(0.020)	(0.020)	(0.022)	(0.023)
Born in the US	-0.007	0.043*	0.018	-0.029
	(0.028)	(0.024)	(0.029)	(0.033)
Highest education level: some college and above	0.002	0.008	-0.001	-0.002
	(0.016)	(0.015)	(0.017)	(0.018)
Liberal/conservative spectrum: Moderate	-0.011	-0.004	0.015	0.015
	(0.017)	(0.016)	(0.018)	(0.019)
Liberal/conservative spectrum: Very conservative/Conservative	-0.021	-0.034*	0.029	0.012
	(0.022)	(0.020)	(0.023)	(0.024)
Voted/would have voted Trump 2020	0.023	0.040**	-0.032*	-0.012
	(0.018)	(0.017)	(0.019)	(0.020)
Most people can be trusted	0.036**	0.006	-0.017	-0.028*
	(0.014)	(0.013)	(0.015)	(0.015)
Universalism index	0.002	-0.000	-0.003	0.001
	(0.003)	(0.003)	(0.004)	(0.004)
Observations	3497	3497	3497	3497
Adjusted R-Squared	0.004	0.003	-0.001	0.002

Notes. The table shows the results of regressions of indicators on demographic and socioeconomic indicators. The dependent variables are indicators equal to 1 if the respondent was assigned to this treatment group. In the regressions, the omitted categories are gender 'male', age '18-29 years old', household income 'low income: below $40,000', race/ethnicity 'white', US region 'Northeast', liberal/conservative position 'Very liberal/liberal', 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'. All regressions control also for respondents who did not vote or voted/would have voted for others in 2020. Robust standard errors are in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A.7.2 Survey B

Table A29: Attrition Analysis

	Abandoned before completion	Abandoned before completion	Failed Attention or Video Checks	Did not watch entire video	Manually dropped because inattentive
	(1)	(2)	(3)	(4)	(5)
Female	0.045***	0.041***	0.017**	-0.002	-0.007**
	(0.006)	(0.006)	(0.008)	(0.007)	(0.003)
30-49 years old	0.005	0.004	-0.024**	-0.036***	0.004
	(0.007)	(0.007)	(0.011)	(0.010)	(0.004)
50-69 years old	0.022***	0.025***	-0.090***	-0.077***	0.011**
	(0.008)	(0.008)	(0.012)	(0.011)	(0.004)
College Degree	-0.016**	-0.009	-0.026***	0.001	-0.004
	(0.007)	(0.007)	(0.009)	(0.008)	(0.004)
Middle income: 40,000-89,999	-0.017**	-0.008	-0.049***	-0.001	-0.003
	(0.008)	(0.008)	(0.012)	(0.010)	(0.004)
High income: 90,000 and above	-0.017*	-0.004	-0.036***	-0.009	-0.001
	(0.009)	(0.008)	(0.012)	(0.010)	(0.005)
African American/Black	-0.010	-0.007	0.068***	0.020*	-0.008**
	(0.008)	(0.008)	(0.013)	(0.011)	(0.004)
Unemployed	0.007	0.007	-0.026**	-0.018*	-0.001
	(0.008)	(0.008)	(0.011)	(0.010)	(0.004)
Trump		0.015**	0.051***	0.035***	-0.007*
		(0.007)	(0.011)	(0.010)	(0.004)
Other		0.084***	0.072***	-0.022	-0.000
		(0.018)	(0.020)	(0.016)	(0.008)
Liberal		-0.003	0.019*	0.008	-0.008**
		(0.007)	(0.010)	(0.009)	(0.003)
Conservative		0.002	-0.005	-0.004	0.012***
		(0.008)	(0.011)	(0.010)	(0.004)
Observations	9626	9576	9576	9576	9576
Adjusted R-Squared	0.008	0.013	0.044	0.010	0.003

Notes. The table reports the results of regressions where the dependent variables are indicator variables for different types of attrition or exclusion. Specifically, the dependent variable equals 1 if the respondent: (1) dropped out voluntarily after completing the questions on targeted demographic characteristics; (2) dropped out voluntarily after answering additional demographic and social questions; (3) was excluded for failing at least one attention check, being unable to view the full video due to technical issues, or being unable to correctly identify the video's content from a set of 3–4 closed-ended options; (4) was excluded for spending less time on the video page than the video's actual duration; or (5) was excluded for providing poor-quality, inconsistent, or repetitive responses to open-ended questions. Respondents who did not provide consent to participate, were younger than 18 or older than 69, or were not residing in the US at the time of the survey and respondents who could not complete the survey because their quota group was full are excluded from the analysis. In the regressions, the omitted categories are gender 'male', age '18-29 years old', household income 'low income: below $40,000', race/ethnicity 'white', liberal/conservative position 'Moderate', education 'below college', voting behavior 'voted/would have voted for Harris in 2024'. All regressions control also for respondents who did not vote or voted/would have voted for others in 2024. Robust standard errors are in parentheses; ${}^{*}p < 0.10$, ${}^{**}p < 0.05$, ${}^{***}p < 0.01$.

Table A30: Balance Analysis

	Positive emotion treatment branch	Positive emotion and cognitive treatment branch	Anger treatment branch	Anger and cognitive treatment branch	Fear treatment branch	Fear and cognitive treatment branch	Control	Cognitive control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.011	0.008	-0.013	-0.011	0.001	-0.008	0.009	0.004
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.011)	(0.010)
30-49 years old	0.009	0.007	0.016	0.003	0.007	0.004	-0.023	-0.024
	(0.014)	(0.011)	(0.012)	(0.011)	(0.011)	(0.010)	(0.015)	(0.014)
50-69 years old	0.006	0.006	0.023*	0.016	0.015	0.012	-0.038**	-0.040***
	(0.015)	(0.012)	(0.013)	(0.012)	(0.012)	(0.011)	(0.016)	(0.015)
College Degree	0.008	-0.004	-0.026**	-0.012	0.022**	0.003	-0.002	0.012
	(0.012)	(0.010)	(0.011)	(0.010)	(0.010)	(0.009)	(0.012)	(0.012)
Middle income: 40,000-89,999	-0.010	0.012	0.004	-0.004	-0.006	0.004	-0.024	0.023
	(0.014)	(0.012)	(0.013)	(0.011)	(0.012)	(0.011)	(0.015)	(0.014)
High income: 90,000 and above	-0.011	0.019	0.008	0.005	-0.015	-0.000	-0.025	0.018
	(0.015)	(0.012)	(0.013)	(0.012)	(0.013)	(0.011)	(0.016)	(0.014)
African American/Black	-0.012	0.002	-0.028**	-0.022*	0.010	-0.012	0.039**	0.022
	(0.015)	(0.013)	(0.013)	(0.012)	(0.013)	(0.011)	(0.017)	(0.016)
Unemployed	0.020	0.021*	0.003	-0.005	-0.004	-0.013	-0.031**	0.007
	(0.014)	(0.012)	(0.013)	(0.011)	(0.012)	(0.010)	(0.014)	(0.014)
Trump	0.010	-0.009	-0.006	-0.014	0.001	0.001	0.023*	-0.005
	(0.012)	(0.010)	(0.012)	(0.011)	(0.010)	(0.010)	(0.013)	(0.013)
Other	0.019	-0.015	-0.030	-0.015	0.014	0.009	0.016	0.003
	(0.026)	(0.020)	(0.021)	(0.021)	(0.022)	(0.020)	(0.027)	(0.026)
Liberal	0.009	-0.006	0.008	-0.008	-0.004	0.001	0.008	-0.008
	(0.012)	(0.010)	(0.011)	(0.010)	(0.010)	(0.009)	(0.013)	(0.012)
Observations	5390	5390	5390	5390	5390	5390	5390	5390
Adjusted R-Squared	-0.001	-0.001	0.001	0.000	-0.001	-0.000	0.003	0.001

Notes. The table shows the results of regressions of indicators on demographic and socioeconomic indicators. The dependent variables are indicators equal to 1 if the respondent was assigned to this treatment group. In the regressions, the omitted categories are gender 'male', age '18-29 years old', household income 'low income: below \$40,000', race/ethnicity 'white', liberal/conservative position 'Moderate', education 'below college', voting behavior 'voted/would have voted for Harris in 2024'. All regressions control also for respondents who did not vote or voted/would have voted for others in 2020. Robust standard errors are in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A.8 Questionnaire: Survey A

A.8.1 Consent

{consent} This is a survey for academic research purposes. It will take approximately 15 minutes to complete. The purpose of this survey is to assess your policy views.

You will be compensated conditional upon completing the survey and passing our survey quality checks, which use sophisticated statistical control methods to detect incoherent and rushed responses. Responding without adequate effort may result in your response being flagged for low quality and you may not receive your payment. Please note that it is very important for the success of our research that you answer honestly and read the questions very carefully before answering. You should know the following: You may not be told everything. As part of this research design, you may not be told about the purpose or procedures of this research. However, the purpose or procedures of the research will be fully disclosed to you following your participation. We might recontact you in one week.

Whether or not you participate is up to you. Your participation is completely voluntary. You can choose not to take part. You can agree to take part and later change your mind. Your decision will not be held against you. Your refusal to participate will not result in any consequences or any loss of benefits that you are otherwise entitled to receive. You can ask all the questions you want before you decide.

If you have questions, concerns, or complaints, or think the research has hurt you, contact the research team at social.economics.research2020@gmail.com.

All of the answers you provide will remain anonymous and be treated with absolute confidentiality. The data are only used for research purposes. Anonymous data collected from this study will be publicly available in an online repository.

Do you agree to participate to the survey?
[Yes, I agree to participate; No, I do not agree to participate]

A.8.2 Socio-Demographics

A.8.2.1 Quotas

{gender} What is your gender?

- Female
- Male
- Other (Please specify: ________________)

{age} How old are you? ________________

{live_us} Do you currently live in the U.S.?

- Yes
- No

{us_area} In which area of the U.S. do you live?

- Northeast

- South
- Midwest
- West

{race} How would you describe your ethnicity/race?

- White
- African American/Black
- Hispanic/Latino
- Asian/Asian American
- Mixed race
- Other (please specify: ________________)

{income_bracket} What was your total household income from all sources in 2023, before taxes and other deductions?

- Less than $10,000
- $10,000 - $19,999
- $20,000 - $29,999
- $30,000 - $39,999
- $40,000 - $49,999
- $50,000 - $69,999
- $70,000 - $89,999
- $90,000 - $109,999
- $110,000 - $149,999
- $150,000 - $199,999
- More than $200,000

A.8.2.2 Demographics

{born_us} Were you born in the United States?

- Yes
- No

{zip_code} In which ZIP code do you live? ____________________________

{educ} Which category best describes your highest level of education?

- 8th Grade or less
- Some high school
- High school degree/GED

- Some college
- 2-year college degree
- 4-year college degree
- Master's degree
- Doctoral degree
- Professional degree (JD, MD, MBA)

{emp_status} What is your current employment status?

- Full-time employee
- Part-time employee
- Self-employed or small business owner
- Unemployed and looking for work
- Student
- Not currently working and not looking for work
- Retiree

{religion} What is your religion (if any)?

- No religion
- Catholic
- Mainline Protestant (for example, Methodist, Lutheran, Presbyterian, Episcopal)
- Evangelical Christian
- Mormon
- Other Christian
- Judaism
- Islam
- Hinduism or Buddhism
- Other

{lib_scale} Where do you see yourself on the liberal/conservative spectrum?

- Very liberal
- Liberal
- Moderate
- Conservative
- Very conservative

{vote_2020} Did you vote in the 2020 Presidential Election?

- Yes
- No

{vote_who_2020} Who did you vote for in the 2020 Election?

- Joseph R. Biden
- Donald J. Trump
- Jo Jorgensen
- Howard G. Hawkins
- Prefer not to say/Don't know

{novote_who_2020} If you had voted, who would you have voted for?

- Joseph R. Biden
- Donald J. Trump
- Jo Jorgensen
- Howard G. Hawkins
- Prefer not to say/Don't know

{vote_2024} Did you vote in the 2024 Presidential Election?

- Yes
- No

{vote_who_2024} Who did you vote for in the 2024 Election?

- Donald J. Trump
- Kamala D. Harris
- Someone else
- Probably not vote
- Prefer not to say / Do not know

{novote_who_2024} If you had voted, who would you have voted for?

- Donald J. Trump
- Kamala D. Harris
- Someone else
- Probably not vote
- Prefer not to say / Do not know

A.8.2.3 Correlates for Voting Behavior

[Block on traditional correlates for voting behavior in the literature: trust, life satisfaction, universalism]

{life_satisf} All things considered, how satisfied or dissatisfied are you with your life as a whole these days?

- Very satisfied
- Somewhat satisfied
- Neither satisfied nor dissatisfied
- Somewhat dissatisfied
- Very dissatisfied

{trust_people} Generally speaking, would you say that...?

- Most people can be trusted
- You can never be too careful when dealing with other people

{trust_gov} How often do you think you can trust the government to do what is right?

- Never
- Some of the time
- Most of the time
- Always

{tax_cents} Of every tax dollar that goes to the federal government in Washington, D.C., how many cents would you say are wasted?

- Slider going from 0 to 100

{compassion} Would you say that compassion for those who are suffering is the most crucial virtue?

- Definitely yes
- Generally yes
- Indifferent
- Generally no
- Definitely no

{child_inherit} Do you think that it is morally wrong, or morally right, that rich children inherit a lot of money while poor children inherit nothing?

- Definitely wrong
- Generally wrong
- Neither right nor wrong
- Generally right
- Definitely right

{fam_loyal} Would you say that people should be loyal to their family members, even when they have done something wrong?

- Definitely yes
- Generally yes
- Indifferent
- Generally no
- Definitely no

{child_respect} Would you say that all children need to learn respect for authority?

- Definitely yes
- Generally yes
- Indifferent
- Generally no
- Definitely no

A.8.2.4 Emotions in Lonely Society

[Block to understand heterogeneity and importance of emotions/affects in society of loneliness]

{work_people} Is your work mostly on your own or working with other people?

- On my own
- With other people, but I don't feel I'm part of a team at work
- With other people, and I feel I'm part of a team at work
- I don't work

{prob_help} How often can you count on someone to help you with a problem in life, such as a friend or relative?

- All the time
- Very often
- Sometimes
- Never

{w_lonely} During a week, how many times would you say you feel lonely?

- All the time
- Very often
- Sometimes
- Never

{now_income_diff} Which of the descriptions below are closest to how you feel about your household's income nowadays?

- Living comfortably on present income
- Coping on present income
- Finding it difficult to live on present income
- Finding it very difficult to live on present income

{emergency_cover} Suppose you needed 400 dollars to cover an emergency (like a car breaking down or a broken pipe). Would it be very easy, fairly easy, not very easy, or not at all easy to get this money?

- Very easy
- Fairly easy
- Not very easy
- Not easy at all

A.8.3 Attention Check 1

{att_1} This is a question to check whether you are paying attention and reading the questions carefully. Please select both "strongly disagree" and "strongly agree" to continue.

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree
- Strongly agree

A.8.4 Policy Issues

A.8.4.1 Trade

[Only to neutral branch]

{novideo_openended} Please describe, in 1 or 2 sentences, how you feel while answering this survey.

{trade_oeq_neu} When you think about US trade with other countries, what are the main considerations that come to your mind?

[Only to negative framing only treatment branch]

{novideo_openended} Please describe, in 1 or 2 sentences, how you feel while answering this survey.

{trade_oeq_neg} When you think about U.S. trade with other countries such as China, what makes you really angry and revolted?

[Only to positive video treatment branch]

Positive Emotion Video

{video_check_relax} Were you able to watch and listen to the video until the end?

- Yes
- No, there was a technical problem
- No, I skipped part of the video

{video_att_relax} What is the video about?

- Informative facts about the causes and consequences of climate change, then it shows a woman stuck in her car in the middle of a wildfire.
- Informative facts about the causes and consequences of climate change, then it explains PG&E's responsibility in starting a particular wildfire.
- It shows peaceful and relaxing landscapes.
- Do not know.

{video_openend_relax} Please describe, in 1 or 2 sentences, what emotions do you feel after watching this video?

{trade_oeq_neu} When you think about US trade with other countries, what are the main considerations that come to your mind?

[Only to positive emotion treatment branch]

Positive Emotion Video

{video_check_relax} Were you able to watch and listen to the video until the end?

- Yes
- No, there was a technical problem
- No, I skipped part of the video

{video_att_relax} What is the video about?

- Informative facts about the causes and consequences of climate change, then it shows a woman stuck in her car in the middle of a wildfire.
- Informative facts about the causes and consequences of climate change, then it explains PG&E's responsibility in starting a particular wildfire.
- It shows peaceful and relaxing landscapes.
- Do not know.

{video_openend_relax} Please describe, in 1 or 2 sentences, what emotions do you feel after watching this video?

{trade_oeq_pos} When you think about US trade with other countries, what are some of the things, if any, that make you feel optimistic?

[Only to negative emotion treatment branch]

Negative Emotion Video

{video_check_relax} Were you able to watch and listen to the video until the end?

- Yes
- No, there was a technical problem
- No, I skipped part of the video

[Participants are removed if "Yes" is not selected.]

{video_att_relax} What is the video about?

- It shows a woman stuck in her car in the middle of a wildfire.
- Informative facts about the causes and consequences of climate change.
- It explains PG&E's responsibility in starting a particular wildfire.
- Do not know.

[Participants are removed if "It explains PG&E's responsibility in starting a particular wildfire" is not selected.]

{video_openend_anger} Please describe, in 1 or 2 sentences, what emotions do you feel after watching this video?

{trade_oeq_neg} When you think about U.S. trade with other countries such as China, what makes you really angry and revolted?

{trade_gen} *[From "Understanding of Trade"]* Which statement comes closest to your view?

- (a) More international trade can make everyone in the U.S. better off. Even if some people lose from it, it creates sufficient gains so that even those who lose from it can be compensated through appropriate policies.
- (b) Free trade will entail winners and losers and it will be impossible to compensate those who lose from it.

{trade_uineq} *[From "Understanding of Trade"]* To what extent do you think that trade with other countries is a major reason for:

- Unemployment in some sectors and the decline of some industries in the U.S.
- A rise of inequality in the U.S.
  - A great deal;
  - A lot;
  - A moderate amount;
  - A little;
  - None at all

{trade_aim} *[From "Understanding of Trade"]* Do you agree or disagree with the following statement: "Increasing trade with other countries and reducing barriers to trade is something the U.S. should aim for."

- Strongly agree
- Agree

- Neither agree nor disagree
- Disagree
- Strongly disagree

(Salient questions specific for US 2024 elections:)

{trade_allies} To what extent do you believe that maintaining strong trade relationships with key allies, such as Canada, Mexico, and the European Union, is important for ensuring U.S. economic growth?

- Extremely important
- Very important
- Somewhat important
- Slightly important
- Not at all important

{trade_60tar} Would you support or oppose raising tariffs on Chinese imports to at least 60 percent, meaning every product coming into the U.S. from China would face at least an extra 60 percent cost? Supporters argue this proposal will protect American industries and jobs, while critics warn it could raise prices for businesses relying on imported inputs and consumers.

- Strongly support
- Somewhat support
- Neither oppose nor support
- Somewhat oppose
- Strongly oppose

A.8.4.2 Immigration

[Only to neutral and positive emotion video only treatment branches]

{imm_oeq_neu} When you think about current immigration in the US, what are the main considerations that come to your mind?

[Only to negative emotion and negative framing only treatment branches]

{imm_oeq_neg} When you think about current immigration in the US, especially issues like illegal border crossings, what really scares you and/or makes you really angry?

[Only to positive emotion treatment branch]

{imm_oeq_pos} When you think about current immigration in the US, what are some of the things, if any, that make you feel optimistic?

{im_unemp} *[From "Immigration and Redistribution", Alesina, Stantcheva, Miano (2022)]* a) Out of every 100 people born in the U.S., how many are currently unemployed? By unemployed, we mean people who are currently not working but searching for a job (and maybe unable to find one). *[Slider from 1 to 100]*

{imm_unemp_imm} b) Now let's compare this to the number of unemployed among legal immigrants. Out of every 100 legal immigrants, how many do you think are currently unemployed? *[Slider from 1 to 100]* {im_number} *[From "Zero-Sum Thinking and the Roots of U.S. Political Divides", Chinoy, Nunn, Sequeira, Stantcheva]* Do you think the number of immigrants from foreign countries who are permitted to come to the United States to live should be:

- Increased a lot
- Increased a little
- Left the same as it is now
- Decreased a little
- Decreased a lot

{im_reason} *[From "Immigration and Redistribution", Alesina, Stantcheva, Miano (2022)]* Which has more to do with why an immigrant living in the U.S. is poor?

- Lack of effort on his or her own part
- Circumstances beyond his or her control

(Salient questions specific for US 2024 elections:)

{im_deport} Would you support or oppose a large-scale deportation operation aimed at expelling millions of undocumented immigrants, including using military resources and deputizing local police for immigration raids?

- Strongly support
- Somewhat support
- Neither oppose nor support
- Somewhat oppose
- Strongly oppose

{im_root} Would you support or oppose spending U.S. funds on programs to address the root causes of migration from Central America, such as poverty and violence, through initiatives like economic development and security partnerships?

- Strongly support
- Somewhat support
- Neither oppose nor support
- Somewhat oppose
- Strongly oppose

{im_screening} Do you think an earned pathway to citizenship for undocumented immigrants should include only objective criteria, such as paying taxes and passing background checks, or should it also involve stronger ideological screening, potentially barring individuals with certain political or religious beliefs?

- Include only objective criteria, such as paying taxes and passing background checks
- Include both objective criteria and stronger ideological screening for visa applicants

- Include mostly a stronger ideological screening for visa applicants

{im_threat} How serious of a threat do you think immigration is to...?

- The U.S. economy
- The U.S. culture
  - Not serious at all
  - Not very serious
  - Somewhat serious
  - Very serious

A.8.4.3 Attention Check 2

{att_2} This is a question to check whether you are reading the questions carefully. Please select both "slightly concerned" and "extremely concerned" to continue.

- Not at all concerned
- Slightly concerned
- Moderately concerned
- Very concerned
- Extremely concerned

A.8.4.4 Tax & Redistribution

[Only to neutral branch]

{tax_oeq_neu} When you think about income and wealth distribution in the U.S., what are the main considerations that come to your mind?

[Only to negative framing only treatment branch]

{tax_oeq_neg} When you think about income and wealth inequality in the U.S., what makes you feel really angry and outraged?

[Only to positive video only treatment branch]

Positive Emotion Video 2 {tax_oeq_neu} When you think about income and wealth distribution in the U.S., what are the main considerations that come to your mind?

[Only to positive emotion treatment branch]

Positive Emotion Video 2 {tax_oeq_pos} When you think about income and wealth distribution in the U.S., what are some of the things, if any, that make you feel optimistic?

[Only to negative emotion treatment branch]

Negative Emotion Video 2 {tax_oeq_neg} When you think about income and wealth inequality in the U.S., what makes you feel really angry and outraged?

{tax_poor_why} *[From "Intergenerational Mobility and Preferences for Redistribution", Alesina, Stantcheva, Teso (2018)]* Which has more to do with why a person is poor?

- Lack of effort on his or her own part
- Circumstances beyond his or her control

{tax_govt_role} Some people think that the government (at the local, state, or federal level) should not care about income differences between rich and poor people. Others think that the government should do everything in its power to reduce income inequality. [Rate on a scale of 1 to 7, with 1 being the government should not concern itself with income inequality and 7 being the government should do everything in its power to reduce income inequality.]

{tax_rich} *[From "Understanding Economic Policies: What do People Know and Learn?", Stantcheva]* Do you think that people with higher incomes pay a higher or lower share of their total income in federal personal income taxes than people with lower incomes?

- People with higher incomes pay a higher share of their income in taxes than those with lower incomes.
- People with higher incomes pay a lower share of their income in taxes than those with lower incomes.

{tax_less_ineq} *[From "Understanding Tax Policy: How do People Reason?", Stantcheva (2022)]* What do you think would ultimately do more to reduce the income differences between poor and rich families?

- Lowering taxes on wealthy people and corporations to encourage more investment in economic growth.
- Raising taxes on wealthy people and corporations to expand programs for the poor.

(Salient questions specific for US 2024 elections:)

{tax_ira_21} The corporate minimum tax was established by the Inflation Reduction Act (IRA) of 2022, setting a 15% minimum tax on corporations with over $1 billion in annual profits. Would you support or oppose raising the corporate minimum tax from 15% to 21%? Proponents argue this would help reduce tax avoidance and increase funding for public programs, while critics warn it could discourage business investment and slow economic growth.

- Strongly support
- Somewhat support
- Neither oppose nor support
- Somewhat oppose
- Strongly oppose

{tax_tcja_rich} Would you support or oppose raising the top federal income tax rate from the current 37% to 39.6% for individuals earning over $400,000? This would restore the top rate to the level before the 2017 TCJA tax cuts, aiming to increase revenue from high earners to fund social programs for the poor. Critics argue this policy could discourage investment, reduce economic growth, and complicate estate planning.

- Strongly support
- Somewhat support
- Neither oppose nor support
- Somewhat oppose

- Strongly oppose

{tax_gouging} Would you support or oppose a federal ban on corporate price gouging for groceries, which would allow the government to impose penalties on companies found to be unfairly raising prices? Supporters argue it could help protect consumers from excessive costs, especially during inflation, while critics caution that it may interfere with market dynamics and discourage investment.

- Strongly support
- Somewhat support
- Neither oppose nor support
- Somewhat oppose
- Strongly oppose

A.8.4.5 Populism

[Only to neutral and positive video only treatment branches]

{pop_oeq_neu} When you think about how democracy works in the US and its impact on political debates among Americans, what are the main considerations that come to your mind?

[Only to negative emotion and negative framing only treatment branches]

{pop_oeq_neg} When you think about how democracy works in the US and its impact on political debates among Americans, what makes you feel really outraged and angry?

[Only to positive emotion treatment branch]

{pop_oeq_pos} When you think about how democracy works in the US and its impact on political debates among Americans, what are some of the things, if any, that make you feel optimistic?

{pop_leader} Do you think having a strong leader who does not have to bother with parliament and elections is a good or a bad way of governing?

- Very bad
- Fairly bad
- Neither bad nor good
- Fairly good
- Very good

{pop_experts} Do you think having experts, not the government, making decisions according to what they think is best for the country is a good or a bad way of governing?

- Very bad
- Fairly bad
- Neither bad nor good
- Fairly good

- Very good

{pop_demo} Do you think having a democratic political system is a good or a bad way of governing?

- Very bad
- Fairly bad
- Neither bad nor good
- Fairly good
- Very good

{pop_fair_elec} Do you agree or disagree that elections in America are fair and each vote is counted fairly?

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

{pop_politician} Do you think most politicians care only about the interests of the rich and powerful, or do they also care about the needs of all citizens?

- They care about the interests of the rich and powerful
- Indifferent
- They care about the needs of all citizens

A.8.5 Societal Issues

{stat_intro} Now we will show you some statements that some people agree with and others disagree with, or have no opinion. For each statement, please indicate how much you agree or disagree with this statement. And please indicate if you would be ready to sign a petition against or in favor.

{stat_metoo} Do you agree with the statement that the MeToo movement, which is a movement against sexual harassment and sexual assault and has been associated with the firing of several high-profile men, has gone too far and is leading to false accusations and unjust persecution of men?

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

{stat_metoo_pet} Would you be ready to sign a petition against or in favor of the MeToo movement?

- Yes, I want to be anonymously counted as one of the respondents to a petition against the MeToo movement.
- No, I do not want to support any petition.
- Yes, I want to be anonymously counted as one of the respondents to a petition in favor of the MeToo movement.

{stat_abortion} Do you agree that abortion should be prohibited except in the case of rape, incest, or if the woman's life is in danger?

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

{stat_abortion_pet} Would you be ready to sign a petition against or in favor of abortion?

- Yes, I want to be anonymously counted as one of the respondents to a petition against abortion.
- No, I do not want to support any petition.
- Yes, I want to be anonymously counted as one of the respondents to a petition in favor of abortion.

{stat_gun_regul} Do you oppose or support lower restrictions and fewer regulations on legal, non-lethal firearms than on lethal firearms?

- Strongly support
- Somewhat support
- Neither support nor oppose
- Somewhat oppose
- Strongly oppose

{stat_gun_regul_pet} Would you be ready to sign a petition against or in favor of lowering restrictions and regulations on legal, non-lethal firearms compared to lethal firearms?

- Yes, I want to be anonymously counted as one of the respondents to a petition against lower restrictions and regulations for legal, non-lethal firearms.
- No, I do not want to support any petition.
- Yes, I want to be anonymously counted as one of the respondents to a petition in favor of lower restrictions and regulations for legal, non-lethal firearms.

A.8.6 Emotion Check

{emo_check} Below, you will see a list of emotions. We ask you to rate the intensity with which you experienced each emotion during the survey. Please make your assessment with the slider on a scale from 1 to 7, where 1 indicates very low intensity and 7 indicates very high intensity. *[Slider 1 to 7]*

- Sadness
- Surprise
- Fear
- Joy
- Anger
- Tranquillity
- Outrage

A.8.7 Affective Polarization

We would like to rate how you feel towards Kamala D. Harris and Donald J. Trump, on a scale from 0 to 100, which we call a "feeling thermometer". On this feeling thermometer scale, ratings between 0 to 49 degrees mean that you feel unfavorable and cold (with 0 being the most unfavorable, coldest). Ratings between 51 and 100 mean that you feel favorable and warm (with 100 being the most favorable, warmest). A rating of 50 means you have no feelings one way or the other.

{affect_trump} How would you rate your feelings toward Donald J. Trump? *[Slider 0 to 100]*

{affect_harris} How would you rate your feelings toward Kamala D. Harris? *[Slider 0 to 100]*

{affect_oeq_harris} Please describe, in 1 or 2 sentences, what emotions you feel towards Kamala D. Harris.

{affect_oeq_trump} Please describe, in 1 or 2 sentences, what emotions you feel towards Donald J. Trump.

A.8.8 Bias and Feedback

{bias} Do you feel that this survey was biased?

- Yes, left-wing bias
- Yes, right-wing bias
- No, it did not feel biased

{feedback} Please feel free to give us any feedback or impressions regarding this survey. *[Textbox]*

A.8.9 Debrief

Debrief Thank you for your participation in our research study. To submit your answers, click on the red arrow at the bottom of this page.

In case you are interested, we would like to discuss the study you just participated in with you in more detail and explain exactly what we are trying to study.

Before we tell you about all the goals of this study, however, we want to explain why it is necessary in some kinds of studies not to tell people all about the purpose of the study until after the study is completed.

As you may know, scientific methods sometimes require that participants in research studies are not given complete information about the research until after the study is completed. Although we cannot always tell you everything before you begin your participation, we do want to tell you everything when the study is completed.

We do not always tell people everything at the beginning of a study because we do not want to influence their responses. If we tell people what the purpose of the study is and our predictions about how they will react, then this could influence their responses and would not be a good measure of how they would react in everyday situations.

The aim of this study is to evaluate the impact of emotions on policy attitudes.

If other people know the true purpose of the study, it might affect how they behave/answer questions, so we are asking you not to share the information we just discussed.

We hope you enjoyed your experience, and we hope you learned some things today. If you have any questions later please feel free to contact us on the email provided in the consent form (social.economics.research2020@gmail.com).

Do you have any other questions or comments about anything you did today or anything we have talked about?

Thank you again for your participation.

END OF THE SURVEY

A.9 Questionnaire: Survey B

A.9.1 Consent and Disclaimer

{b00_1_consent} **What is the purpose of this research?** Our research aims at better understanding the way people choose the policies they support. **What can I expect if I take part in this research?** During this study, you will be asked around 30 questions, all clearly stated and non-intrusive. All the data will be entirely de-identified by the survey software and we will not be able to access any identification, IP address and so on. Hence the data will be entirely anonymous. The **entirely de-identified and anonymized data** will be made publicly available after the research has been completed. **What should I know about this research study?**

- Whether or not you take part is up to you.
- Your participation is completely voluntary.
- You can choose not to take part.
- You can agree to take part and later change your mind.

Your decision will not be held against you. Your refusal to participate will not result in any consequences or any loss of benefits that you are otherwise entitled to receive. You can ask all the questions you want before you decide. As part of this research design, you may not be told everything about the purpose or procedures of this research. However, the purpose or procedures of the research will be disclosed to you following your participation. **Who can I talk to?** If you have questions, concerns, or complaints, or think the research has hurt you, talk to the research team at emotionseconomicsharvard@gmail.com.

A.9.2 Sociodemographics

{b1_3_gender} What is your gender?

- Male
- Female
- Other/Prefer not to say

{b1_2_age} What is your age?

- *[Number]*

{b1_1_zipcode} In which ZIP code do you live?

- *[ZIP code]*

{b1_6_ethnicity_new} How would you describe your ethnicity/race?

- White
- African American/Black
- Hispanic/Latino

- Asian/Asian American
- Mixed race
- Other (please specify)

{b1_12_totalincome} What was your total household income, before taxes, last year (2023), in thousands of U.S. dollars?

- $0-$9,999
- $10,000-$14,999
- $15,000-$19,999
- $20,000-$29,999
- $30,000-$39,999
- $40,000-$49,999
- $50,000-$69,999
- $70,000-$89,999
- $90,000-$109,999
- $110,000-$149,999
- $150,000-$199,999
- $200,000+

{b1_13_education} Which category best describes your highest level of education?

- 8th Grade or less
- Some high school
- High school degree/GED
- Some college
- 2-year college degree
- 4-year college degree
- Master's degree
- Doctoral degree
- Professional degree (JD, MD, MBA)

{b1_13b_employment} What is your current employment status?

- Full-time employee

- Part-time employee
- Self-employed or small business owner
- Unemployed and looking for work
- Student
- Not currently working and not looking for work
- Retiree

{b1_15_libconsspect} Where do you see yourself on the liberal/conservative spectrum?

- Very liberal
- Liberal
- Moderate
- Conservative
- Very conservative

{b1_15b_vote2024} Did you vote in the 2024 Election?

- Yes
- No

[If Did you vote in the 2024 Election? = Yes]
{b1_15c_votewhom2024} Who did you vote for in the 2024 Election?

- Kamala D. Harris
- Donald J. Trump
- Someone else
- Prefer not to say/Don't know

[If Did you vote in the 2024 Election? = No]
{b1_15d_ifnot2024} If you had voted, who would you have voted for?

- Kamala D. Harris
- Donald J. Trump
- Someone else
- Prefer not to say/Don't know

A.9.3 Attention Check 1

{b1_23_fullattention} To show that you are attentive, please select "A little" in the list below.

- Not at all
- A little
- Moderately
- A lot
- A great deal

A.9.4 Video Treatment

[Only to cognitive + fear treatment branch]
Video cognitive + fear
{video fear} Please watch this 2-minute video about climate change before proceeding to the next questions (it is really important to watch it until the end).

{valid_mainfear} Were you able to watch and listen to the video until the end?

- Yes
- No, there was a technical problem
- No, I skipped part of the video

{attent_mainfear} What is the video about?

- Informative facts about the causes and consequences of climate change, then it shows a woman stuck in her car in the middle of a wildfire.
- Informative facts about the causes and consequences of climate change, then it explains PG&E's responsibility in starting a particular wildfire.
- It shows peaceful and relaxing landscapes.
- Don't know

{openended_mainfear} Please describe, in 1 or 2 sentences, what emotions do you feel after watching this video.
[Only to fear treatment branch]
Video fear
{video fear only} Please watch this 1-minute video about climate change before proceeding to the next questions (it is really important to watch it until the end).
{valid_mainfearonly} Were you able to watch and listen to the video until the end?

- Yes
- No, there was a technical problem

- No, I skipped part of the video

{attent_mainfearonly} What is the video about?

- It shows a woman stuck in her car in the middle of a wildfire.
- It explains PG&E's responsibility in starting a particular wildfire.
- It shows peaceful and relaxing landscapes.
- Don't know

{openended_mainfearon} Please describe, in 1 or 2 sentences, what emotions do you feel after watching this video.
[Only to cognitive + anger treatment branch]
Video cognitive + anger
{video anger} Please watch this 2-minute video about climate change before proceeding to the next questions (it is really important to watch it until the end).

{valid_mainanger} Were you able to watch and listen to the video until the end?

- Yes
- No, there was a technical problem
- No, I skipped part of the video

{attent_mainanger} What is the video about?

- Informative facts about the causes and consequences of climate change, then it shows a woman stuck in her car in the middle of a wildfire.
- Informative facts about the causes and consequences of climate change, then it explains PG&E's responsibility in starting a particular wildfire.
- It shows peaceful and relaxing landscapes.
- Don't know

{openended_mainanger} Please describe, in 1 or 2 sentences, what emotions do you feel after watching this video.
[Only to anger treatment branch]

- Video anger
  {video anger only} Please watch this 1-minute video about climate change before proceeding to the next questions (it is really important to watch it until the end)

  {valid_mainanger} Were you able to watch and listen to the video until the end?

  - Yes

– No, there was a technical problem
– No, I skipped part of the video

{attent_mainanger} What is the video about?

- Informative facts about the causes and consequences of climate change, then it shows a woman stuck in her car in the middle of a wildfire.
- Informative facts about the causes and consequences of climate change, then it explains PG&E's responsibility in starting a particular wildfire.
- It shows peaceful and relaxing landscapes.
- Don't know

{openended_mainanger} Please describe, in 1 or 2 sentences, what emotions do you feel after watching this video.
[Only to cognitive treatment branch]
Video Cognitive
{video control cog} Please watch this 50-second video about climate change before proceeding to the next questions (it is really important you watch it until the end).

{valid_maincog} Were you able to watch and listen to the video until the end?

- Yes
- No, there was a technical problem
- No, I skipped part of the video

{attent_maincog} What is the video about?

- It shows a woman stuck in her car in the middle of a wildfire.
- Informative facts about the causes and consequences of climate change.
- It explains PG&E's responsibility in starting a particular wildfire.
- It shows peaceful and relaxing landscapes.
- Don't know

{openended_maincog} Please describe, in 1 or 2 sentences, what emotions do you feel after watching this video.
[Only to positive emotion treatment branch]
Positive Emotion Video
{video control rel} Please watch this 1-minute video before proceeding to the next questions (it is really important you watch it until the end).

{valid_mainrelax} Were you able to watch and listen to the video until the end?

- Yes
- No, there was a technical problem
- No, I skipped part of the video

{attent_mainrelax} What is the video about?

- It shows a woman stuck in her car in the middle of a wildfire.
- Informative facts about the causes and consequences of climate change.
- It explains PG&E's responsibility in starting a particular wildfire.
- It shows peaceful and relaxing landscapes.
- Don't know

{opended_mainrel} Please describe, in 1 or 2 sentences, what emotions do you feel after watching this video.
[Only to cognitive + positive emotion treatment branch]
Video Cognitive + Positive Emotion Video
{video cogrel} Please watch this 2-minute video about climate change before proceeding to the next questions (it is really important to watch it until the end).

{valid_main_cogrelax} Were you able to watch and listen to the video until the end?

- Yes
- No, there was a technical problem
- No, I skipped part of the video

{attent_main_cogrelax} What is the video about?

- Informative facts about the causes and consequences of climate change, then it shows a woman stuck in her car in the middle of a wildfire.
- Informative facts about the causes and consequences of climate change, then it shows peaceful and relaxing landscapes.
- Informative facts about the causes and consequences of climate change, then it explains PG&E's responsibility in starting a particular wildfire.
- It shows only peaceful and relaxing landscapes.
- Don't know

{opended_main_cogrel} Please describe, in 1 or 2 sentences, what emotions do you feel after watching this video.

A.9.5 General Attitudes

{b3.1_1_trustgov} Do you trust information on climate change when it comes from the government?

- Always distrust
- Generally distrust
- Neither trust nor distrust
- Generally trust
- Always trust

{b3.1_3_viewoncc} Here are two statements people sometimes make when discussing climate change. Which of them comes closer to your own point of view?

- Climate change is mainly caused by human activity
- Climate change is mainly a natural phenomenon
- There is no climate change
- I don't know

{protectorgrow1} To what extent do you support the statement that the environmental crisis is an unfortunate side effect of positive economic growth?

- Strongly oppose
- Somewhat oppose
- Neither oppose nor support
- Somewhat support
- Strongly support

{protectorgrow2} How necessary do you think it is to slow down U.S. economic growth to help alleviate the environmental crisis?

- Not at all
- A little
- Moderately
- A lot
- A great deal

{meat} Research has shown that eating meat can be harmful to the environment and accelerates climate change more than other food. Would you be willing to **reduce your meat consumption**?

- Not at all

- A little
- Moderately
- A lot
- A great deal

{flights} Research has shown that taking flights is harmful to the environment and accelerates climate change more than other means of transportation. Would you be willing to **reduce the number of flights you take**?

- Not at all
- A little
- Moderately
- A lot
- A great deal

{30_Otherflights} When it comes to climate action, what would you say should other people do, for instance with respect to taking flights?

- People should take as many flights as they want
- Only very rich people (the top 1%) should reduce the number of flights they take
- Everyone should reduce the number of flights they take
- The government should cap the maximum number of flights people are allowed to take every year

A.9.6 Policy Questions

A.9.6.1 Policy Ban

{b3.4_ban_winlose} Do you think that your household would win or lose financially from a ban on combustion-engine cars?

- Win a lot
- Mostly win
- Neither win nor lose
- Mostly lose
- Lose a lot

{b3.4_ban_cars} Do you support or oppose a ban on combustion-engine cars?

- Strongly oppose

- Somewhat oppose
- Neither support nor oppose
- Somewhat support
- Strongly support

A.9.6.2 Policy Tax

{b3.5_0_text} To fight climate change, the U.S. federal government can make greenhouse gas emissions costly, to make people and firms change their equipment and reduce their emissions. The government could do this through a policy called a carbon tax with cash transfers. Under such a policy, the government would tax all products that emit greenhouse gas. For example, the price of gasoline would increase by 40 cents per gallon. To compensate households for the price increases, the revenues from the carbon tax would be redistributed to all households, regardless of their income. Each adult would thus receive $600 per year. We will now ask you a few questions regarding this specific policy.

{b3.5_3_tax_winlose} Do you think that your household would win or lose financially under a carbon tax with cash transfers?

- Win a lot
- Mostly win
- Neither win nor lose
- Mostly lose
- Lose a lot

{b3.5_5_tax_support} Do you support or oppose a carbon tax with cash transfers?

- Strongly oppose
- Somewhat oppose
- Neither support nor oppose
- Somewhat support
- Strongly support

{b3.5_5_tax_rich} Governments can choose to levy the carbon tax on specific populations. Would you support or oppose introducing a progressive carbon tax that would raise gasoline prices by 40 cents per gallon for high-income people only?

- Strongly oppose
- Somewhat oppose
- Neither support nor oppose
- Somewhat support
- Strongly support

A.9.6.3 Policy Preference: Tax vs Ban

{b3.5_ban_vs_tax} If you had to choose between these policies, which one would you prefer to fight climate change?

- A ban on combustion-engine cars
- A carbon tax

A.9.6.4 Policy Redistribution

{tax_redistribute} Would you support or oppose an increase in the income tax of households making more than $731,200 a year, if the government used this revenue to finance cash transfers to the poorest households?

- Strongly oppose
- Somewhat oppose
- Neither support nor oppose
- Somewhat support
- Strongly support

A.9.6.5 Harris vs Trump Policy Proposals

{elprop_Paris} Do you support or oppose the U.S. participating in the Paris Climate Agreement? This agreement sets a limit on the greenhouse gases the U.S. can emit and imposes a fee whenever the limit is exceeded.

- Strongly oppose
- Somewhat oppose
- Neither oppose nor support
- Somewhat support
- Strongly support

{elprop_InflationAct} Do you support or oppose tax incentives for renewable energy projects, such as the installation of solar panels?

- Strongly oppose
- Somewhat oppose
- Neither oppose nor support
- Somewhat support
- Strongly support

{elprop_evehicle} Do you support or oppose legislation to increase the proportion of electric cars sold from 10% today to 50% by 2035?

- Strongly oppose
- Somewhat oppose
- Neither oppose nor support
- Somewhat support
- Strongly support

{elprop_oil} Do you support or oppose expanding oil, gas, and coal production in the U.S.? This includes measures like lifting restrictions on federal drilling permits, building more coal plants, and expanding offshore drilling.

- Strongly oppose
- Somewhat oppose
- Neither oppose nor support
- Somewhat support
- Strongly support

{elprop_climate} How important was climate policy in your vote in favor of Donald Trump or Kamala Harris?

- Not important at all
- A little important
- Moderately important
- Very important
- Extremely important

A.9.7 Booster Videos

[Only to cognitive + fear treatment branch]

- Video cognitive + fear 2
  {booster fear} video Please watch the rest of the video you watched a few minutes ago. It should take you approximately 50 seconds.

  [Only to fear treatment branch]

- Video fear 2
  {booster fear only} Please watch the rest of the video you watched a few minutes ago. It should take you approximately 1 minute.

  [Only to cognitive + anger treatment branch]

- Video cognitive + anger 2
  {booster anger video} Please watch the rest of the video you watched a few minutes ago. It should take you approximately 1 minute.

  [Only to anger treatment branch]

- Video anger 2
  {booster anger only} Please watch the rest of the video you watched a few minutes ago. It should take you approximately 1 minute.

  [Only to cognitive treatment branch]

- Video cognitive 2
  {boos control cog vi} Please watch the rest of the video you watched a few minutes ago. It should take you approximately 20 seconds.

  [Only to positive emotion treatment branch]

- Positive emotion video
  {booster video relax} Please watch the rest of the video you watched a few minutes ago. It should take you approximately 1 minute.

  [Only to cognitive + positive emotion treatment branch]

- Video cognitive + positive emotion video
  {booster video cogrel} Please watch the rest of the video you watched a few minutes ago. It should take you approximately 1 minute.

A.9.8 Emotions Feedback

{b5_emotion} Below, you will see a list of emotions. We ask you to rate the intensity with which you experienced each emotion during the survey until now. Please make your assessment with the slider on a scale from 1 to 7, where 1 indicates very low intensity and 7 indicates very high intensity.

- Sadness
- Surprise
- Fear
- Joy
- Anger
- Tranquility
- Disgust

A.9.9 Distortion of Reality 1

{b3.2_1_question} Between 1980 and 1999, the United States experienced an average of 4.5 weather and climate disasters each year (such as droughts, floods, storms, and wildfires), with each individual event resulting in overall damages reaching or exceeding $1 billion. Please guess how many weather events for which the overall damage cost reached or exceeded $1 billion has been sustained by the U.S. in 2023. If your guess is close enough to the correct answer (i.e. $\pm$ 2 events from the exact number), you will earn $5. You will receive the payment through the same channel as you receive your basic compensation for taking part to this survey. No further action is required from you.

A.9.10 Distortion of Reality 2

{b3.2_2a_answerdirect} According to the Intergovernmental Panel on Climate Change (IPCC)'s Sixth Assessment Report, released in 2021, the human-caused rise in greenhouse gases has madeextreme weather events 6 times more frequentbetween the 1990s and today. NASA's satellite missions, including the upcoming Earth System Observatory, provide vital data for monitoring and responding to extreme weather events. Source: science.nasa.gov/climate-change/extreme-weather/

A.9.11 Distortion of Reality 3

{b3.2_4_feedback} Recall that you guessed that the U.S. has sustained${b3.2_1_question/ChoiceTextEntryValue} weather and climate disasters where overall damages/costs reached or exceeded $1 billion in 2023, given that this figure was 4.5 between 1980 and 1999, on average. Following the information presented to you, your views may have changed. We will now ask you the same question as before, and we will use this new guess to determine your bonus payment. In your opinion, how frequent were weather and climate disasters in the U.S. in 2023 where the overall damage/cost reached or exceeded $1 billion?

A.9.12 Framing: Neutral

{b3.3_a_control} Do you support or oppose a policy that would require all residential buildings to be insulated to a certain energy efficiency standard by 2040?

- Strongly oppose
- Somewhat oppose
- Neither support nor oppose
- Somewhat support
- Strongly support

A.9.13 Framing: Negative

{b3.3_c_negative} Insulation can help your home stay warm in the winter and cool in the summer. Do you support or oppose a policy that would require all residential buildings to be insulated to a certain energy efficiency standard by 2040?

- Strongly oppose
- Somewhat oppose
- Neither support nor oppose
- Somewhat support
- Strongly support

A.9.14 Framing: Positive

{b3.3_b_positive} Insulation can reduce your carbon footprint by using less energy and emitting fewer greenhouse gases. Do you support or oppose a policy that would require all residential buildings to be insulated to a certain energy efficiency standard by 2040?

- Strongly oppose
- Somewhat oppose
- Neither support nor oppose
- Somewhat support
- Strongly support

A.9.15 Climate Policies 2

{policytype1} Do you support or oppose a policy that requires electric utilities to produce at least 20% of their electricity from wind, solar or other renewable energy sources, even if it costs the average household an extra $100 per year?

- Strongly oppose
- Somewhat oppose
- Neither support nor oppose
- Somewhat support
- Strongly support

{policytype2} Would you pay 5% more on your monthly utility bill to get your electricity from renewable energy sources, like wind or solar?

- Strongly oppose
- Somewhat oppose
- Neither support nor oppose
- Somewhat support

- Strongly support

{policytype5} Do you support or oppose a policy that increases federal funding to low-income communities and communities of color that are disproportionately harmed by air and water pollution?

- Strongly oppose
- Somewhat oppose
- Neither support nor oppose
- Somewhat support
- Strongly support

A.9.16 Democracy

{democracy} Who do you think would be better at governing this country to find a solution to climate change?

- A strong leader who does not have to bother with elections
- A democratically elected parliament and political system

A.9.17 Donation

{Donation - willyou} Taking part in this survey, you were automatically registered for a lottery where you could win $1,000. You will know whether you won in a few days. If you win, you will receive the payment through the same channel as you receive your basic compensation for taking part to this survey. No further action is required from you. Were you the winner of the $1,000 lottery, would you be ready to give a proportion of your gain to an organization that fights climate change?

- Yes, I would be ready to give a proportion of my gain from the lottery to such an organization (details will be given in next question)
- No, I wouldn't be ready to give a proportion of my gain from the lottery to such an organization

[If Taking part in this survey, you were automatically registered for a lottery where you could win $... = Yes, I would be ready to give a proportion of my gain from the lottery to such an organization (details will be given in next question)]
{Donation} how much You will find below two organizations that fight climate change. You may enter how much money, over your $1,000 potential gain, you wish to give to each one of them. Were you the winner of the lottery, you would receive $1,000 minus the total amount of your donation.

- Organization 1 - Greenpeace: [Insert value]
- Organization 2 - World Wide Fund for Nature (WWF): [Insert value]
- *[Display total value]*

[If Taking part in this survey, you were automatically registered for a lottery where you could win $... = Yes, I would be ready to give a proportion of my gain from the lottery to such an organization (details will be given in next question)]

{Q215} Were you the winner of the lottery, you would finally receive: [$1000-Total Value]. Do you agree or do you change your mind?

- I agree: If I win the $1,000, I will give $*[Previous Answer for Greenpeace]* to Greenpeace and $*[Previous Answer for WWF]* to the WWF, and get only $*[Total Value]* for myself.
- I change my mind: Finally, I want to get the $1,000 for myself.

A.9.18 Petition

{b6_petition} Finally, are you willing to sign a petition to stand up for real climate action? As soon as the survey is complete, we will send the results to the President's office, informing him what share of people who took this survey were willing to support the following petition: I agree that immediate action on climate change is critical. Now is the time to dedicate ourselves to a low-carbon future and prevent lasting damage to all living things. Science shows us we cannot afford to wait to cut harmful carbon emissions. I'm adding my voice to the call to world leaders in the U.S. and beyond to act so we do not lose ground in combating climate change. Do you support this petition (you will not be asked to sign, only your answer here is required and remains anonymous)?

- Yes, I want to be anonymously counted as one of the respondents that showed support for the petition
- No, I do not want to support the petition

A.9.19 Do You Look for Information? (1 Dollar)

{infoWTP01} Are you interested in learning the correct answer to the question on extreme weather events we previously asked you and other facts about climate change?

- Yes
- No

[If Are you interested in learning the correct answer to the question on extreme weather events we pr... = Yes]

{infoWTP1dollar} By taking this survey, you are automatically enrolled in a lottery to win $1000. In a few days you will know whether you won the $1000. The payment will be made to you in the same way as your regular survey pay, so no further action is required on your part. In case you won, would you be willing to pay $1 to have in order to have the correct answer to the question on extreme weather events, along with a selection of research-backed facts and figures on the causes and consequences of climate change in the U.S.?

- Yes, I am willing to pay $1
- No, I am not willing to pay anything

[If By taking this survey, you are automatically enrolled in a lottery to win $1000. In a few days yo... = Yes, I am willing to pay $1]

{information display1} **Answer to the question** "From 1980 to 1999, the U.S. has sustained, on average, 4.5 weather and climate disasters every year (droughts, flooding, storms, wildfires) for which the overall damage cost reached or exceeded $1 billion. How many weather events for which the overall damage cost reached or exceeded $1 billion has been sustained by the U.S. in 2023?" Only in 2023, the U.S. has sustained 28 weather events for which the overall damage cost reached or exceeded $1 billion. **Research-backed facts, causes and consequences of climate change.**

- Average world temperature has increased 2°F from that in 1850.
- In 1963, 10bn tons of CO2 were released worldwide. In 2000 this figure more than doubled (25.50bn tons) and in 2022 it more than tripled (36.8bn tons).
- On average, each person on Earth emits 4.9 tons of CO2 annually. However, the average American contributes over three times that amount, with 15.2 tons of CO2 emissions per person per year.
- The region contributing the most to global greenhouse gas emissions is China, followed by the U.S., the E.U., and India (JRC 2018).
- Beef is the dish that emits the most greenhouse gases, followed by chicken wings and pasta (we consider each dish weighs half a pound). (Poore and Nemecek, 2018).
- Aviation accounted for 1.03 GtCO2, or 3.1% of total global CO2 emissions from fossil fuel combustion.
- 99.48 kg of greenhouse gas are emitted per kilogram of food product.
- 22 million tons of plastic leaked in the environment in 2019, and this estimate is projected to double by 2060.

A.9.20 Do You Look for Information? (2 Dollar)

{info_WTP02} Are you interested in learning the correct answer to the question on extreme weather events we previously asked you and other facts about climate change?

- Yes
- No

[If Are you interested in learning the correct answer to the question on extreme weather events we pr... = Yes]

{info_WTP2dollar} By taking this survey, you are automatically enrolled in a lottery to win $1000. In a few days you will know whether you won the $1000. The payment will be made to you in the same way as your regular survey pay, so no further action is required on your part. In case you won, would you be willing to pay $2 to have in order to have the correct answer to the question on extreme weather events, along with a selection of research-backed facts and figures on the causes and consequences of climate change in the U.S.?

- Yes, I am willing to pay $2
- No, I am not willing to pay anything

[If By taking this survey, you are automatically enrolled in a lottery to win $1000. In a few days yo... = Yes, I am willing to pay $2]

{information display2} **Answer to the question** "From 1980 to 1999, the U.S. has sustained, on average, 4.5 weather and climate disasters every year (droughts, flooding, storms, wildfires) for which the overall damage cost reached or exceeded $1 billion. How many weather events for which the overall damage cost reached or exceeded $1 billion has been sustained by the U.S. in 2023?" Only in 2023, the U.S. has sustained 28 weather events for which the overall damage cost reached or exceeded $1 billion. **Research-backed facts, causes and consequences of climate change.**

- Average world temperature has increased 2°F from that in 1850.
- In 1963, 10bn tons of CO2 were released worldwide. In 2000 this figure more than doubled (25.50bn tons) and in 2022 it more than tripled (36.8bn tons).
- On average, each person on Earth emits 4.9 tons of CO2 annually. However, the average American contributes over three times that amount, with 15.2 tons of CO2 emissions per person per year.
- The region contributing the most to global greenhouse gas emissions is China, followed by the U.S., the E.U., and India (JRC 2018).
- Beef is the dish that emits the most greenhouse gases, followed by chicken wings and pasta (we consider each dish weighs half a pound). (Poore and Nemecek, 2018).
- Aviation accounted for 1.03 GtCO2, or 3.1% of total global CO2 emissions from fossil fuel combustion.
- 99.48 kg of greenhouse gas are emitted per kilogram of food product.
- 22 million tons of plastic leaked in the environment in 2019, and this estimate is projected to double by 2060.

A.9.21 Do You Look for Information? (5 Dollar)

{info_WTP05} Are you interested in learning the correct answer to the question on extreme weather events we previously asked you and other facts about climate change?

- Yes
- No

[If Are you interested in learning the correct answer to the question on extreme weather events we pr... = Yes]

{info_WTP5dollar} By taking this survey, you are automatically enrolled in a lottery to win $1000. In a few days you will know whether you won the $1000. The payment will be made to you in the same way as your regular survey pay, so no further action is required on your part. In case you won, would you be willing to pay $5 to havein order to have the correct answer to the question on extreme weather events, along with a selection of research-backed facts and figures on the causes and consequences of climate change in the U.S.?

- Yes, I am willing to pay $5
- No, I am not willing to pay anything

[If By taking this survey, you are automatically enrolled in a lottery to win $1000. In a few days yo... = Yes, I am willing to pay $5]

{information display5} **Answer to the question** "From 1980 to 1999, the U.S. has sustained, on average, 4.5 weather and climate disasters every year (droughts, flooding, storms, wildfires) for which the overall damage cost reached or exceeded $1 billion. How many weather events for which the overall damage cost reached or exceeded $1 billion has been sustained by the U.S. in 2023?" Only in 2023, the U.S. has sustained 28 weather events for which the overall damage cost reached or exceeded $1 billion. **Research-backed facts, causes and consequences of climate change.**

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- In 1963, 10bn tons of CO2 were released worldwide. In 2000 this figure more than doubled (25.50bn tons) and in 2022 it more than tripled (36.8bn tons).
- On average, each person on Earth emits 4.9 tons of CO2 annually. However, the average American contributes over three times that amount, with 15.2 tons of CO2 emissions per person per year.
- The region contributing the most to global greenhouse gas emissions is China, followed by the U.S., the E.U., and India (JRC 2018).
- Beef is the dish that emits the most greenhouse gases, followed by chicken wings and pasta (we consider each dish weighs half a pound). (Poore and Nemecek, 2018).
- Aviation accounted for 1.03 GtCO2, or 3.1% of total global CO2 emissions from fossil fuel combustion.
- 99.48 kg of greenhouse gas are emitted per kilogram of food product.
- 22 million tons of plastic leaked in the environment in 2019, and this estimate is projected to double by 2060.

A.9.22 Do You Look for Information? (10 Dollar)

{info_WTP10} Are you interested in learning the correct answer to the question on extreme weather events we previously asked you and other facts about climate change?

- Yes
- No

[If Are you interested in learning the correct answer to the question on extreme weather events we pr... = Yes]

{info_WTP10dollar} By taking this survey, you are automatically enrolled in a lottery to win $1000. In a few days you will know whether you won the $1000. The payment will be made to you in the same way as your regular survey pay, so no further action is required on your part. In case you won, would you be willing to pay $10 to havein order to have the correct answer to the question on extreme weather events, along with a selection of research-backed facts and figures on the causes and consequences of climate change in the U.S.?

- Yes, I am willing to pay $10

- No, I am not willing to pay anything

[If By taking this survey, you are automatically enrolled in a lottery to win $1000. In a few days yo... = Yes, I am willing to pay $10]

{informationdisplay10} **Answer to the question** "From 1980 to 1999, the U.S. has sustained, on average, 4.5 weather and climate disasters every year (droughts, flooding, storms, wildfires) for which the overall damage cost reached or exceeded $1 billion. How many weather events for which the overall damage cost reached or exceeded $1 billion has been sustained by the U.S. in 2023?" Only in 2023, the U.S. has sustained 28 weather events for which the overall damage cost reached or exceeded $1 billion. **Research-backed facts, causes and consequences of climate change.**

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- The region contributing the most to global greenhouse gas emissions is China, followed by the U.S., the E.U., and India (JRC 2018).
- Beef is the dish that emits the most greenhouse gases, followed by chicken wings and pasta (we consider each dish weighs half a pound). (Poore and Nemecek, 2018).
- Aviation accounted for 1.03 GtCO2, or 3.1% of total global CO2 emissions from fossil fuel combustion.
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- 22 million tons of plastic leaked in the environment in 2019, and this estimate is projected to double by 2060.

A.9.23 Feedback

{b5_bias} Do you feel that this survey was left- or right-wing biased or unbiased?

- Left-wing biased
- Right-wing biased
- Unbiased