Emotions and Policy Views*

Yann Algan Eva Davoine Thomas Renault Stefanie Stantcheva

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[*FIRST DRAFT – COMMENTS VERY WELCOME!*]

Abstract

This paper investigates the growing role of emotions in shaping policy views. Analyzing citizens' social media postings and political party messaging over a variety of policy issues from 2013 to 2025, we document a sharp rise in anger on both the supply side (content provided by policy makers) and the demand side (emotional responses by citizens) since 2016. Content generating anger drives significantly more engagement. While anger in policymakers' discourse follows cycles tracking shifts in political power, anger among citizens seems to have been persistently triggered and does not revert back. 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.

*Algan: HEC (algan@hec.fr); Davoine: UC Berkeley (eva_davoine@berkeley.edu); Renault: University Paris 1 Panthéon-Sorbonne (thomas.renault@univ-paris1.fr). Stantcheva: Harvard, CEPR, and NBER (e-mail: sstantcheva@fas.harvard.edu). The project is approved by IRB at Harvard University (IRB22-0936), and was preregistered in the AER RCT Registry (AEARCTR-0015205 and AEARCTR-0015432). We thank Alberto Dario Zanettin, Roberto Fani, Filippo Giorgis, Alfonso Merendino, and Gregory Tham for outstanding research assistance. We thank participants of the NBER SI Political Economy group, Wasington PECO conference as well as seminar participants at Microsoft, Basel University, Pedro Bordalo and Saad Gulzar for useful feedback and suggestions.

1 Introduction

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

There has been widespread anger and outrage expressed both in the growing support for anti-establishment candidates 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 the 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. (2025), the expansion of populist support over the past two decades has also coincided with a striking 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.

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 research gap through a two-step approach. First, we examine the role of emotions in online and offline political speech. 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 seven distinct datasets, on the "supply" side (policy makers and politicians, supplying the content) and "demand" side (citizens and voters consuming the content).

One demand side, we collect three samples of tweets from X (formerly Twitter) users spanning the period 2013–2025. The first dataset is a random sample representing approximately 0.02% of all tweets posted on the platform, collected during four distinct 5-second intervals per day between 2013 and 2025 (approximately 690,000 tweets in total). These tweets are filtered to include at least one keyword related to the policy issues of interest: trade, immigration, taxation and inequality, democracy, and societal issues (abortion, gender equality, gun control). From this dataset, we construct a second dataset by identifying X users whose

accounts can be matched to official electoral registries. Although this sample is therefore selected, it yields a panel of users for whom we observe verified demographic characteristics and political affiliation. In addition, we extract a random sample comprising one-twelfth of all tweets containing the keywords "climate change" or "global warming" posted on X between January 2013 and April 2023. Together, these three datasets comprise approximately 11 million tweets authored by about 2 million distinct users.

On the supply side, we analyze four datasets. The Official party tweets dataset includes all tweets and retweets from the main official accounts of each political party on the policy issues under study over this period. The Congressional tweets dataset covers all tweets posted by members of Congress between 2013 and 2025, amounting for 1.5 million tweets on the same set of policy topics as for the demand side. The Congressional floor speeches dataset consists of all floor speeches delivered by members of Congress over the period, comprising 1,796,583 individual turns (sets of sentences) across 15 congressional sessions. Finally, we analyze all public interventions by Kamala Harris, Joe Biden, and Donald Trump between January 2023 and November 2024 that pertain to the policy issues of interest. This Campaign speech dataset includes 1,992 individual interventions.

For all these datasets, we employ large language models (LLM) combined with embedding-based representations and supervised machine learning classifications to categorize the content into different emotions and topics.

As a second step, we design and run two large-scale surveys and experiments that systematically induces both positive and negative emotions, enabling us to identify the causal effects of emotions on a broad range of policy views. Do emotions systematically change the way citizens think about public policies?

In the first experiment (survey A), we use video treatments and priming questions to focus on the distinction between negative and positive emotions. This experiment studies 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 ("priming" questions) to elicit either positive or negative emotions, or to serve as a neutral control group. 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 and control for the most relevant and commonly-studied factors in the literature, such as moral universalism, generalized trust, and existing political leaning.

In the second experiment (survey B), 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. 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 negligence, specifically, the 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 the positive emotion video featuring serene landscapes.

Our paper yields three sets of findings.

The first set of results relates key patterns in our political discourse data. We document a sharp rise in emotionality in political discourse over time, with anger emerging as the dominant emotion both among citizens and voters and policymakers.

Among citizens and voters, the proportion of tweets addressing policy issues and expressing anger increased from 20% to 50%, while non-emotional tweets declined from 60% to 50% over the same period. The rise in anger starts sharply after the 2016 U.S. presidential election and continues steeply during first Trump administration. We show that this temporal pattern is not driven by self-selection or changes in user composition on the platform: by analyzing within-individual changes, conditional on topic, we find similar trends. Moreover, a Shapley decomposition exercise confirms this interpretation: most of the increase in anger is explained by existing users switching to angrier content and by rising tweet volume among those same continuing users—rather than by entry or exit on the platform. Anger is particularly pronounced in discussions of abortion, democracy, immigration, and tax and inequality.

These patterns closely mirror trends on the supply side of political communication, highlighting an alignment between citizens' emotional expressions and politicians' rhetoric. On the supply side too, anger consistently stands out as the most prominent emotion in political rhetoric, across all forms of communication– tweets, campaign speeches, and floor speeches– and for the same policy issues as on the demand side. There has also been a significant rise in anger over time among policymakers, which is not driven by compositional effects, selection, or a change in policy topics. These findings suggest that political and citizen discourses mutually reinforce emotional narratives, amplifying the emotional intensity of public debate on policy issues.

This observation raises a critical question: Do political leaders deliberately employ emotional rhetoric to shape public sentiment? In other words, is there a strategic supply of emotions by political parties and leaders aimed at boosting citizen engagement? We provide two pieces of evidence to answer this question. First, we examine how the emotional content of messages influences their likelihood of being retweeted. We find that tweets from members of Congress, party officials, or citizens expressing anger generate significantly higher engagement, even after controlling for time fixed effects, user fixed effects, and policy issue fixed effects. For instance, congressional tweets classified as conveying anger receive almost 50% more retweets than non-emotional tweets. This provides a demand-driven explanation for the growing reliance of political parties on rhetoric infused with negative emotions, particularly anger. Second, we see that expressions of anger are subdued and have exhibited a much slower rise over time when the communication is offline and, arguably, less public facing, as in Congressional floor speeches. For almost all members of Congress, the prevalence of angry content is higher on social media than on the Congressional floor. This reinforces the idea that emotions might be used strategically by policy makers when facing citizens.

Our findings thus highlight a striking and robust pattern: both the demand and supply sides of political discourse exhibit a marked rise in anger, cutting across all political leanings. This surge, while evident in both online and offline contexts, is more muted offline, suggesting that digital platforms may amplify

emotional expression.

Beyond the overall alignment between supply and demand side, there are, however, some key differences in the dynamics. On the supply side, the rise in anger is more pronounced among Republican policymakers. Furthermore, it follows clear political cycles that track shifts in political power and key events. It rises when the president is from the opposition party or the opposition takes over during midterms. For instance, anger is consistently higher in all datasets among Democrat politicians during the first part of the Trump presidency 2016 but the pattern is flipped right after the 2018 midterms and for the duration of the Biden presidency. In contrast, on the demand side, the rise in anger appears more constant and sustained, across all political leanings, set in motion by the first Trump term and persisting since then without significant reversion. Therefore, it appears that while policymakers' expressed anger might be responsive to whether they are in power or not, anger in citizens' discourse across all political stripes seems to have been persistently triggered by the overall rise in anger since 2016, and not just the anger expressed by their own party.

The second set of results relates to our first survey experiment. We find that, as intended, exposure to our negative emotions treatment 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. The positive effect on the redistribution perception index is primarily driven by negatively treated respondents being more likely to attribute poverty to external circumstances. 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.

Finally, our third finding centers around the second experiment, which further highlights differences between two key negative emotions, namely fear and anger. Our treatments work as intended, in the sense that 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. Anger leads 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 has no significant effect on 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. A newer 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 institution, 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 line 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 role of emotions for voting versus 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), with anger specifically identified as a key correlate of populist support (Rico et al., 2017; Widmann, 2021; Ward et al., 2025). 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 negative 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 paper also contributes to the emerging literature that measures the evolution of citizens' emotions and affect over recent decades, as a complement to the measure of social attitudes and preferences. Ward et al. (2025) document, using the Gallup World Poll, a 43% increase in negative emotional states — such as anger and worry — between 2016 and 2022. While this sharp rise is mainly driven by countries in Africa, India, and South Asia, we also observe a decline of 12 percentage points in positive emotions and a 5-percentage-point increase in negative emotions, particularly worry (though not anger), in the US. Unfortunately, to the best of our knowledge, the Gallup World Poll is the only social survey that tracks emotions over such a long period, and the quality of its data is debatable, as it relies on a series of self-reported yes/no questions about emotions experienced "a lot of the day yesterday." Other types of sources nonetheless provide complementary evidence of a decline in positive emotions and a rise in negative ones over the past decades. Brand et al. (2019) analyze Anglo-Saxon pop songs over the past 50 years (1965–2015) and find a growing prevalence of negatively charged emotional content alongside a decline in positively charged content. Similarly, Morin and Acerbi (2017) study the emotional content of Anglo-Saxon literary fiction using the Google Books corpus and find a steady decrease in the use of positive emotion-related words, while the frequency of negative emotion-related words has increased slightly, particularly in more recent years.

We build on and complement this literature by providing new and rich datasets on the evolution of emotions specifically related to policy issues. On both the demand and supply side, we can track the evolution of citizens' emotions on various policy topics using large sample of X users over the period 2013–2025, as well as Congressional and campaign speeches. We show that the rise in anger related to policy issues is not merely driven by self-selection or composition on X; instead, panel regressions with user fixed effects reveal that negative emotions increase even within user. We find a strong alignment between the emotional content ("supply") from political actors and the emotional responses ("demand") expressed by citizens. Notably, anger in political rhetoric surged dramatically after Trump's 2016 election, mirroring citizens' sentiment. This phenomenon is widespread among both Republican and Democrat citizens and political actors.

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 remainder of the paper is structured as follows. Section 2 describes our data sources, which include social media posts, political speeches, and two original surveys and experiments designed 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, documenting the rise of emotional rhetoric—particularly anger—in citizens' social media conversations about policy issues. Section 4 analyzes the supply side of emotions in public and political discourse over the past decade, exploring how policymakers strategically deploy emotions to persuade and mobilize citizens. Finally, Section 5 presents the experimental results, showing 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 inequality, democracy, societal issues, and climate change.

2 Data, Sample, and Surveys

2.1 Observational data

Our observational data is comprised of seven distinct datasets.

The first five datasets are X-based. The first three (a random sample of tweets from X users, a sample of tweets from X users that could be matched to electoral registry data, and a collection of tweets on climate change) constitute the demand-side data, while the remaining two provide supply-side data. Importantly, from the random sample we identify the accounts that can be linked to electoral registries, yielding what we refer to as the "voter data."

The other two datasets examine political speech outside of social media, namely in Congress and on the campaign trail.

2.1.1 X data

We collected the following data from X according to a process outlined in detail in Appendix A.2.

Random sample of X users, "the citizen sample". This dataset consists of a random sample representing approximately 0.02% of all tweets posted on X, collected from four distinct 5-second intervals per

day between 2013 and 2025.[1] These tweets were filtered to include at least one of the keywords related to policy issues of interest.[2]

Voter's Data. We also construct a panel of X users that we match to the electoral registries. Starting from the random citizen sample, we infer users' U.S. states from self-reported locations using a classification procedure based on a GeoNames-derived gazetteer, which yields 183,501 users with reliably coded names and state identifiers. We then link these records to the voter file, an enhanced aggregation of publicly available state and local voter-registration data, by constructing state-specific, uniqueness-filtered normalized name keys following the deterministic approach of Grinberg et al., 2019. This procedure results in 17,792 users whose names and inferred states generate an exact one-to-one match to a voter-file registrant. For these matched individuals, we retrieve the full original voter-file entries and collect all tweets posted since 2013 that contain a predefined set of salient policy-related keywords, which we subsequently classify by topic and emotion using the same methodology employed in the main analysis. Refer to Appendix A.6 for a detailed description of the procedure.

Climate change tweets. We also extract a random sample of 1/12th of all tweets containing the keywords "climate change" and "global warming" sent on X between January 2013 and April 2023.[3]

Summary statistics on the number of tweets and distinct X users of these three datasets are provided in Table 1.

Table 1: Demand Dataset Summary Statistics

Dataset	Sample	Sentences	Unique Tweets	Unique Users
Citizen	Full dataset	1,053,106	791,426	608,160
Citizen	Excluding "other topic"	194,712	172,607	153,099
Voter	Full dataset	9,896,945	7,070,038	15,968
Voter	Excluding "other topic"	4,194,568	3,592,890	15,099
Climate	Full dataset	4,321,084	3,308,686	1,369,183

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 2 shows a breakdown of the data by source. Our database is comprised of 395,272 tweets sent between January 2013 and November 2024.[4] We also collected official accounts of the President (@POTUS), Vice President (@VP), First Lady (@FLOTUS), and the White House (@WhiteHouse). For these four institutional accounts, we identified both the current account (e.g., @POTUS) and its archival predecessors (e.g., @POTUS46Archive for President Biden or @POTUS45 for President Trump during his first term). Moreover, we also identify accounts from Cabinet members of both Democratic and Republican administrations. These are @SecBlinken, @SecCardona, @SecGranholm, @SecMayorkas, @SecPompeo, @SecretaryPete, @DHS_Wolf, @EsperDoD.

[1] In practice, we collected tweets back to 2010 but restrict to the period after 2013 when X use became more widespread).

[2] 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.

[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. The reason for extracting these tweets separately is because our two surveys (A and B) focus on these distinct policy issues.

[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.

Table 2: X Official Account

X 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 compile a list of every member of Congress (House and Senate) who served from the 109th Congress (January 3, 2005 – January 3, 2007, the first Congress for which Twitter existed) through the 118th Congress (beginning January 3, 2025). Over that span, 1,393 individuals have held a congressional seat and we are able to match them to 1,008 distinct congressional handles. Adoption rose from around 30% in 2010 to 98% most recently. We collect every tweet from those handles, from the creation of the account to June 1, 2025. Our database comprises 4.3 million tweets sent in that period.

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, Subtil, 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 comprises 1,796,583 individual turns[6] across 15 congressional sessions.

Campaign speeches. 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

2.1.3 Methods for Analyzing Emotions in Policy-Related Textual Data

To systematically analyze emotional content in policy-related textual data (political speeches and tweets), we first standardize documents by splitting them into sentences. We then use a two-step process. First, 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 of 200,000 sentences. These sentences are selected to come from official accounts' tweets (25%), the random users' tweets (25%), campaign speeches (25%), and

[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.

floor speeches (25%). Using the precise prompt formulations are detailed in Appendix A.3, we ask the LLM to classify these into emotions. We manually check a random subsample and provide evidence that the algorithm classifies emotions very well in the Appendix. 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 (which is too large to be done through a chat-based LLM). 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.

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 3 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 3: 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.

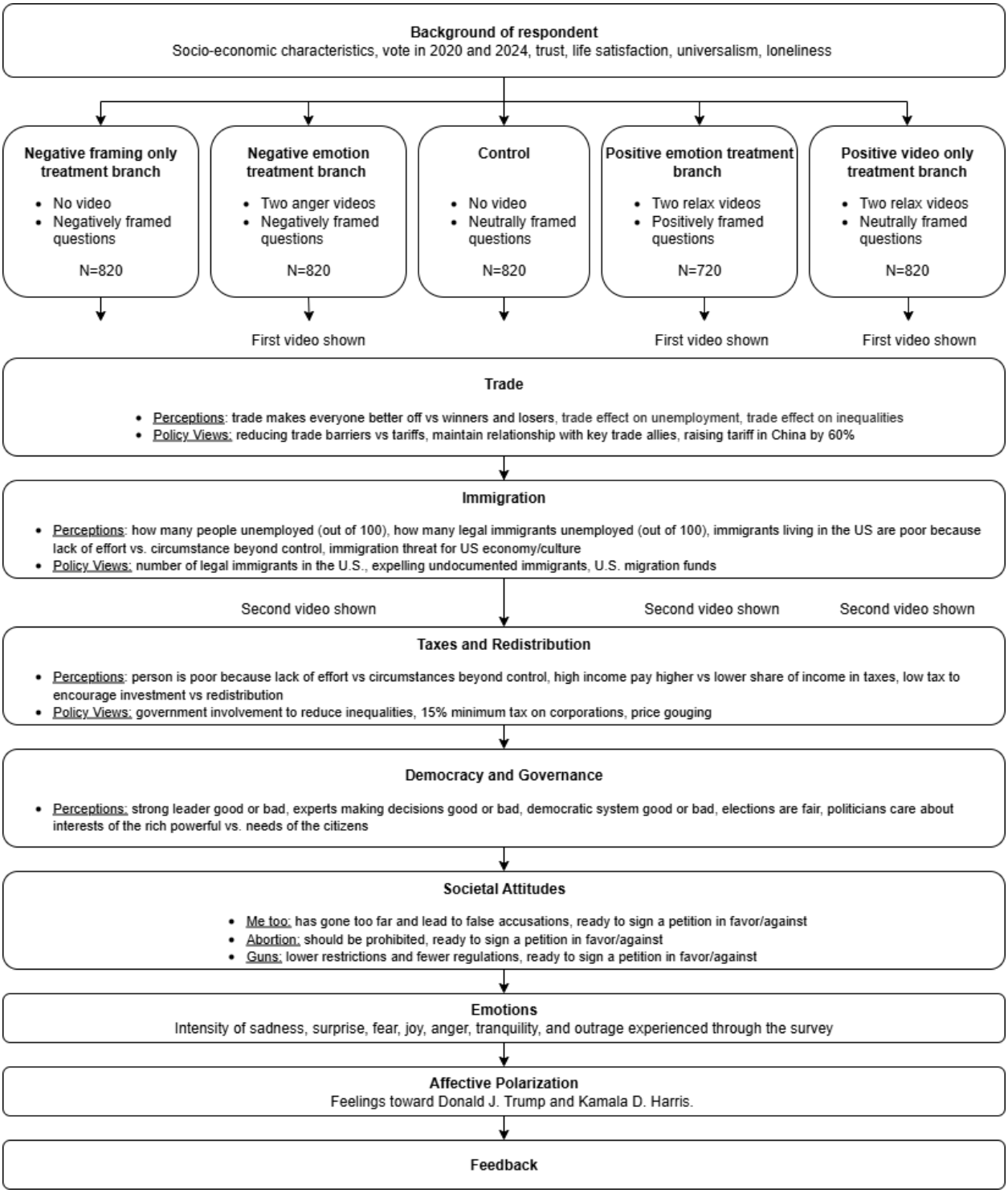
Data Quality. To ensure the highest possible data quality, we implemented several measures. On the introductory consent page, we emphasized the importance of careful and honest responses, appealing to participants' sense of social responsibility. Additionally, we informed respondents that monetary compensation 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 3) were obtained after excluding participants who were screened 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 A2 (Survey A) and Appendix Table A4 (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. The figure provides more detail on the types of questions contained in each block.

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 this survey, respondents are randomly assigned to five different experimental branches, designed to evoke either positive or negative emotions by combining video treatments and variations in the framing of open-ended questions at the start of each policy block. We start by describing the videos and then turn to the priming questions.

Emotional videos. The first video in each branch is shown just before the trade block and a second video just before the taxes and redistribution block.

In the positive treatment branch, 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.

In the negative treatment branch, 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.

Open-ended priming questions. The open-ended priming 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 priming questions.

We primarily focus on the three following treatments arms: (i) The *Positive emotion treatment branch* showing the positive videos and asking positively-framed open-ended questions; (ii) the *Control branch* with no video and asking neutral open-ended policy questions; (iii) the *Negative emotion treatment branch* showing respondents the negative videos and asking negatively-framed open-ended questions at the start of each policy block.

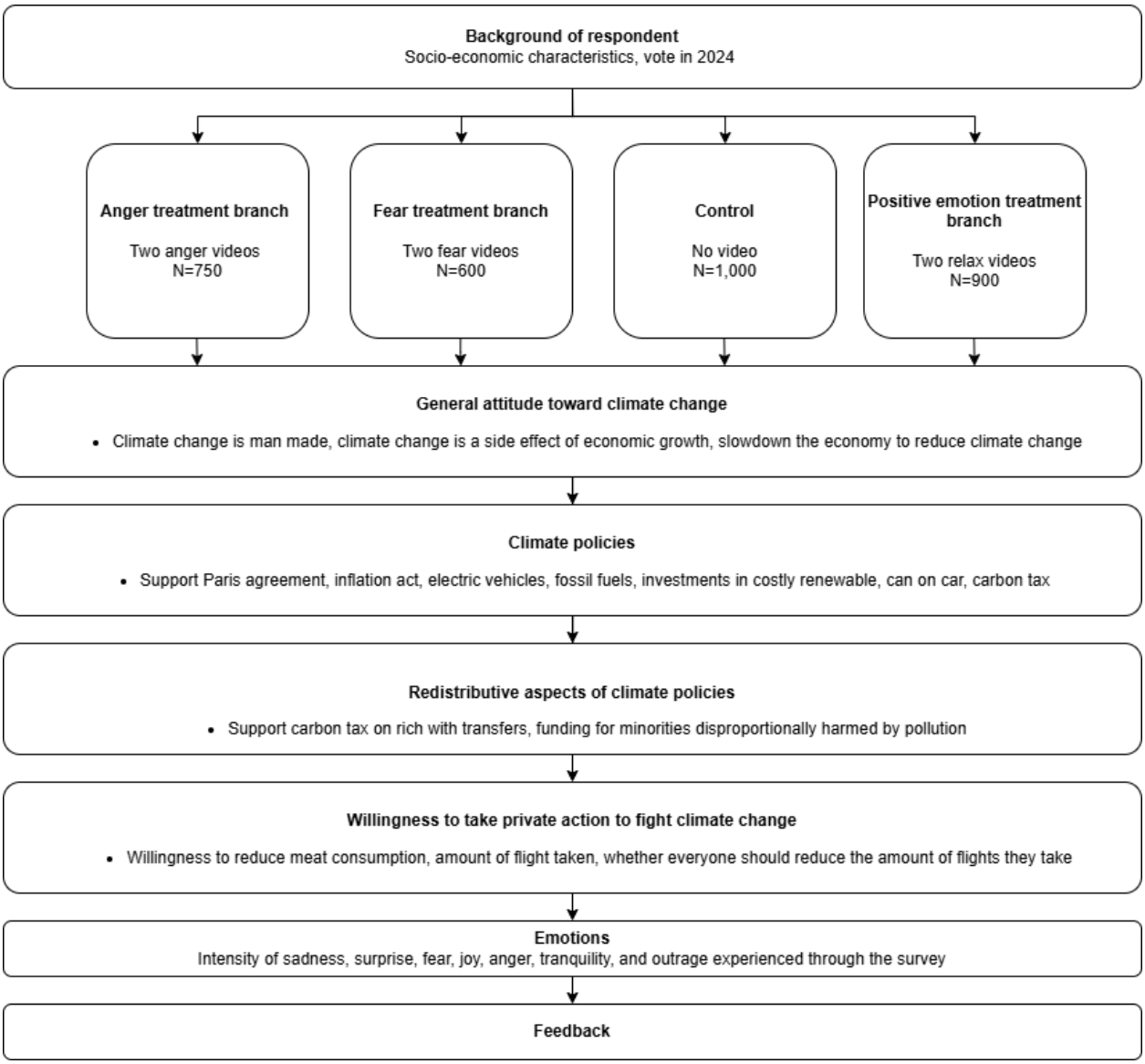
For robustness we also include two other treatment arms, that are slight variations of these main arms: *Negative framing only treatment branch*: Respondents do not see any video but the open-ended policy questions at the beginning of each policy block are framed in a negative way and the *Positive video only treatment branch*, in which respondents watch only the positive videos but the open-ended policy questions are framed neutrally.

Appendix Table A3 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.

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 branch, 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 also randomly assigned to one of three treatment groups and a control group. The treatment groups see two short videos: the first before block

assessing general attitudes toward climate change and the second before the block on emotions. Specifically, the *Positive emotion treatment branch* sees the positive two treatment videos described for survey A; the *Anger treatment branch* see the two negative videos from survey A; the *Fear treatment branch* sees two one-minute videos designed to be similar in content as the anger treatment branch video but emphasizing fear sentiments over anger. Like the anger video, 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.

Appendix Table A5 shows that our treatment assignment is balanced across socio-demographic characteristics as well as political affiliation.

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)

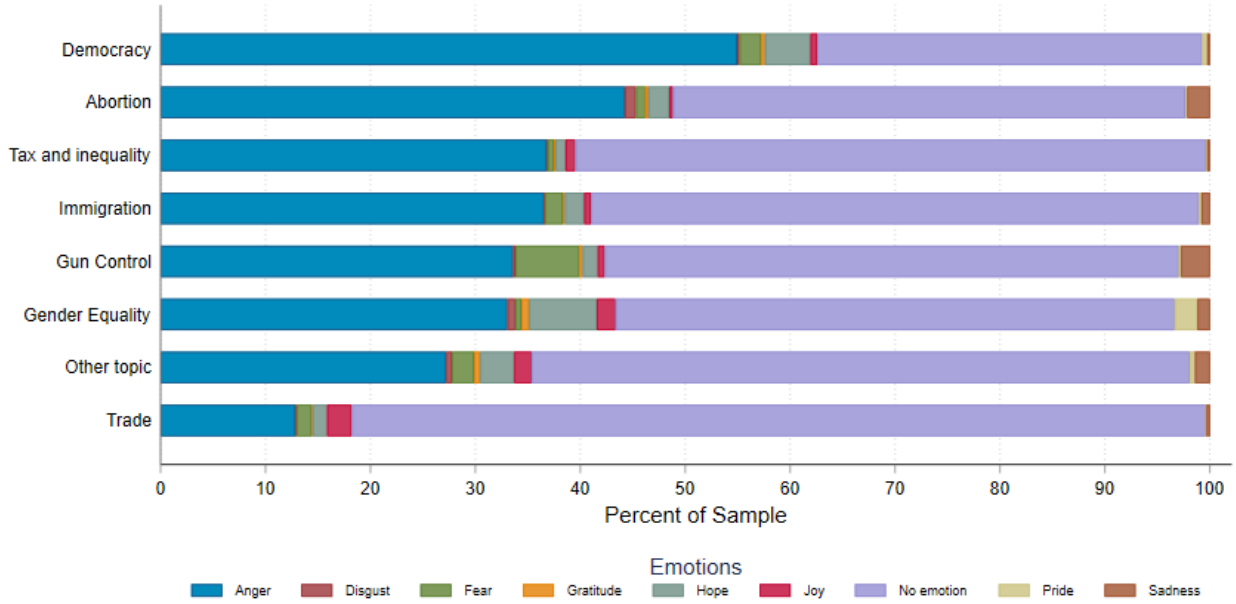


(b) First fear video (ii)



(c) Second fear video

FIGURE 6: EMOTIONS IN VOTERS' TWEETS ON POLICY ISSUES 2013-2025



Notes. The figure shows the share of sentences across all tweets that contain a given emotion for the period 2013-2025.

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

This section analyzes the emotional content of tweets posted by registered voters, hereafter, the "voters tweets". We focus on this sample because it allows us to track the same users over time—enabling within-user analyses—and because it includes richer covariates, which facilitate heterogeneity analyses. We acknowledge that this is a selected sample. To show that our findings are not driven by selection or by specific characteristics of registered voters, we replicate all main results (when feasible) using the random sample of citizens' tweets, reported in Appendix A.6.2 and Appendix A.6.4.2.

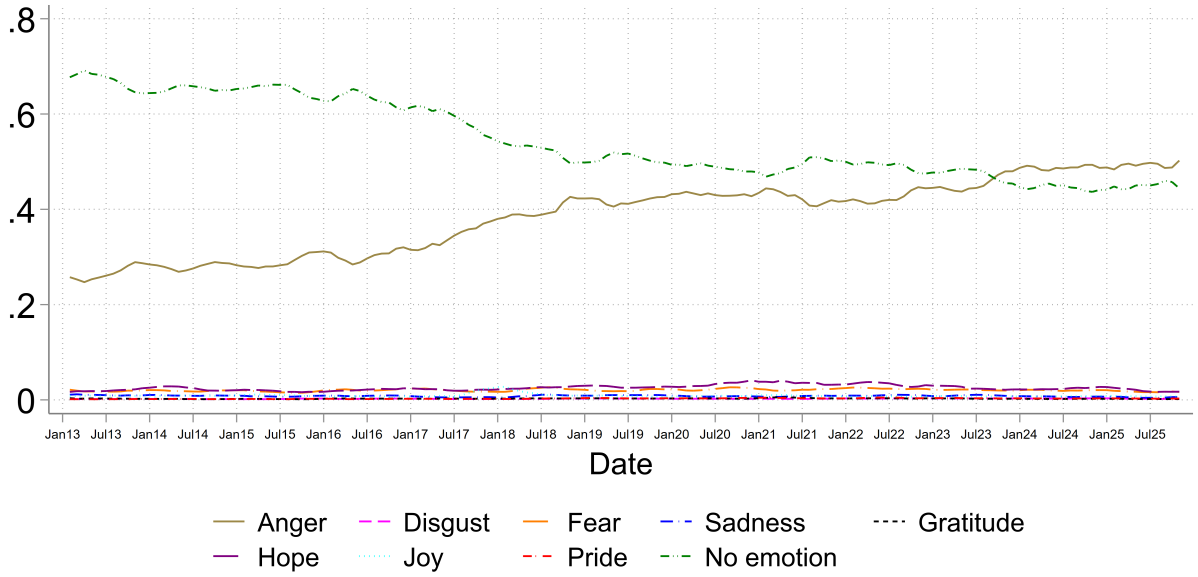
3.1 Emotional Expressions of Voters : Analyzing Tweets on policy issues

Distribution of emotions by policy topic. Figure 6 presents the distribution of emotions expressed in tweets across the various policy topics. Strikingly, anger emerges as the dominant emotion across all policy issues in both samples, highlighting its pervasive role in voters' discourse. Abortion, democracy, tax and inequality, and immigration elicit the highest levels of anger, with this emotion appearing in 35–60% of posts on these topics. Conversely, trade tends to elicit relatively lower levels of anger, appearing in only 12% of posts. In fact, trade is the topic with the lowest overall level of emotional content. The topic on gun control also generate a significant amount of fear (7%). Finally, among the topics that also generate positive emotions, gender equality stands out, with posts expressing hope or joy (10%). Figure A4 replicates the results on the random citizen sample, yielding highly consistent patterns.

Evolution of emotions. Figure 7 illustrates the evolution of emotional expressions in voters' tweets about the policy issues detailed previously in Figure 6.[7] The most striking finding is the strong and persistent

[7]Except the category "Other topic" that is excluded in Figure 7. Including it does not change the pattern.

FIGURE 7: THE EVOLUTION OF EMOTIONS IN VOTERS' TWEETS 2013-2025



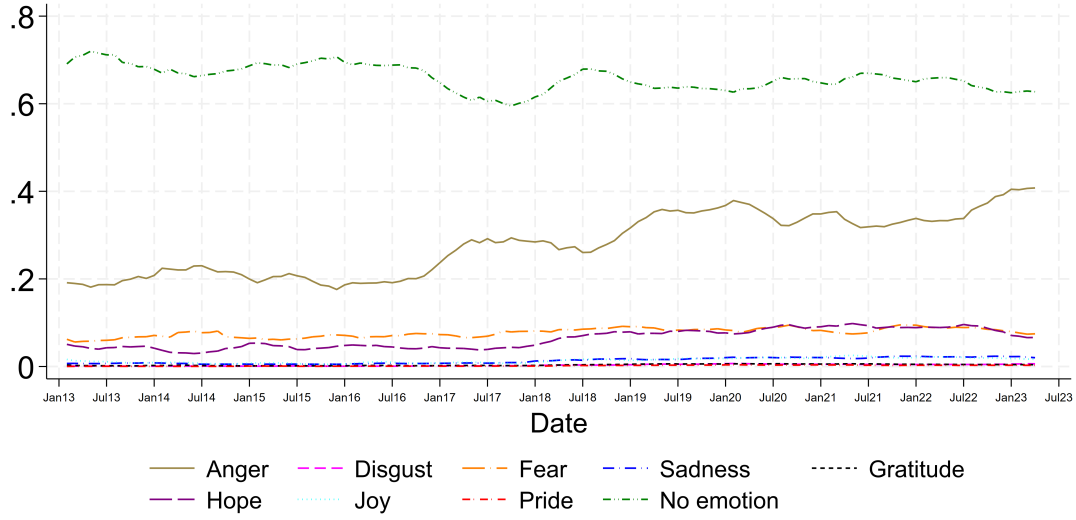
Notes. The figure shows, for each month from January 2013 to June 2025, the share of sentences in tweets classified into each emotion. For readability, the graph displays a 6-month moving average of monthly percentages. The sample is restricted to tweets by citizens or partisan users whose primary topic is one of the following: 'abortion', 'democracy', 'gender equality', 'gun control', 'immigration', 'tax and inequality', or 'trade'. The category 'other topic' is excluded.

rise in the proportion of tweets expressing anger since Donald Trump's first election in 2016–2017. Over the observed period, the share of angry posts doubled, increasing from 25% to 50%. Concurrently, the proportion of tweets without any emotional content has substantially declined, falling from around 70% to less than 50%. In contrast, the prevalence of other emotions, both positive or negative, has remained largely stable and account for less than 5% of tweets throughout the entire period. This pattern aligns closely with the evolution of emotion shares in the citizens' tweets, shown in Figure A5.

Figure 8 depicts the evolution of emotions in discussions on the key policy issue examined in Survey B, namely climate change. While this topic was largely devoid of emotion at the beginning of the period, expressions of anger about climate change doubled between 2013 and 2023, reaching a peak of 40% of posts by the end of the period — a pattern consistent with the trends observed for other policy issues discussed above. In contrast, the overall level of fear regarding climate change has remained relatively stable. The rise in anger may reflect growing frustration with perceived inaction as well as increasing opposition to climate policies, whereas the stagnation of fear suggests a persistent awareness of the risks associated with climate change. These findings underscore the importance of distinguishing between different types of emotions — even among negative ones — when analyzing their influence on policy attitudes, as we do in Survey B.

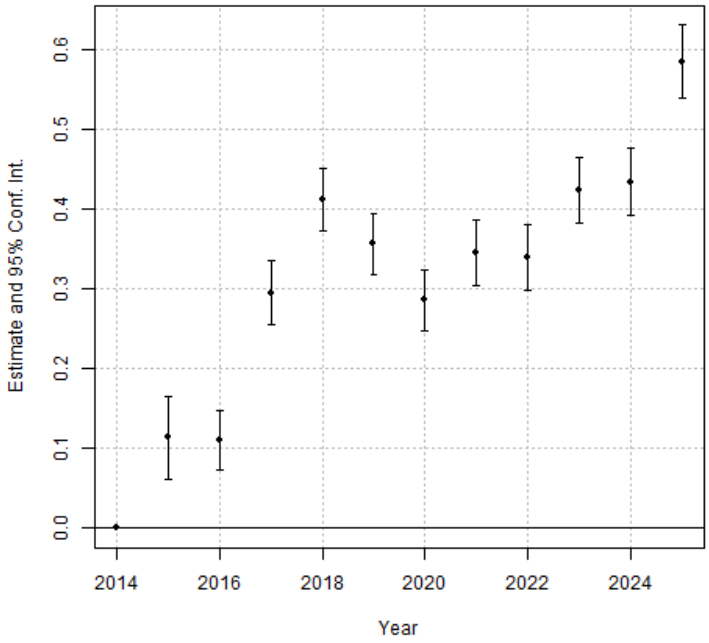
Evolution of anger over time with users' fixed effects Another important issue concerns the self-selection of voters on the X platform over time. Are voters genuinely becoming angrier about policy issues as time passes, or is it rather that more angry and polarized individuals join or remain on X while less angry, more moderate users gradually leave the platform?

FIGURE 8: EVOLUTION OF EMOTIONAL CONTENT IN TWEETS ON CLIMATE CHANGE



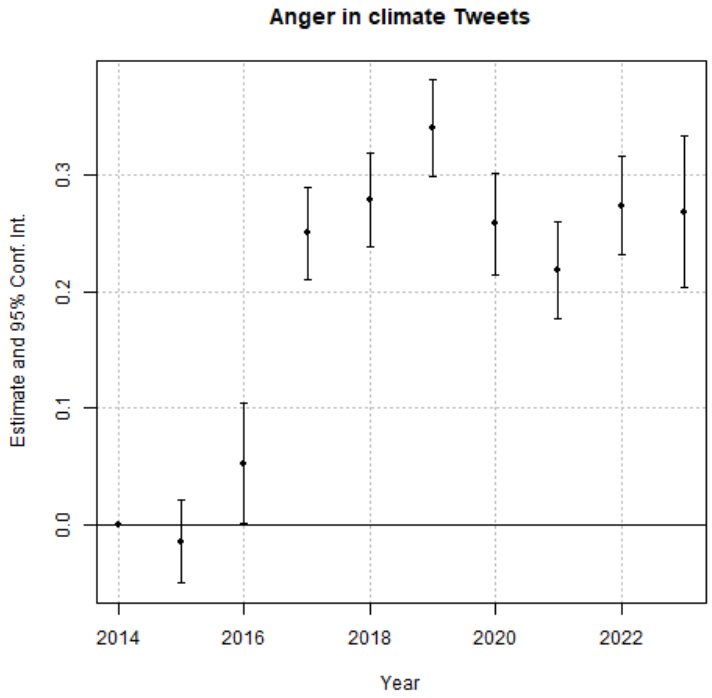
Notes. The figure shows, for each month from January 2013 to April 2023, the share of tweets classified under each emotional tone for climate change-related tweets. The numerator represents the number of tweets by X users in a given month that are classified in a specific emotion category, while the 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.

FIGURE 9: WITHIN-VOTER RISE IN ANGER ON POLICY ISSUES 2013-2025



Notes. The figures show the coefficients on year fixed effects in a regression of anger on year fixed effects, user fixed effects, and topic fixed effects in the two datasets. The reference year is 2014. The regression model used is a fixed-effects Quasi-Poisson Generalized Linear Model (GLM). Error bars represent 95% confidence intervals.

FIGURE 10: WITHIN-USER RISE IN ANGER ON CLIMATE CHANGE 2013-2025



Notes. The figure shows the coefficients on year fixed effects in a regression of anger on year fixed effects and user fixed effects. The reference year is 2014. The regression model used is a fixed-effects Quasi-Poisson Generalized Linear Model (GLM). Error bars represent 95% confidence intervals.

To shed light on this question, we examine the evolution of anger within voters over time, leveraging user fixed effects. Figure 9 reports the effects of different years (relative to 2014) on the anger content of tweets, using a fixed-effects Quasi-Poisson Generalized Linear Model (GLM) in voters' tweets. It reveals a marked increase in the anger expressed by the same individuals on the same policy topics over time, relative to 2014. This sharp rise begins in 2017 coinciding with the first Trump administration, and intensifies again after the 2022 midterms. We replicate the analysis on the citizens' sample in Figure A6, and results are broadly consistent, while statistical significance is lower due to a limited number of repeated users in the sample, given that it was not drawn to be a panel. Figure 10 reveals a similar temporal pattern of anger in climate-related tweets with users' fixed effect.

Decomposing the increase in anger Figure 11 presents the cumulative Shapley decomposition of the aggregate share of angry tweets from 2013 to 2025, anchored at the observed 2013 baseline, as measured on the voter dataset[8]. The stacked bands report the cumulative contributions of the four sources of change to the evolution of the aggregate level. *Share of Angry Tweets* changes represent the change in a user share of angry tweets leaving the number of tweets unchanged. *Number of Tweets* changes represent the change in the number of tweets per year from a user, leaving the share of angry tweets unchanged. *Entry* and *Exit* changes represents the change due to first-time users entering the platform and users exiting the

[8]The citizens' tweet sample does not include a sufficiently large cohort of users observed consistently over time to support this longitudinal decomposition.

platform, respectively. The increase is driven predominantly by the within component: emotional changes in users' content and reallocation of tweet volume among continuing users. Both forces contribute steadily and account for most of the upward trajectory, whereas selection effects (entry and exit) are positive but comparatively modest. Appendix A.6.3 provides a more detailed methodological description.

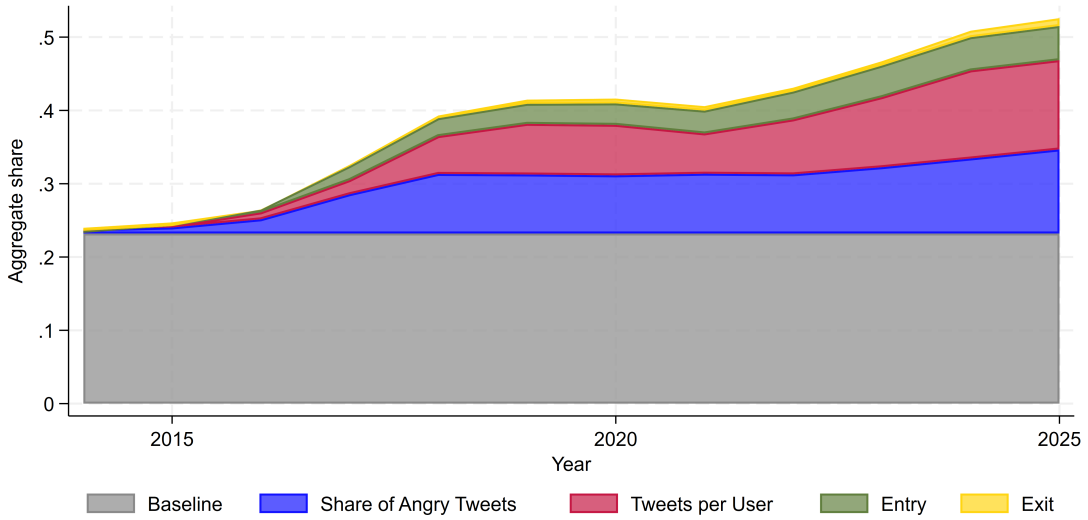


FIGURE 11: CUMULATIVE SHAPLEY DECOMPOSITION

Notes. The figure shows the yearly change in the proportion of tweets classified as anger in the voters' sample decomposed in entry, exits, which represent the between-users effect, and share of angry tweets, number of tweets, which represent the within-users effects. Small discrepancies of the cumulative level of anger compared to the time series plot obtained in the same dataset (Figure 7) reflect the different temporal aggregation, as this figure uses annual proportions while the main figures report monthly data smoothed with a six-month moving average.

Is it the algorithm? Is it bots? First, is the increase in anger mechanically due to the X algorithm? When X released the code of its algorithms in 2023, there was no direct mention of emotions or anger entering the ranking algorithms.[9] However, the algorithm is designed to maximize retention and engagement. Through a large-scale field experiment on X, Gauthier, Hodler, et al., 2026 show that it successfully does so: replacing a chronological feed with an algorithmic feed increased user engagement and shifted political attitudes in a more conservative direction. This would not be contradictory to our story but instead show one mechanism through which anger can be perpetuated – because it causes more engagement.

A second concern is that the increase in anger might be driven by bots, which have become more prevalent in recent years. This issue is alleviated in the voter sample, where each X user is matched to a registered voter, ensuring that the account corresponds to a real person. It is more relevant for the random citizen sample, where no such match is performed. For this sample, however, we conduct a thorough bot-detection analysis, detailed in Appendix A.6.2.

[9]See for instance https://quso.ai/blog/twitter-algorithm and https://blog.x.com/engineering/en_us/topics/open-source/2023/twitter-recommendation-algorithm.

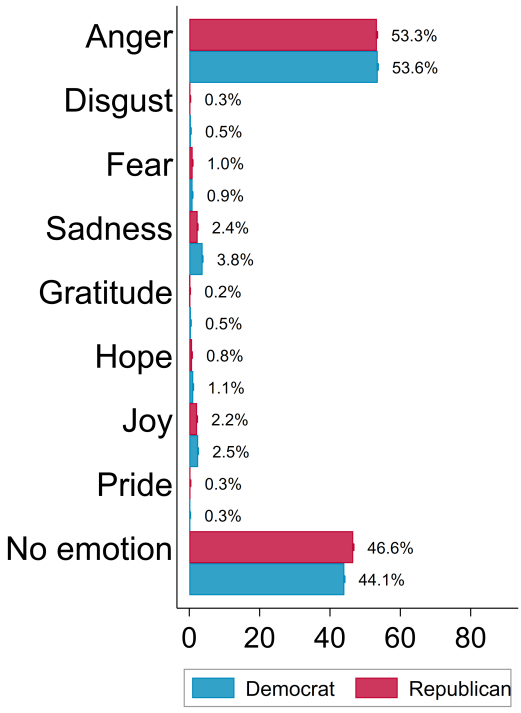
3.2 Emotional Expressions of Voters by Political Affiliation

Next, we examine how the expression of emotions on social media varies by political leaning. In the voter sample, we use party registration to infer users' political leaning; summary statistics are provided in Appendix A.6.4.1. In the citizen sample, since this information is not available, we assign political leaning using the methodology proposed by Mosleh and Rand, 2022, as discussed in Appendix A.6.4.2.

Figure 12 reports the distribution of tweets by emotional category separately for Democratic- and Republican-affiliated users. A substantial share of tweets in both groups are classified as having no detectable emotion—46.6% among Republicans and 44.1% among Democrats. Among emotionally expressed tweets, anger overwhelmingly dominates for both affiliations, accounting for 53.3% of Republican tweets and 53.6% of Democratic tweets. All other emotions appear at very low frequencies. Sadness and joy are the most common non-anger emotions, but each accounts for less than 4% of tweets in either group. Disgust, fear, gratitude, hope, and pride are rare, each representing around 1% or less of tweets. Overall, the emotional profiles of Democratic and Republican users are remarkably similar, with near-identical shares of anger and broadly comparable distributions across the remaining emotional categories. We replicate the results on the random citizen sample in Figure A10, and the patterns are aligned.

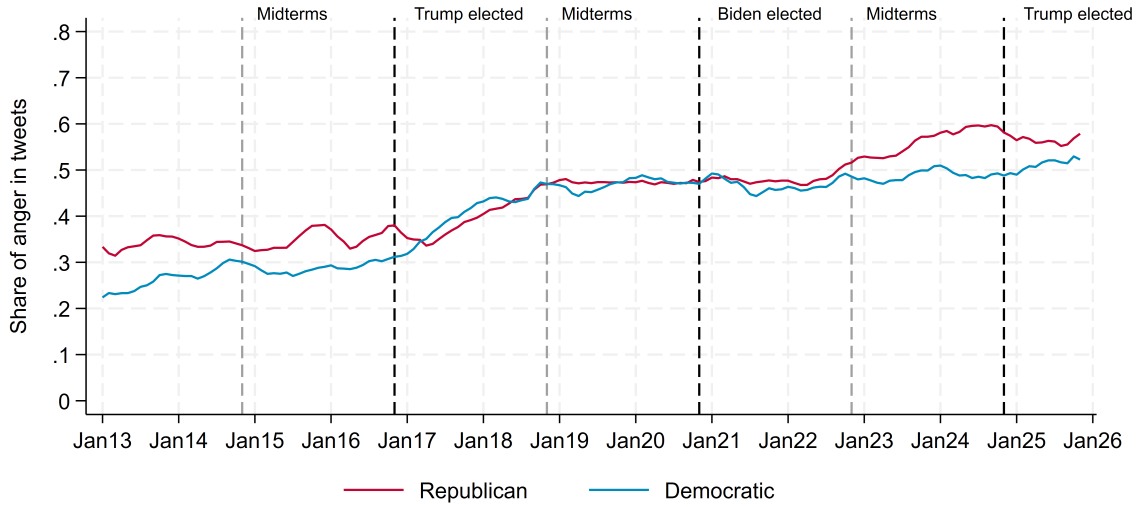
Figure 13 illustrates the evolution of anger among Democrat- and Republican-affiliated X users. It shows that anger sharply increases among both groups starting around 2016-2017, at the time of the first half of Trump's first mandate, and then reached a plateau from 2019 to the end of 2022. Among Democratic partisans, anger increases more sharply following Trump's election in November 2016 and declines slightly after Biden's election. However, it remains significantly above the levels from before 2016. Anger starts rising a little after among Republican users, but accelerates similarly during the first half of Trump presidency and continues to rise (albeit at a lower rate) during the Biden presidency. Figure A12 replicates the same results using citizens' tweets, and results stay very consistent.

FIGURE 12: EMOTIONAL CONTENT OF VOTERS' TWEETS BY POLITICAL AFFILIATION



Notes. The figure shows, for each emotion, the share of tweets classified in a given emotional category by political affiliation. The numerator represents the number of tweets by X users within a given political affiliation classified in that emotion category, while the denominator is the total number of tweets by X users in that political affiliation.

FIGURE 13: EVOLUTION OF ANGER IN VOTERS' TWEETS ON POLICY TOPICS BY PARTY



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 group classified anger, while the denominator is the total number of tweets by X users in that group. For readability, the graph displays a 6-month moving average of monthly percentages.

3.3 Emotions in Different Groups

In this section, we present the results of the heterogeneity analysis conducted using the matched voter panel dataset, showing the share of tweets classified as anger over time by demographic groups.[10] Summary statistics on the prevalence of each demographic group in the voter dataset are provided in Appendix A.6.5.

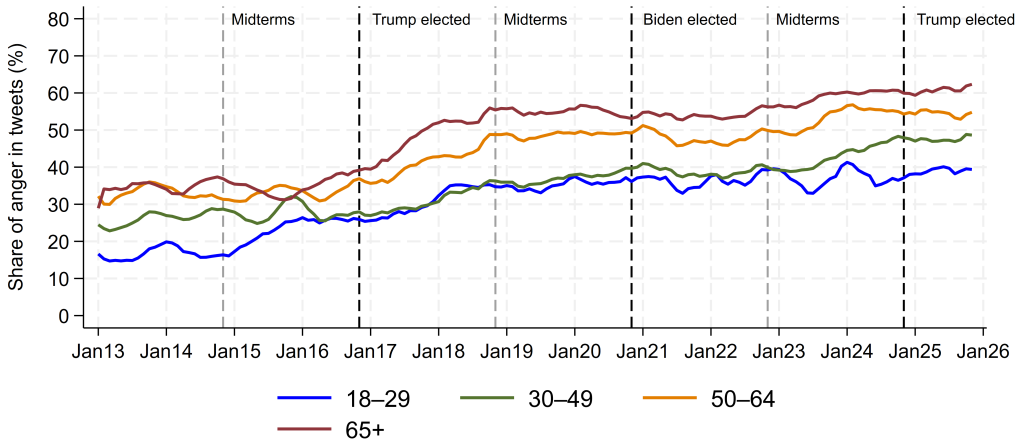
The heterogeneity analysis reveals a clear and persistent stratification in the expression of anger across demographic groups. Older users consistently display higher shares of anger-classified tweets than younger users, with the 50–64 and 65+ groups exhibiting both the highest baseline levels and the strongest upward trends over time, while the youngest cohort (18–29) remains markedly less prone to expressing anger. Gender differences are also pronounced: although male and female users begin at comparable levels, female users subsequently exhibit higher anger shares, with the gender gap widening after Trump's 2016 presidential election and remaining largely stable thereafter. A similarly monotonic gradient emerges across educational groups, with users with lower educational attainment systematically expressing higher levels of anger than college-educated users throughout the sample period. Spatial differences further reinforce this pattern of stratification. Rural users consistently exhibit the highest shares of anger-classified tweets, followed by suburban users, while urban users display substantially lower levels across the entire period, with the rural–urban gap remaining sizeable and persistent.

Despite differences in levels, all demographic groups exhibit similar dynamics: a sharp rise in anger after the 2016 Trump election, followed by stabilization at elevated levels with only moderate fluctuations around later political events.

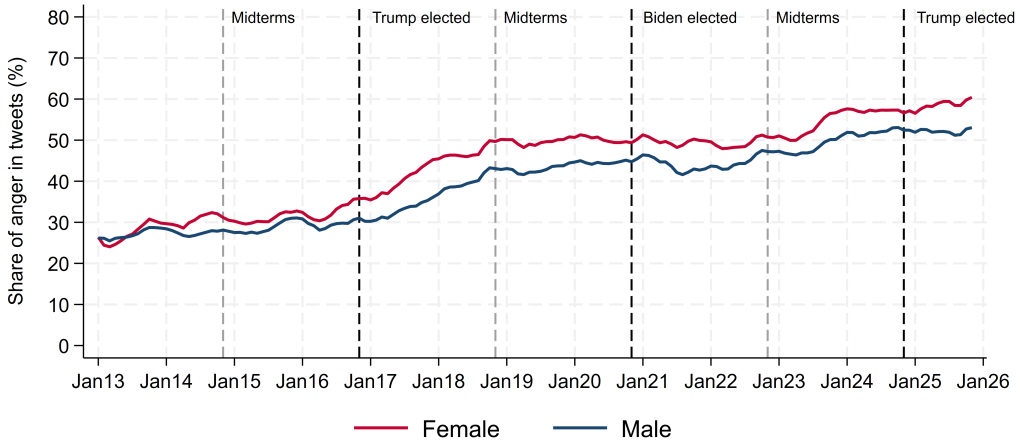
[10] This analysis cannot be replicated using the random citizen dataset, which does not contain the necessary demographic variables.

Figure 14: Evolution of Anger in Voters' Tweets on Policy Topics by Demographic Groups

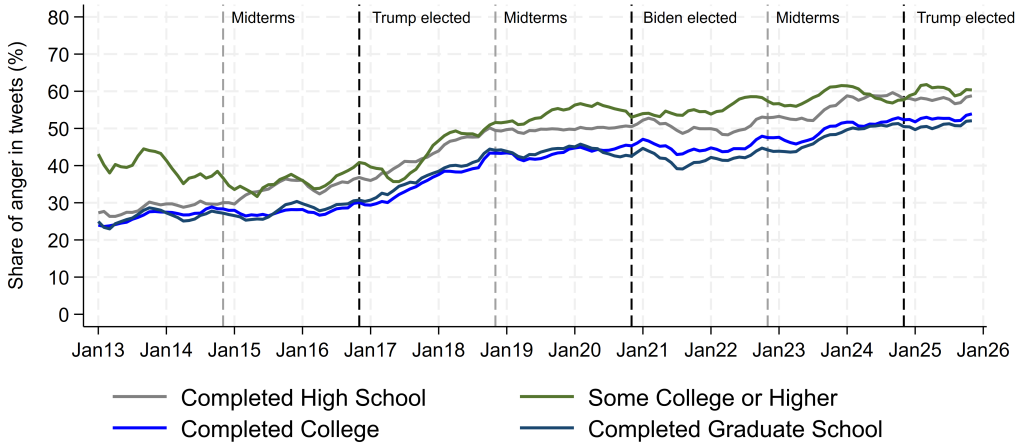
(a) By Age



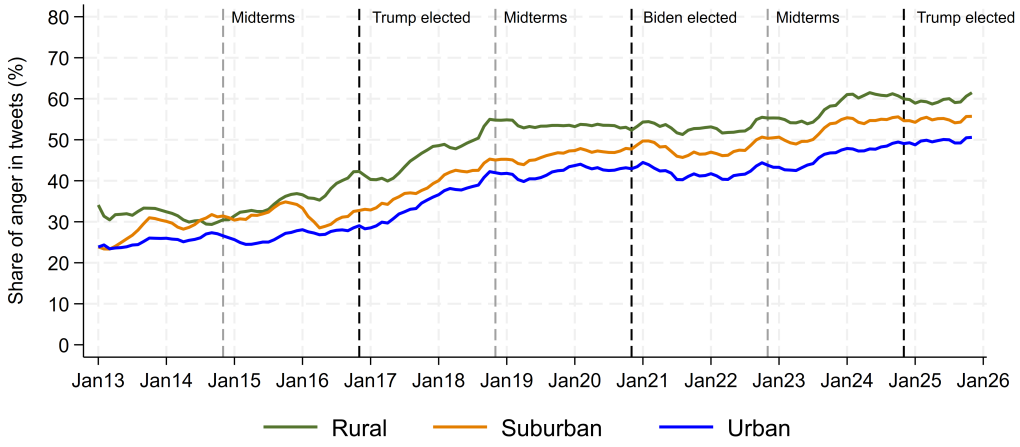
(b) By Gender



(c) By Education



(d) By Urbanicity



Notes. The figure shows, for each year, the share of tweets classified as anger by group. The numerator represents the number of tweets by X users within a given group classified as anger, while the denominator is the total number of tweets by X users in that group. 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.

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

On the demand side, we have seen that anger has risen sharply and significantly starting around 2016 and, although the speed of increase was lower during the Biden presidency, it has remained far above its earlier levels. How do these patterns compare and contrast to the supply side of emotions, stemming from policy makers and politicians? This section examines the supply side through tweets and speeches.

4.1 Emotions in Political Communication: Tweets and Speeches

Distribution of emotions by topic. Figure 15 starts by plotting the distribution of emotions for our policy topics across four different types of political communications: official party tweets (panel 15a), congressional tweets (panel 15b), congressional floor speeches (panel 15c), and campaign speeches (panel 15d). On average, over this period, there is a clear 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 citizens' sentiment. Furthermore, anger is particularly prevalent in discussions surrounding abortion, democracy, immigration, and tax and inequality across all four types of political communications. These findings are a first suggestive evidence that political and citizen discourses mutually reinforce emotional narratives, contributing to heightened emotional intensity in public debates on policy issues.

Yet, a notable difference relative to citizens' tweets is that, despite the overall dominance of anger, political discourse frequently incorporates expressions of hope. This likely reflects strategic rhetorical choices made during critical moments, such as election campaigns, when politicians seek to mobilize and inspire voters — in the spirit of iconic slogans like Martin Luther King's "I Have a Dream," Barack Obama's "Yes We Can," or "Make America Great Again." 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 among policy makers and politicians. Figure 16 illustrates the evolution of emotions in political communication across three of our samples: official party tweets (panel 16a), tweets from members of Congress (panel 16b), and congressional floor speeches (panel 16c).[11] 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 60% in 2013 to around 38% in 2025 in panel 16a. This reduction is significantly more pronounced in congressional tweets and official party tweets than in floor speeches. This suggests strategic differences in emotional communication online versus offline or in a more public versus less-public facing setting.

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 20% in early 2013 to nearly 60% by 2025 (panel 16a)[12]. Similarly, Congress members' tweets saw anger increase substantially, from roughly 20% to 50% in the same period (panel 16b). Although floor speeches display a lower overall level of anger remaining below 40% over the period (panel 16c), they still exhibit a clear upward trajectory from roughly 20% to 30% over the period. These patterns indicate a

[11] The 2024 Campaign speeches are over a too short period to be able to study the evolution.

[12] Figure A20 also displays the evolution for other official accounts that are not the six main accounts from the Republican and Democratic Parties

convergence toward increasingly emotionally charged political messaging, particularly in online platforms where emotional rhetoric appears especially amplified.

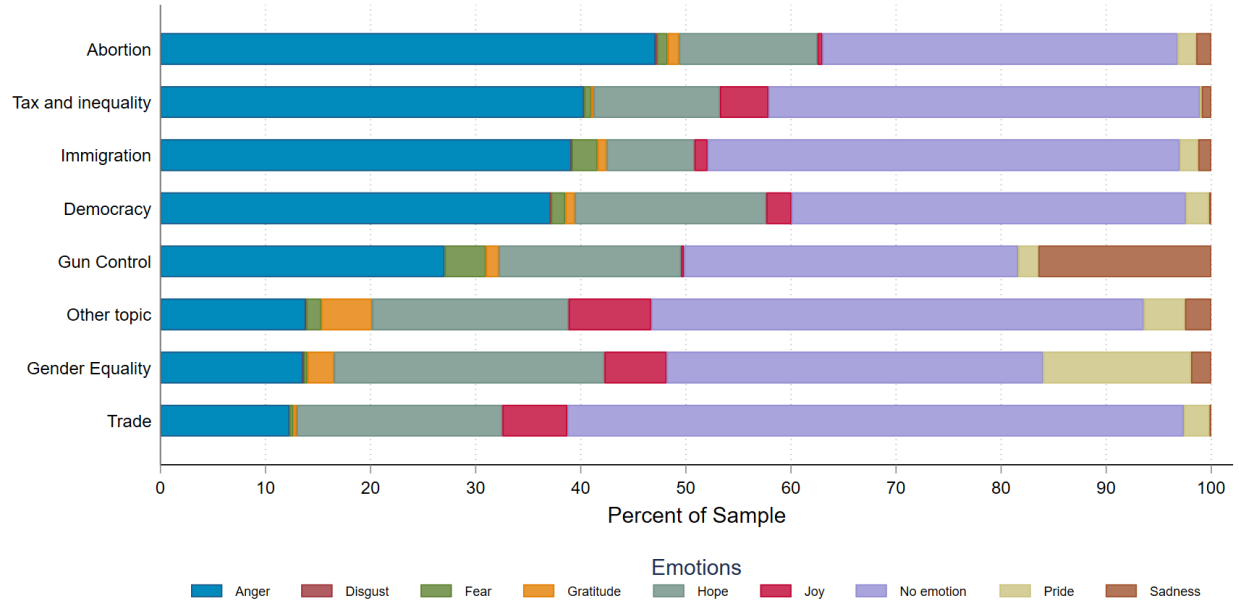
Evolution of anger over time with individual fixed effects. As in the previous section, we assess the issue of self-selection of members of Congress on the X platform over time. We examine the evolution of anger within members of congress' tweets over time by including individual fixed effects, as well as topic fixed effects. The regression sample comprises 326,667 tweets authored by 689 unique members of Congress observed at different moments in time, and standard errors are clustered at the member of Congress level. The discrepancy to the numbers mentioned above is because we are still scraping this data due to API limitations on a per-day basis.

Figure 17 displays the effects of different years (relative to 2014) on the anger content of tweets, estimated using a fixed-effects Quasi-Poisson Generalized Linear Model (GLM). It shows a pronounced increase in the anger expressed by the same member of Congress on the same policy topics over time. Anger rises sharply by nearly 60% during the 2017 campaign, and continues to climb steadily, reaching a peak during the 2024 presidential election, where anger in congressional tweets is almost 232% higher as compared to 2014. Unlike in the citizen sample, the dataset includes a sufficiently large number of repeat members of Congress to allow for precise estimation. Note that the rise in anger overall in the congressional sample in Figure 16b showed an increase of 150%. Thus, the estimates conditional on individual fixed effects are very consistent with the overall time pattern, suggesting that the latter are not driven by a change in composition.

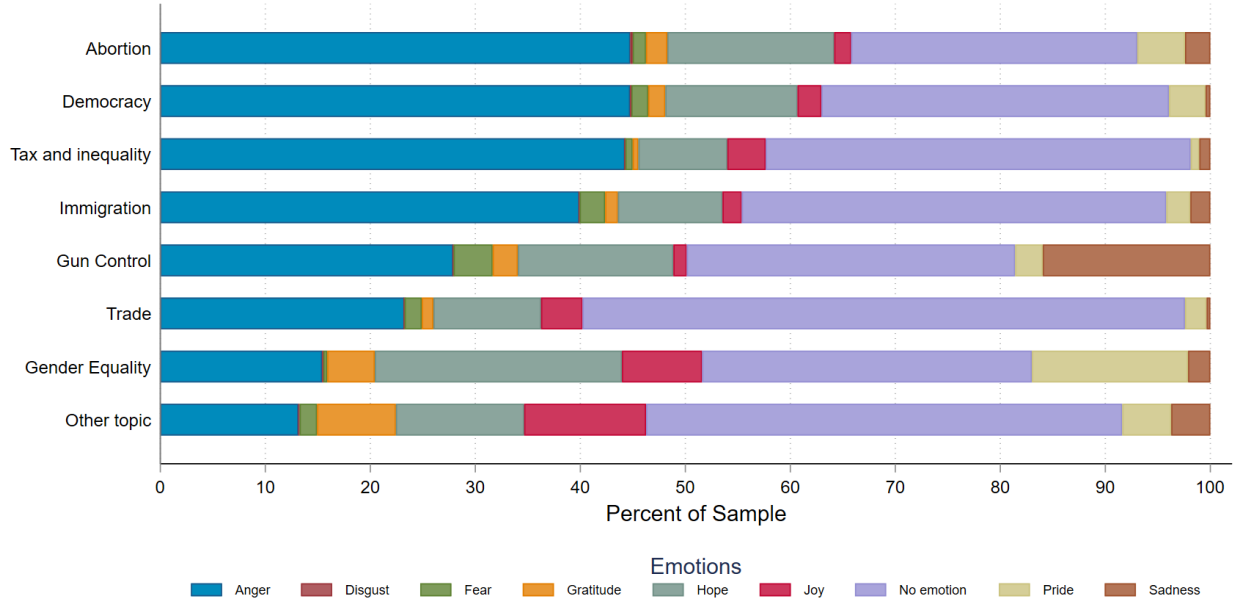
Finally, Figure 18 also reveals a similar temporal pattern of anger in official party tweets, including account fixed effects.

Figure 15: Emotional content of political communications on policy issues

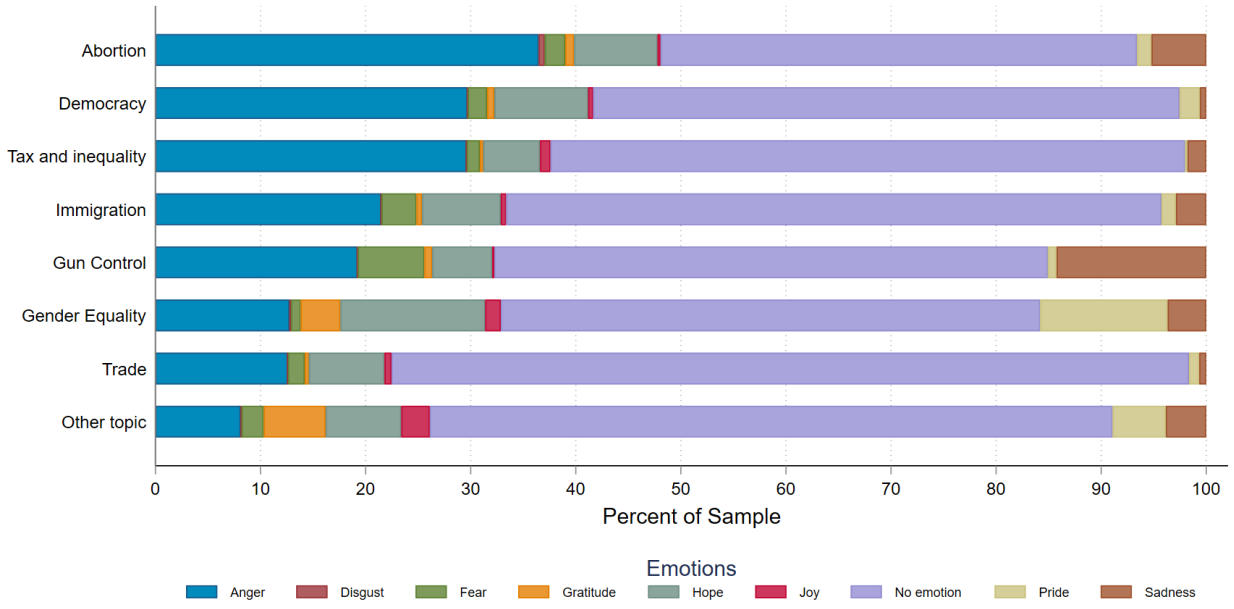
(a) Official Tweets



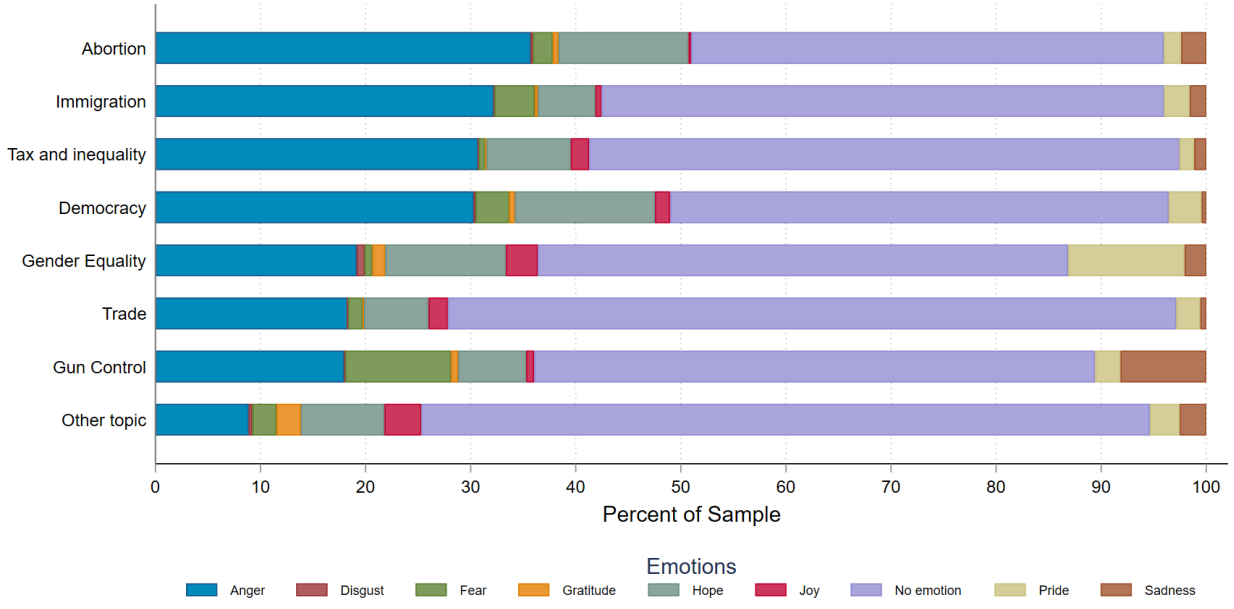
(b) Congressional tweets



(c) Congressional floor speeches



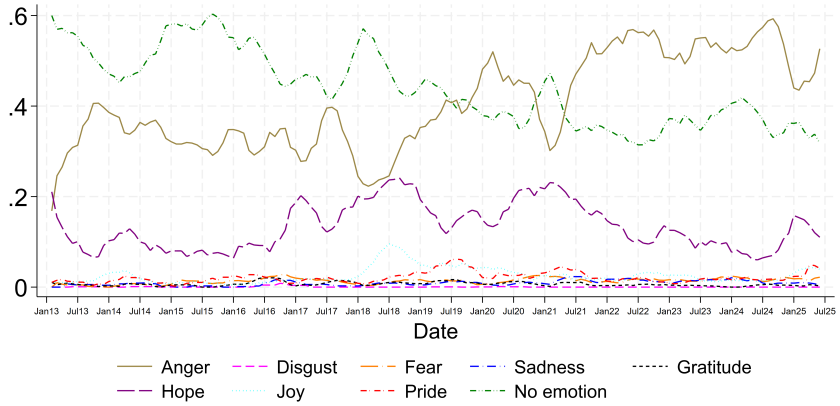
(d) Campaign speeches



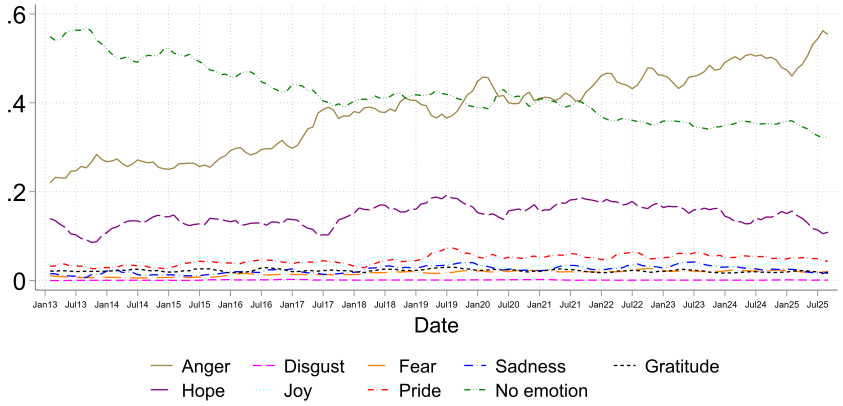
Notes. The figure shows the share of tweets or speech segments by emotion for each policy topic for the period 2013-2025. The numerator represents the number of tweets or speech segments that express a given emotion within a specific topic, while the denominator is the total number of tweets or speech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

Figure 16: Evolution of Emotions in Political Communication

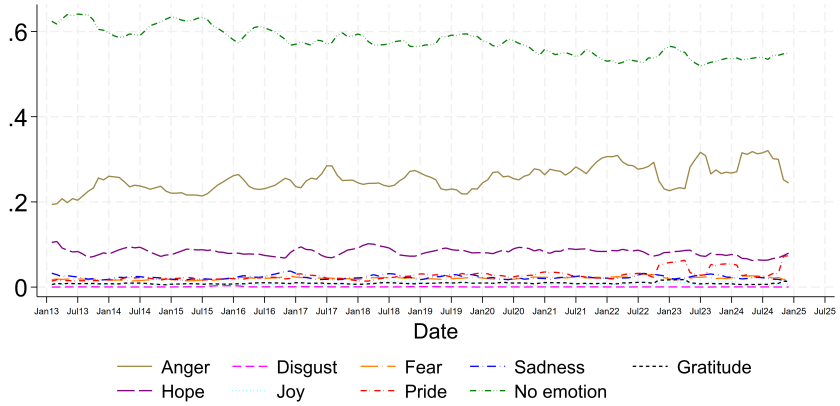
(a) Official Tweets



(b) Congressional Tweets

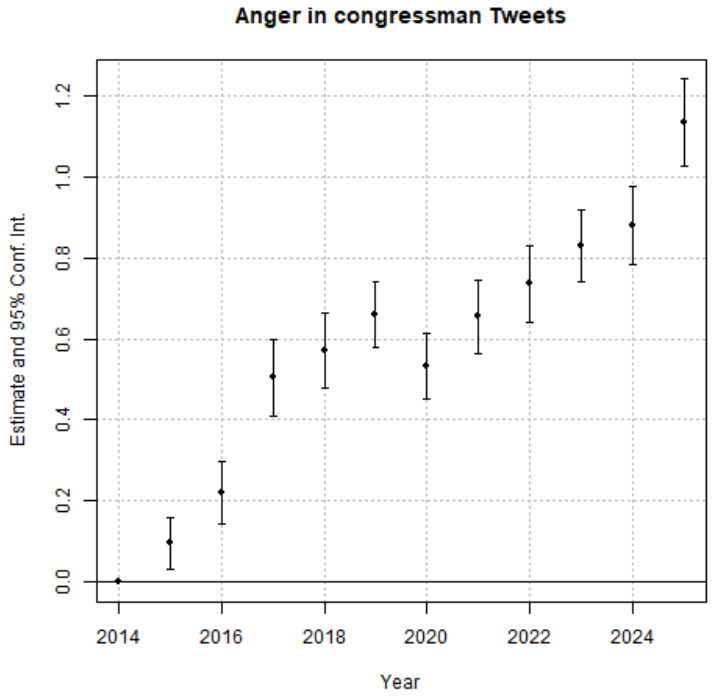


(c) Congressional Floor Speeches



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).

Figure 17: The Rise in Anger in Congressional Tweets, Conditional on Individual Fixed Effects



Notes. The figure shows the coefficients on year fixed effects in a regression of anger on year fixed effects, topic fixed effects, and user fixed effects. The reference year is 2014. The regression model used is a fixed-effects Quasi-Poisson Generalized Linear Model (GLM). Error bars represent 95% confidence intervals.

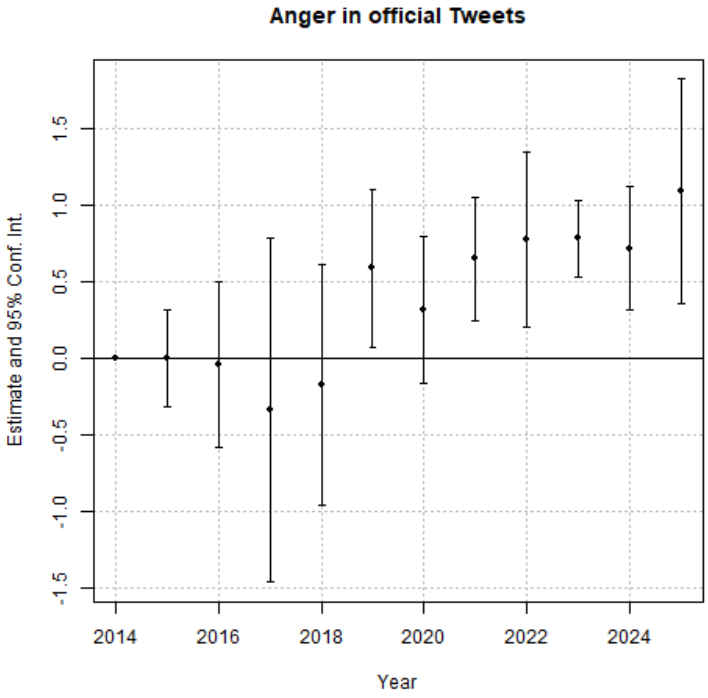
4.2 Emotional Expressions of Political Communication by Political Affiliation

We next examine the emotional content of political communication by party affiliation across all four samples in Figure 19.

Distribution of emotions by political affiliation. Once again, the overall pattern closely mirrors that observed in citizen tweets and remains consistent across communication formats. Panel 19a shows that 43% of Democratic Party official tweets and 42% of Republican Party official tweets are classified as non-emotional. This share is slightly lower in congressional tweets and campaign speeches (panels 19b and 19d), and significantly higher in congressional floor speeches (panel 19c), where 55%-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 19d), 38% of Republican statements express anger, compared to 23% among Democrats. The gap is also substantial in official or congressional tweets, with approximately 50% of Republican posts expressing anger, compared to 37% of Democratic posts. In contrast, Democratic communication is more likely to contain positive emotions—particularly hope. In official party tweets (panel 19a), 20% of Democratic tweets express hope compared to 9% among Republicans. The contrast is most striking in campaign speeches (panel 19d), where 17% of Democratic statements express hope—more than two times

Figure 18: The Rise in Anger in Official Tweets, Conditional on Account Fixed Effects



Notes. The figure shows the coefficients on year fixed effects in a regression of anger on year fixed effects, topic fixed effects, and account fixed effects. The reference year is 2014. The regression model used is a fixed-effects Quasi-Poisson Generalized Linear Model (GLM). Error bars represent 95% confidence intervals.

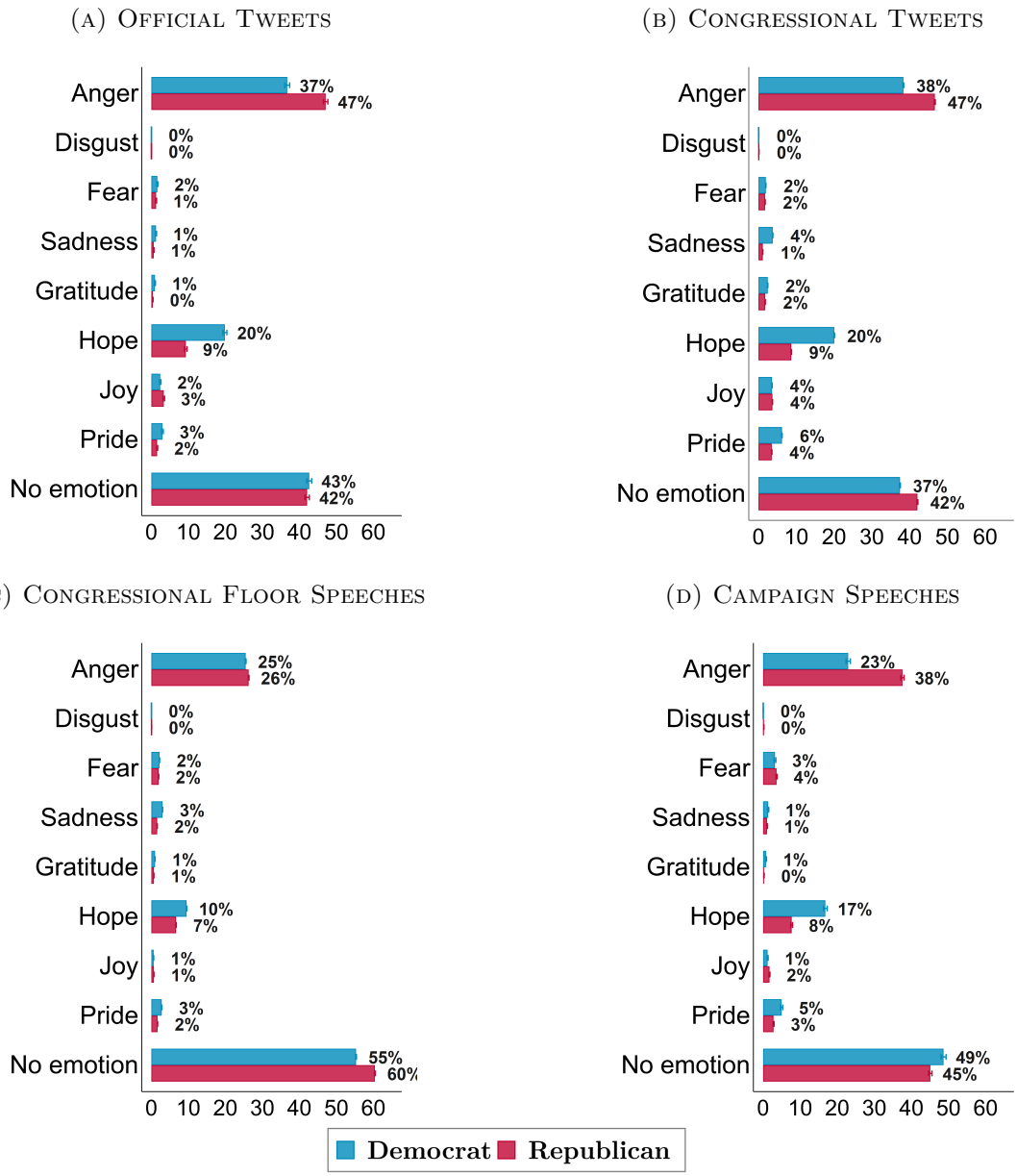
the share observed for Republicans (8%). This consistent divergence in emotional tone underscores distinct rhetorical strategies across parties.

On- and Off-line Anger by Political Affiliation. Figure 20 complements the analysis by comparing the online and offline expression of anger among members of congress. The figure plots the share of congressional tweets classified as expressing anger on the vertical axis, against the share of sentences in floor speeches classified as anger on the horizontal axis. Each dot represents a member of Congress.

The first insight is that anger is almost always amplified online, as evidenced by the fact that nearly all points lie above the 45 degree dashed line. Second, the online amplification of anger is more pronounced among Republican members of Congress than among Democrats, as shown by the red regression line lying above the blue one. Third, this amplification mechanism is largely driven by a fair amount of Republican outliers, whose expression of anger on X is more than twice as high as in their offline floor speeches.

Evolution of emotions by political affiliation. Figure 21 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 for most of the time, while this pattern reversed sharply 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.

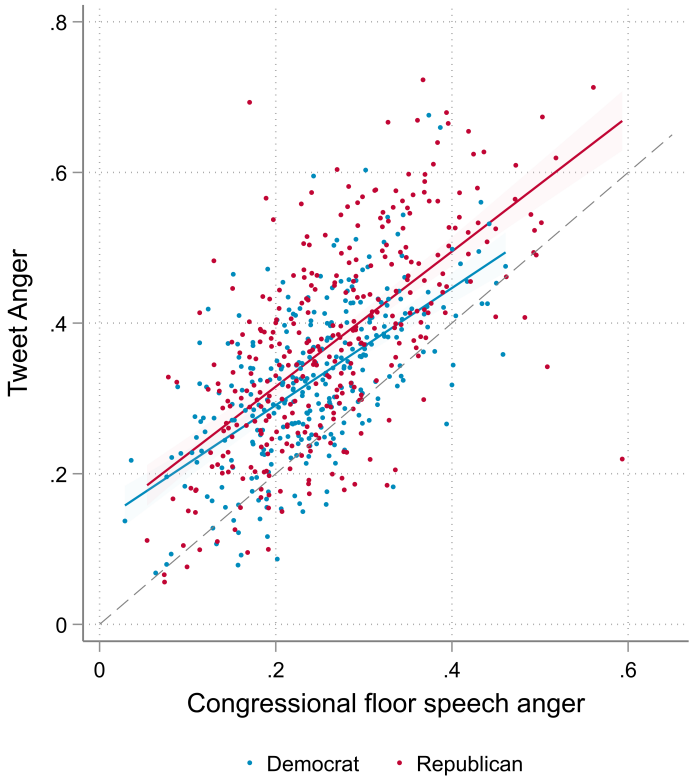
FIGURE 19: EMOTIONAL CONTENT OF POLITICAL COMMUNICATIONS BY POLITICAL AFFILIATION



Notes. The figure shows, for each emotion, the share of tweets or sentences classified in that emotional category for Democrat and Republican leaning. The numerator represents the number of tweets or sentences classified in that emotion category, while the denominator is the total number of tweets or sentences 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.

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 21a). A

Figure 20: Anger in the Political Discourse

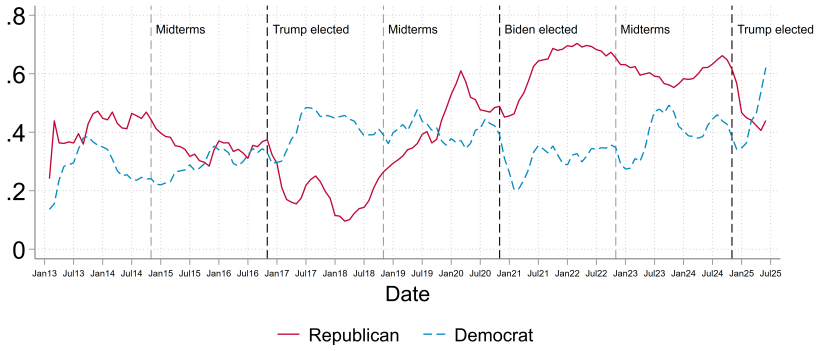


Notes. The figure shows the share of congressional tweets classified as anger on the vertical axis and the share of sentences in floor speeches classified as anger on the horizontal axis. Each dot represents a member of Congress.

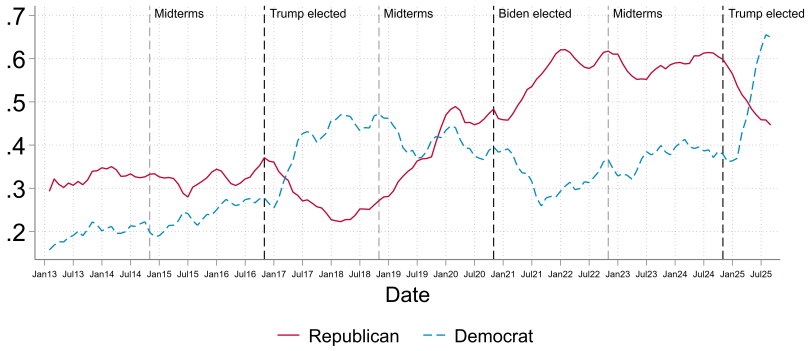
similar pattern is observed following Biden's election in 2020, with a surge in Republican anger and a decline in Democratic anger in the same panel. Note that within presidential terms, we observe further fluctuations. Republican anger began to decline in congressional floor speeches (panel 21c) after the party regained control of the House in 2022, though it remained consistently higher than Democratic anger throughout Biden's term. These dynamics reinforces the validity of the anger classification, as it reliably tracks major political events and shifts in partisan status.

Figure 21: Evolution of Anger in Political Communication by Political Affiliation

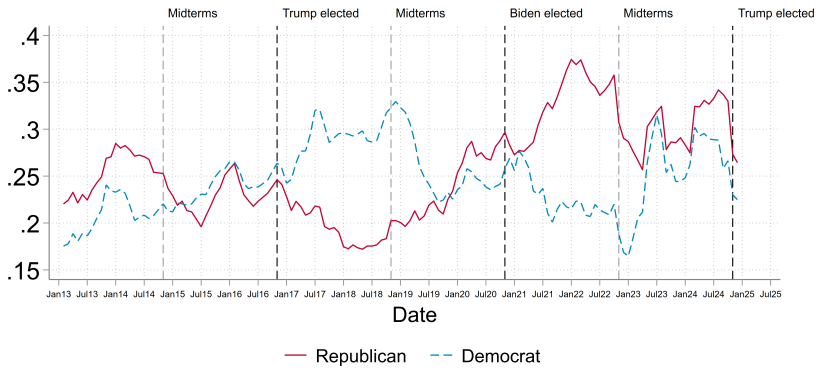
(a) Official Tweets



(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 study how the emotional content of messages affects their likelihood of being retweeted. 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 4.

Our findings reveal that tweets expressing anger receive significantly higher engagement: on average, official part accounts and congressional tweets classified as angry generate 38% and 48% 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 90% more retweets among citizens on our various policy issues and 38% more in (the larger) dataset of climate change-related tweets.

Interestingly, we also find variation in the impact of other emotions on engagement. In official party tweets, disgust generates by far the largest effect on retweets. Across all samples, gratitude is associated with significantly fewer retweets. In congressional tweets, fear generates higher retweets, but less so than anger (20% higher retweets) and all positive emotions are strongly and significantly associated with lower retweets.

Table 4: Emotions and retweets on social media

	(1) Voters' Tweets	(2) Climate Change Tweets	(3) Official Party Tweets	(4) Congressional Tweets
Anger	0.37***	0.32***	0.32***	0.36***
	(0.03)	(0.05)	(0.06)	(0.03)
Disgust	0.07	0.04	1.15***	0.41***
	(0.11)	(0.21)	(0.38)	(0.13)
Fear	0.22***	0.08	0.05	0.14***
	(0.07)	(0.06)	(0.13)	(0.03)
Gratitude	-0.30***	-0.71***	-0.15	-0.35***
	(0.10)	(0.19)	(0.12)	(0.12)
Hope	-0.19***	-0.07	-0.12**	-0.25***
	(0.07)	(0.06)	(0.06)	(0.05)
Joy	-0.05	-0.03	0.04	-0.44***
	(0.09)	(0.10)	(0.12)	(0.07)
Pride	-0.16*	0.33	0.08	-0.20***
	(0.08)	(0.30)	(0.13)	(0.05)
Sadness	0.15	0.13	0.05	-0.06
	(0.14)	(0.11)	(0.11)	(0.06)
Observations	3205624	1309189	47814	923313
Time fixed-effects	Yes	Yes	Yes	Yes
User fixed-effects	Yes	Yes	Yes	Yes
Topic fixed-effects	Yes	No	Yes	Yes

Notes. All regressions are estimated using Poisson Pseudo-Maximum Likelihood (PPML) and include month-year fixed effects. Model [1], [3] and [4] also include topic fixed effect (abortion,' democracy,' gender equality,' gun control,' immigration,' taxation and inequality,' or 'trade.'). Model [2] focuses only on tweets about climate change and thus do not include topic fixed-effects. All models include user fixed effects (the sample of citizens' tweets will be updated to become a proper panel).
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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. We therefore classified answers to these open-ended questions into topics using Chat GPT. Appendix A.4 provides more details.

Tables 5, 6, 7, 8 report the results from this topic classification. Answers highlight that for most policy topics, respondents express predominantly negative views even when questions are framed neutrally, and a substantial share of responses remain negative even under positive framing. This pattern is particularly highlighted in Appendix A.5, where we apply the same emotion classifier described in Section 2.1.3 to classify the answers to the open-ended question. It also supports our broader finding that negativity has become more prevalent over time and that negative emotions dominate contemporary political discourse. It also underscores how difficult it is to prompt individuals to think positively, even with explicit cues.

Trade Both negatively and neutrally framed questions elicited concerns—negative prompts led to worries about reliance on foreign goods (35%) and exploitation by China (34%), while neutral prompts focused on fairness (57%). Interestingly, trade is the only policy area where positive framing succeeded in shifting the tone: 41% of respondents emphasized the benefits of trade in response to the positively framed question (Table 5).

Immigration Responses consistently focused on the need to control illegal immigration, although with a gradient in how the concern was expressed: 34% of respondents to the positive prompt described it as a growing issue, 35% of those responding to the neutral prompt called for stopping it, and 31% of those answering the negative prompt raised fears of criminals entering the country (Table 6).

Taxation and redistribution Inequality emerged as a central concern across all framings: 35% of respondents to the positive prompt expressed little optimism about wealth distribution, 59% of those answering the neutral prompt identified inequality as a major concern, and 42% of responses to the negative prompt emphasized that inequality limits opportunities for upward mobility (Table 7).

Democracy Respondents to the positively and neutrally framed questions voiced concerns about national division (59%) and political polarization (29%), while the negative framing prompted concerns about feeling unheard and disenfranchised (29%) (Table 8).

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 22 summarizes the emotions elicited by the positive and negative emotions treatments. Consistent with our expectations, the negative emotion treatment significantly

Table 5: Classification of open-ended questions on trade by framing

Positive	**Neutral**	**Negative**
Optimism around international trade benefits (41%) *In the age of the Internet, I think people from all over the world are becoming more aware and accepting of other countries and cultures.*	Fairness in trade is essential (57%) *Fairness; quality; sitution of the workers involved; overall cost and benefit to US and other country.*	Reliance on foreign goods is concerning (35%) *That we trade with other countries things that can be produced here in America.*
Access to diverse products enhances variety (15%) *acquiring things that are not available here*	Tariffs impact prices negatively (15%) *Tariff's are intended to hurt foreign countries but usually end up hurting Americans with higher fees*	China takes advantage of the US (34%) *That they charge us tariffs and we don't. Their labor camps are disgusting.*
Importance of fair trade agreements (13%) *The ability to mutually agree on specifics of fair trade*	Jobs are lost due to imports (12%) *That we are taking work away from people in our country.*	Trade imbalance harms US economy (12%) *the prospect of a 100% tariff on imported Chinese goods*
Interdependence of all countries is essential (13%) *that we are all interdependent*	The balance of trade must be equitable (9%) *China's impact on the US's economy and how their lack of trade with us would impact our country.*	Child labor issues in foreign countries (7%) *Knowing that children and china are doing minor labor*
Need for US to manufacture more domestically (9%) *some jobs are being returned to the USA computer chips for instance they found the minerals they need down by the Saltin Sea in Southern Ca*	Quality of imported goods is a concern (7%) *My main concern is that the USA is importing inferior products from overseas. More items shoild be manufactured in the USA.*	Low quality products from China (6%) *That China sells crappy stuff*
Not much cause for optimism or pessimism (9%) *Not much cause for optimism or pessimism—the variables are in constant flux*		We should produce more goods in America (6%) *We have the ability to make everything in this country without importing it.*

Notes. This table 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.

increases feelings of anger, fear, outrage, and sadness, while substantially reducing joy and tranquility. Conversely, the positive emotion treatment enhances joy and tranquility but has no or very little negative effect on negative emotions.

Effects of the negative emotions treatment on policy views. Figure 23 depicts the effects of the treatments on perceptions and policy views for trade, immigration, redistribution, and democracy.[13] 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

[13]The societal issues were too diverse to be grouped into indices, so we present these results separately in Appendix Table A17.

Table 6: Classification of open-ended questions on immigration by framing

Positive	**Neutral**	**Negative**
Illegal immigration is a growing concern to be controlled (34%)	Stop illegal immigration (35%)	Fear entry of criminals (31%)
Building a secure wall on the southern border and properly vetting immigrants will help reduce the amount of crime and monies spent in the US.	*Illegal immigration can destroy this country if it is not curtailed*	*The thugs killers and thieves that are also coming in. Has to stop*
Immigrants seek better life opportunities (18%)	Safety concerns (22%)	Illegal immigration burdens resources (22%)
I don't like how refugees are being handled at the border, especially the separation of children and their parents. However, I think that so many people want to immigrate here because of the vast opportunities that we provide here. That's gotta be something, right?	*I AM SCARED OF THE IMMIGRATES BEENING THE DRUGS INTO USA. THEY ARE ALSO BRING IN IMMIGRATES OVER BY UNAUTHORISED MEANS.*	*I am scared that natural US citizens will suffer from illegal border crossing because US does not need anymore people, aside from natural births of US citizens.*
Immigrants have a positive economic contribution (13%)	Protect legal immigration (18%)	Anger over treatment of immigrants (21%)
That new blood is needed in certain areas, including aiding the flagging purchasing power of an older America	*I think there are a lot of resovable issues that need to be addressed; however, overall, I believe we need to allow immingrants and provide a way for them to immigrate legally and make it easier for them ot enter the*	*What makes me angry is that our government has not made clear, easy paths to citizenship. I'm also angry at how families are seperated at the border.*
Diversity enriches society (12%)	Vet immigrants (17%)	Lack of border control is concerning (19%)
I think the US has and always needs to be a country where different people come together and integrate with each other.	*Makein sure they have a green card*	*The immigration process is not sufficient meaning people need to cross illegally.*
Protect legal immigration (12%)	Take jobs from citizens (8%)	Take jobs from citizens (8%)
removing illegal aliens but giving them a chance to renter by following the laws and do it legally	*We have too much crime and losing our jobs.*	*They getting jobs that is Americans need*
Reforms are needed (9%)		
I think with the Harris administration some much needed immigration legislation will be passed		

Notes. This table 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.

TABLE 7: CLASSIFICATION OF OPEN-ENDED QUESTIONS ON TAXATION AND REDISTRIBUTION BY FRAMING

Positive	**Neutral**	**Negative**
Not much optimism about wealth distribution (35%)	Income inequality is a major concern (59%)	Income inequality limits opportunities for upward mobility (42%)
I can't think of anything that makes me feel optimistic about it.	*Is there really a way to distribute wealth equally ? Or is this just a*	*the exclusion amount for inheritance tax*
Growing awareness of wealth inequality leads to change (26%)	Everyone should have equal opportunities (17%)	The rich get richer while the poor get poorer (26%)
The potential defeat of Trumpist oligarchs and their Koch Brothers policies	*There are adequate opportunities for all to be successful in america*	*Racism, classism, minimum wage, inflation*
Everyone can succeed with hard work (18%)	Taxes on the wealthy need to be higher (11%)	There are too many tax loopholes for the rich (20%)
The US is one of the few countries in the world where people can succeed if they work hard and play by the rules.	*Bigger tax rates*	*Wealthy getting tax cuts and the rest of us pay more taxes*
There are opportunities for upward mobility (17%)	Wealth distribution is extremely uneven (8%)	Corporations prioritize profits over employee welfare (8%)
I read in a sociology textbook it is common to move up the economic ladder	*There is too much divide now and the wealthy have advantages for increasing their assets that are unavailable to middle class even if they are deserving and work hard for*	*We need to make those companies more responsible.*
Tax the wealthy more (4%)	The middle class is shrinking (3%)	The middle class is disappearing (3%)
that maybe the wealthy will pay their fair share of taxes	*The middle class is shrinking.*	*What makes me angry is the divide is getting bigger between the rich and the poor. Middle class doesn't really exist anymore.*
	The rich keep getting richer (3%)	
	The rich keep getting richer and everyone else gets poorer	

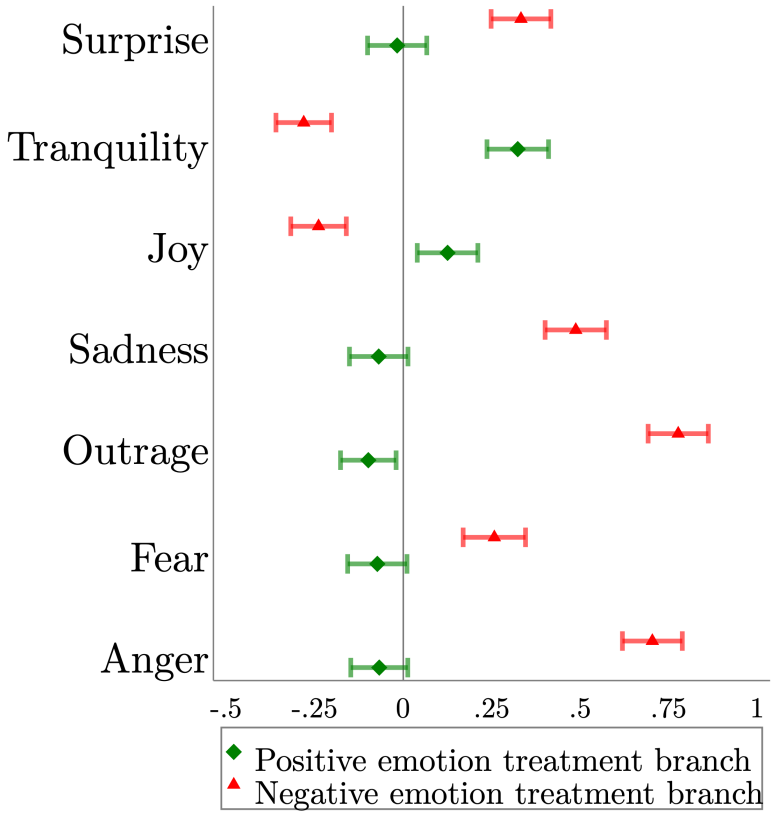
Notes. This table displays the classification of respondents' answers into the five or six most popular topics. Frequency shares sum to 100% within each framing (positive, neutral, and negative) and are conditional on responses that were successfully classified. The share of unclassified responses over 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.

TABLE 8: CLASSIFICATION OF OPEN-ENDED QUESTIONS ON DEMOCRACY AND GOVERNANCE BY FRAMING

Positive	**Neutral**	**Negative**
Division in the country affects optimism about democracy (59%)	Political polarization is harming democracy (29%)	People feel unheard and disenfranchised (29%)
Someday, the ignorant, angry old white men will be dead. Although there are too many angry young idiots vying to replace them.	*The nation is severely divided which is wrong. One side is not Satan and the other perfect. They both have flaws.*	*That the wrong people are in the offices.*
Democracy allows for citizen participation and voting (16%)	Democracy needs protection from corruption (26%)	The polarization of political debates is frustrating (28%)
that we are still voting	*Democracy must be allowed to remain and not be obliterated in the courts under false lawsuits*	*the divisiveness of it all.*
Freedom of speech is essential in democracy (13%)	Lack of respect in political debates (18%)	Misinformation spreads and distorts reality (16%)
People, even idiots, do get heard. Everyone does not have groupthink.	*We need to come together snd wuit bickering*	*politicians always lying*
Political debates serve as a platform for discussion (5%)	Media bias influences public opinion (10%)	The influence of money corrupts democratic process (15%)
the debates that want to help those in need and help them survive	*Biased media and news sources not accurately depicting the interviews*	*I am worried about corruption and Trump making it okay to be on your worst behavior*
Need for compromise across political parties (5%)	People do not understand how democracy works (9%)	There is a lack of constructive dialogue and compromise (10%)
Listening to both sides and compromising	*I do not believe that people really understand how a democracy works and what democracy is.*	*The total disrespect for each other*
Younger generations are more engaged in democracy (3%)	Elections are not fair (9%)	The electoral college undermines fair representation (3%)
In the age of the Internet, people have gotten exposed to more world views and others' perspectives. I think it allows for a better understanding of what each political party stands for and helps someone determine what party works best for them.	*Election stealing. Racism towards white people*	*that popular vote is not outcome determinative in presidential elections*

Notes. This table 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.

FIGURE 22: 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 A9 displays all the coefficients. Confidence intervals are displayed at the 90% significance level.

is classified in the trade policy index. Appendix Section A.8 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 A10 shows that the effect on trade perceptions is primarily driven by two of the three variables included in the index: respondents exposed to the negative emotion treatment are more likely to perceive trade as a zero-sum game and to believe that it increases unemployment. Quantitatively, this effect is substantial, equivalent to roughly 48% of the perception gap between Trump and Harris voters. Additionally, Appendix Table A11 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 A14. Additionally, Appendix Table A15 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 A10. 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.

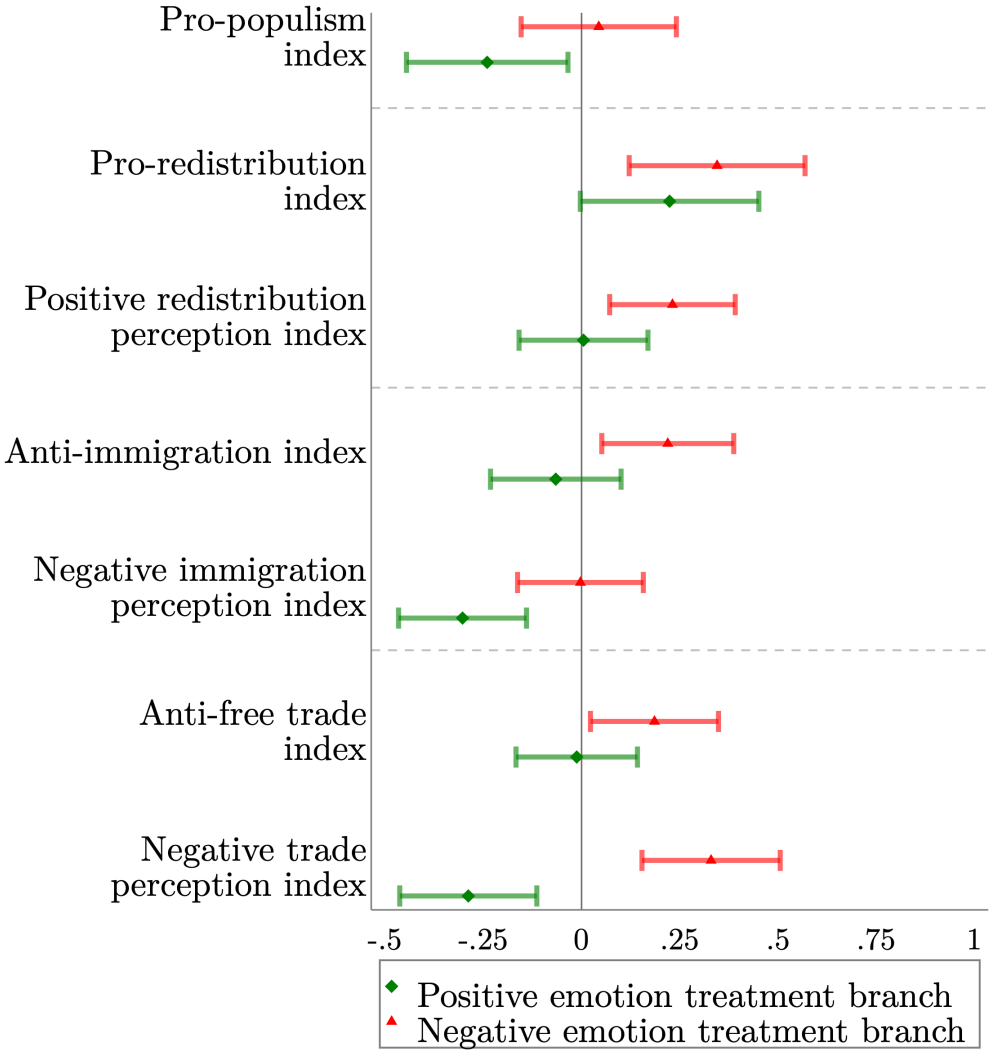
Similarly, Appendix Table A12 illustrates that the positive emotion treatment diminishes negative perceptions toward immigration, by an effect equivalent to 16% of the Harris-Trump voter gap, primarily because positively treated respondents are less likely to view immigration as a threat to the economy or cultural integrity.[14] 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 A16).

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

[14]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 23: 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.8 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 24 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.

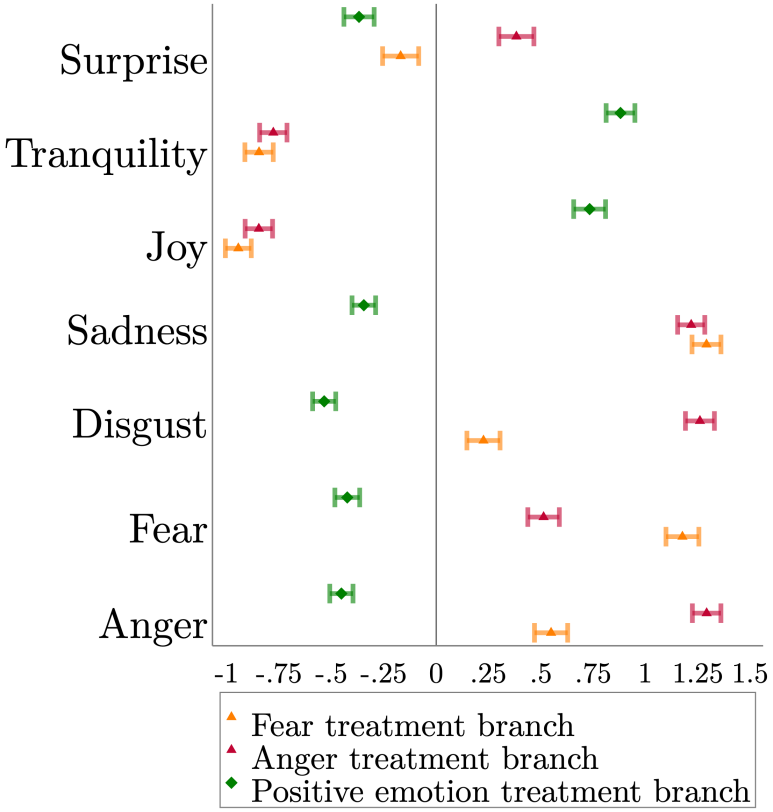
Effects on policy views. Figure 25 illustrates the effects of the anger and fear treatments on attitudes and policy preferences regarding climate change. Survey questions have been grouped into three distinct indices: policy views on climate change, preferences regarding redistributive climate policies, and willingness to take private actions to fight against climate change. Specifically, survey questions 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.9 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. 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 A19 and A20). Additionally, Appendix Table A21 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 A22, 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 generates insignificant effects across most climate indices.

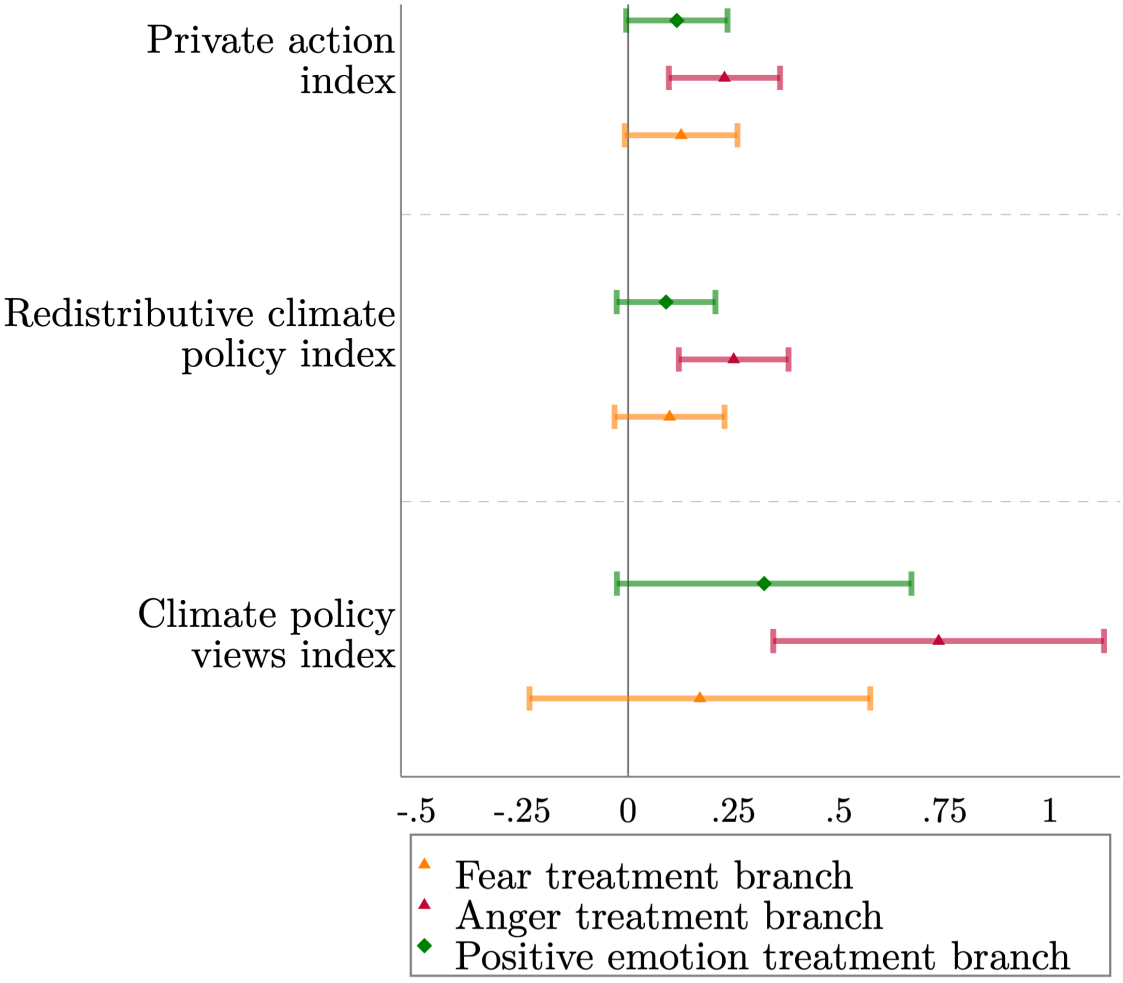
These findings highlight the need to distinguish the role of different negative emotions: while fear and anger are both typically categorized as negative emotions, anger substantially shapes climate-related attitudes and policy views, whereas fear does not. In that sense, "anger mobilizes, fear paralyzes."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

FIGURE 24: 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 A18 displays all the coefficients. Confidence intervals are displayed at the 90% significance level.

FIGURE 25: 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.9 displays one table per index, presenting the variables composing each index. Confidence intervals are displayed at a 90% significance level.

6 Conclusion

XX STEFANIE 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 cit-

izens. 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. Taken together, our observational and experimental results provide converging evidence that anger is the dominant emotional force shaping both contemporary citizen and political discourse, as well as public policy views and preferences.

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

"Emotions and Policy Views"

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

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A.1 Sample description

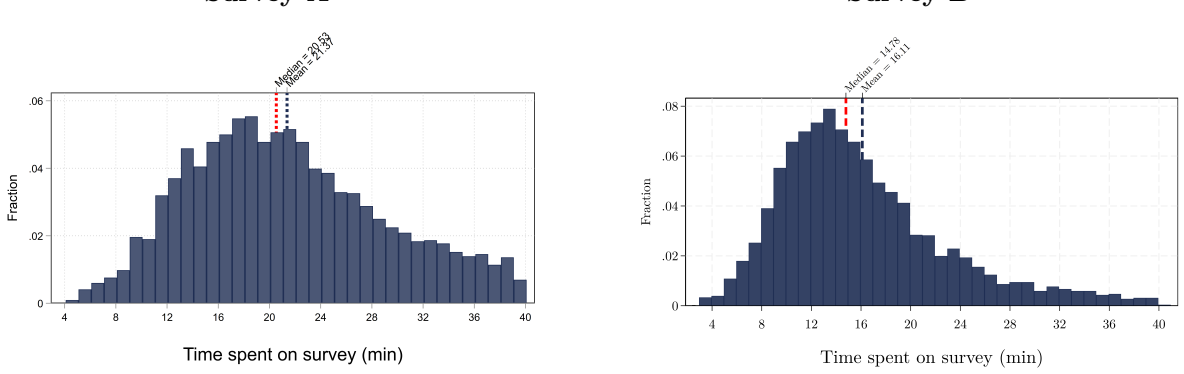
A.1.1 Sample evolution and duration

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



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.1.3 Attrition and Balance across Treatment Arms

TABLE A2: ATTRITION ANALYSIS IN SURVEY A

	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 A3: Balance Analysis in Survey A

	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; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A4: Attrition Analysis in Survey B

	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 A5: Balance Analysis in Survey B

	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.2 Details on the Data Collection for the Demand and Supply Side

A.2.1 Demand Side

Random sample of tweets. We used the Twitter Pro API to extract a random sample of English-language tweets — excluding retweets — that contained 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. Tweets were gathered during four separate five-second windows each day (00:18:18–00:18:23, 06:18:18–06:18:23, 12:18:18–12:18:23, and 18:18:18–18:18:23 UTC) from January 1, 2010, through June 1, 2025.[A1] This schedule captures 20 seconds of content per day—about 0.02 percent of all tweets containing our keywords (20s/86400s). For each tweet, we recorded the exact timestamp, author identifier, public metrics (retweets and likes), and full text. For each unique user, we also collected their user ID, username, total number of tweets sent, and follower count. Extraction was performed on June 1, 2025, and initially included tweets dating back to 2010. To ensure sufficient volume and consistency, we limit our main analysis to tweets sent on or after January 1, 2013. Our final sample comprises 688,224 tweets from 540,401 distinct users. The overall volume is constrained by the Twitter Pro API's maximum of 1 million tweets per monthly subscription.

Climate change tweets. We used the Twitter Academic API to assemble a dataset comprising one-twelfth of all tweets containing the keywords "climate change" or "global warming." Tweets were sampled during the first five minutes of each hour throughout the study period, i.e., we collected all tweets from minute 0 to minute 5 of every hour. We restricted our sample to English-language tweets and excluded retweets. For each tweet, we recorded the exact timestamp, user identifier, retweet count, and like count. For each user, we collected the user ID, username, location, and profile description. Our sample comprises 3,032,887 million tweets from 1,270,117 users spanning January 1, 2013, through April 18, 2023. Data collection ceased in April 2023 following the shutdown of the Twitter Academic API after Twitter's acquisition by Elon Musk.

A.2.2 Supply Side

Congressional tweets. We manually compiled a list of every member of Congress (House and Senate) who served from the 109th Congress (January 3, 2005 – January 3, 2007) through the 118th Congress (beginning January 3, 2025). We started with the 109th Congress because Twitter launched in March 2006. Over that span, 1,393 individuals have held a congressional seat. For each member, we manually searched for a X presence and, when multiple accounts existed (e.g., Alexandria Ocasio-Cortez's personal @AOC versus her official @RepAOC), we retained only the official account. This yielded 1,008 distinct congressional X handles. Account adoption in the latest session of Congress was approximately 98 percent. Using a web scraper, we retrieved every original tweet (excluding retweets) posted by those accounts from their creation through June 1, 2025, resulting in a database of 1.7 million tweets. Each X user ID was matched to the member's ICPSR identifier to facilitate linkage between tweet content and congressional floor speeches.

[A1] We did not sample on the hour, as bots tend to post more frequently at exact clock times than during other intervals.

Congressional floor speeches. We use the floor-speeches dataset compiled by Gauthier, Subtil, et al., 2025, which spans January 1994 through December 2024. It was generated with the Congressional-Record parser developed by Judd et al., 2017.[A2] That tool downloads the official Congressional Record HTML files from the U.S. Congress website and extracts both the full text and associated metadata. The dataset preserves each speech in its original form and comprises 1,796,583 individual *turns* across 15 congressional sessions. In this context, a "turn" is a continuous block of floor debate granted to a Member of Congress, often spanning multiple paragraphs. For each turn, we record the date, speaker name, chamber (House or Senate), and complete text. Each speaker is then matched to their ICPSR code to determine party affiliation.

Official tweets. We manually compiled a list of official X accounts, including each party's three main accounts (@GOP, @HouseGOP, and @SenateGOP for Republicans; and @TheDemocrats, @HouseDemocrats, and @SenateDemocrats for Democrats) as well as the official accounts of the President (@POTUS), Vice President (@VP), First Lady (@FLOTUS), and the White House (@WhiteHouse). For these four institutional accounts, we identified both the current account (e.g., @POTUS) and its archival predecessors (e.g., @POTUS46Archive for President Biden or @POTUS45 for President Trump during his first term). Using a web scraper, we collected all original tweets — excluding retweets — sent by these accounts from their inception through June 1, 2025, yielding a database of 230,310 tweets. We assign the political leaning of the @POTUS, @FLOTUS, @VP, and @WhiteHouse accounts based on the party in power at the time of each tweet.

Campaign speech. We used a web scraper to collect all public interventions by Kamala Harris, Joe Biden, and Donald Trump between January 2023 and November 2024, extracting transcripts from Factba.se / Roll Call. A key advantage of this dataset is that each transcript is timestamped and clearly attributes every speaker, allowing us to distinguish journalist questions, remarks from other participants, and statements by the presidential candidates themselves. The database covers a variety of intervention types, including interviews, press briefings, press conferences, press gaggles, speeches, remarks, and vlogs. In total, our corpus comprises 1,992 interventions and 274,921 segments.[A3]

A.3 Details on the Emotional Classification Algorithm

Our datasets include documents of various types and lengths: tweets are short messages of approximately 180 characters; campaign-speech segments average 220 characters; and floor-speech turns span an average of 3,900 characters. To standardize our analysis across documents of differing lengths and to apply a single classifier uniformly, we first extract every sentence from each document type (tweets, segments, and turns). We employ the `sentence_tokenizer` module from the Python NLTK package to identify sentences within both demand- and supply-side documents.

To systematically analyze emotional content in policy-related textual data (floor speeches, campaign speeches and tweets), we use a large language model (LLM) combined with embedding-based representations and supervised machine learning classification. First, we drew a random sample of 200,000 sentences: 100,000 from tweets (50,000 from official political accounts and 50,000 from citizen accounts), 50,000 from campaign speeches and 50,000 from floor speeches. To ensure each excerpt provides sufficient context for emotion and

[A2] https://github.com/unitedstates/congressional-record

[A3] Factba.se and Roll Call automatically segment interventions and speeches into discrete units for analysis. A "segment" may consist of a single sentence or a group of sentences; the average segment length is 40 words.

topic detection, we retained only sentences containing at least ten words. Then, we use GPT-4o-mini to classify each sentence along three principal dimensions: cognition versus affect, specific emotional category, and primary topic. The precise prompt formulations are detailed below.

We then use the classifications generated by GPT-4o-mini as labeled training data for a supervised classifier tasked with systematically categorizing the entire text corpus. We adopt this two-stage approach because our corpus contains over 13 million sentences of more than ten tokens, making direct classification by a large language model prohibitively expensive and time-consuming. 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.

A.3.1 Prompt

Below, we present the prompt used for the three LLM-generated labeling tasks (emotion, topic, and affect versus cognition). We applied the same prompt across all datasets at the sentence level, restricting to sentences containing at least ten words.

A.3.1.1 Emotion Classifier

You are an AI assistant that must only classify the given sentence 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?
Sentence: [SENTENCE ADDED HERE]
Potential Answers: - sadness - fear - anger - disgust - joy - hope - gratitude - pride - no emotion
Your response should be only one of these words.

A.3.1.2 Topic Classifier

You are an AI assistant that must only classify the given sentence 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 topic is unclear or ambiguous, default to "other topic".
Task: Question: What is the main topic conveyed in the following sentence?
Sentence: [SENTENCE ADDED HERE]
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.3.2 Validation of the classification

To validate our classification, we manually cross-check (human-based check) a random subsample of items from each database. The classification seems to work very well.

As an illustration, we examined the most frequent keywords the LLM associated with each emotion and topic. The keyword analysis demonstrate that GPT-4o-mini's classifications reliably capture the targeted emotional and topic dimensions.



(A) Anger



(B) Sadness



(C) Disgust



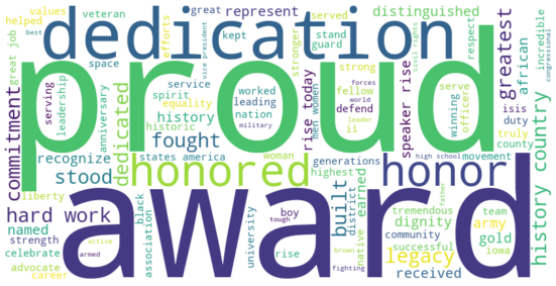
(D) Fear



(E) Joy



(F) Hope



(G) Pride



(H) Gratitude

Figure A2: Most Frequent keywords by Emotion Type

A.4 Details on the Open-Ended Question Classification

We first present the prompt used to automatically extract the 10 most common narratives for each policy topic and for each framing of the open-ended question asked in Survey A. The classification is fully unsupervised, but we subsequently group and clean some of the extracted narratives manually. We then present the prompt used to classify each open-ended response into one of the identified narratives (plus a "none" category for answers such as "don't know," "nothing," or other irrelevant responses). In the prompts below the variable "d" contains all answers for a topic and a framing separated with a "" . The variable " + answer + " contains all the categories identified in step 1 to classify each answer. It generates a CSV with 4 columns : "topic","framing","document","classification".

A.4.1 Prompts

Step 1 You are an AI assistant that must identify the 10 most common narratives in a sample of answers to a survey.
Rules: - Do not provide explanations, justifications, or additional context. - Do not infer narratives outside what are presented in the documents. - Provide the list of the 10 most common narratives as a semi-colon separated list, in lowercase - Do not consider emotion or sentiment in the narratives (only the topics) - Provide each narrative as a short independent sentence and not as a list of keywords - Do not start the answer by "Here are the 10 most common narratives identified in the survey responses" or any variant - Do not use semi-colon in the narrative description
Documents: """ + d + """

Step 2 You are an AI assistant that must identify the main narrative in a document.
Rules:- Do not provide explanations, justifications, or additional context. - Do not infer narratives outside what are presented in the documents. - Only answer "none" is the document is not related at all with the other proposed answers. Even if unsure, try to fit into one of the proposed category and minimize the number of "none"
Documents: """ + d + """
Potential Answers: - """ + answer + """ - none
Your response should be only one of these words.

A.5 Emotions of the Open-Ended Question

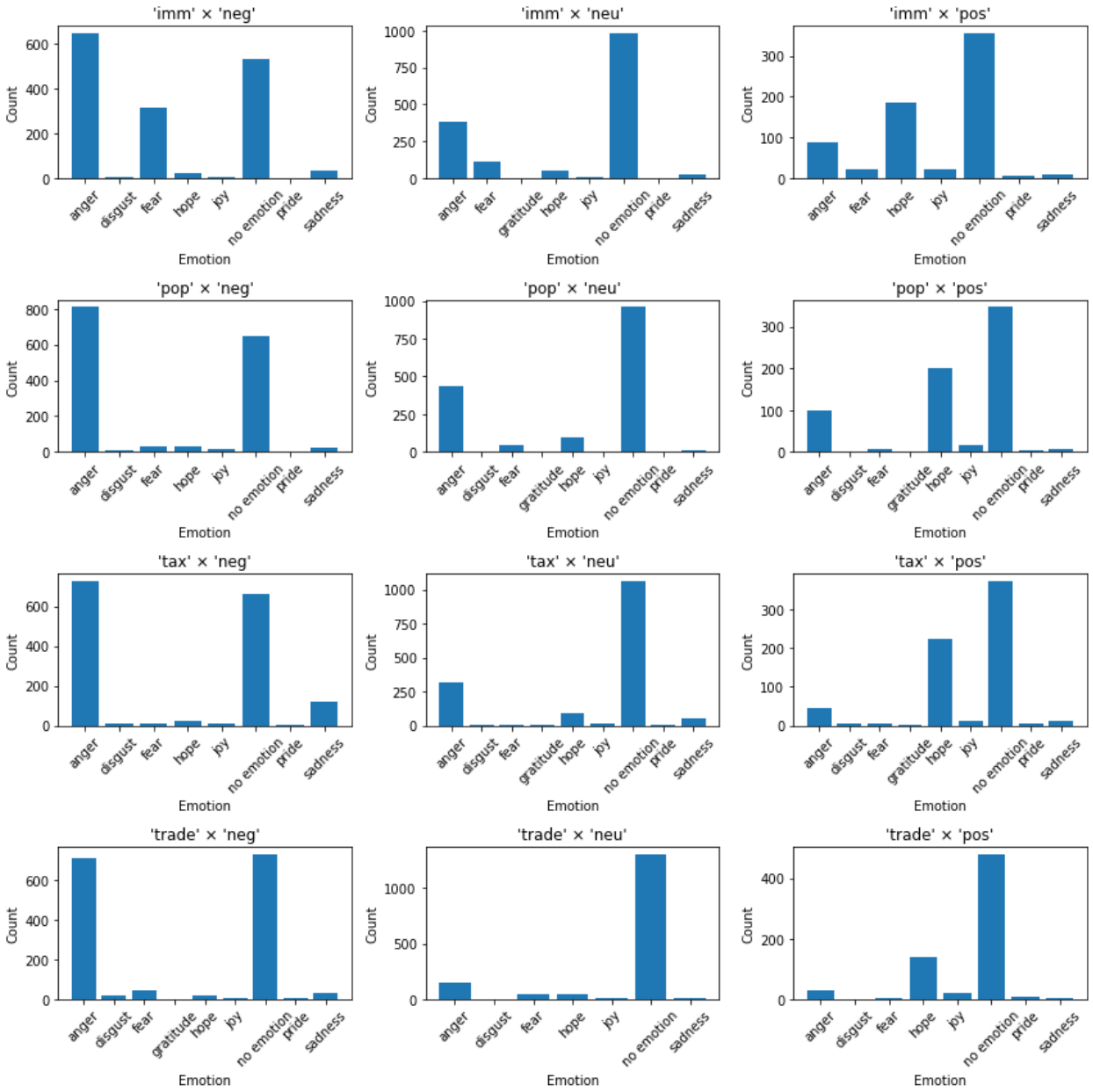


FIGURE A3: EMOTIONS OF OPEN-ENDED QUESTIONS

Notes. The figure displays the distribution of emotions across the four topics topics and the three framing conditions (negative, neutral, and positive) for responses to the open-ended questions. Each bar represent the frequency with which each emotion appears within a given topic–framing combination.

A.6 Matched Voter Dataset and Results' Replication on the Citizen Sample

We constructed a panel dataset of X users that was matched to a registered voter dataset. This allows us to assess the quality of the political leaning measure we construct and adopt throughout the paper following Mosleh and Rand (2022), to investigate heterogeneity by demographics, and to infer from this sample the behavior of real voters. Information on registered voter is derived from the Statara national voter file, which aggregates publicly available voter registration data from state and local election offices. It includes information such as voter names, addresses, party affiliation, and voting history, and is further enhanced with demographic features. This dataset is made available by the Center for American Political Studies at Harvard University.

A.6.1 Dataset construction

Our panel is constructed as follows:

Step 1. First, from our citizens sample, we collect the declared location for the accounts that have one. We then implement a deterministic pipeline for assigning a U.S. state to free-text self-reported locations. The classification logic proceeds hierarchically through increasingly permissive rules. First, it recognizes canonical "City–State" constructions with flexible punctuation (commas, slashes, dashes, or parentheses) and accepts both full state names and uppercase two-letter USPS abbreviations as valid signals. Second, it detects "State, USA" and "City, USA" configurations, resolving the latter through a population-dominant single-city gazetteer. Third, if the entire string matches a dominant U.S. city name—for example, Chicago, Philadelphia, or San Francisco—it directly assigns the state associated with that city in the gazetteer. Fourth, it captures any isolated uppercase USPS abbreviation (e.g., "TX" alone) as a sufficient indicator of the corresponding state, excluding states for which this may be ambiguous. The gazetteer used for these determinations was derived from the GeoNames U.S. dataset (https://download.geonames.org/export/dump/US.zip). To resolve possible ambiguity in city names, we designed a population dominance rule. A city name is considered population dominant if its largest instance (the top-ranked state) has a population at least five times greater than the next largest instance (or if it is the only instance) and exceeds a minimum population threshold of 5,000 residents. Only that top state is retained for the final mapping, while all others are dropped as ambiguous. For example, Miami overwhelmingly satisfies this criterion for Florida, whereas Springfield—which appears with comparable populations in multiple states—does not. Foreign city or state names, or clear indicators of junk, led to immediate discarding. Together, these deterministic heuristics produce a conservative but highly interpretable mapping of textual locations to U.S. states. This procedure yielded a list of users with full name and properly coded state for 183,501 users from the 540,401 distinct users in our random sample of tweets described in A.2.

Step 2. We linked our social-media list of 183,501 U.S. accounts to the Statara national voter file described earlier, using a deterministic name-and-state procedure modeled after Grinberg et al. (2019). For each record in the voter file, we constructed normalized name keys by lower-casing and removing punctuation from the concatenation of first, middle, and last names and from first + last names. Within each state, we retained only records for which the key was unique and both first and last names were present, ensuring that every

surviving voter identifier corresponded to exactly one registrant. We then joined the cleaned user data to these unique voter keys by exact equality on the normalized name and the inferred state abbreviation. We first attempted using the three-part key and, for unmatched users, the two-part key. This procedure produced a set of roughly 17,792 users (about 10 percent of the original list) whose names and states yielded a one-to-one match to a unique voter-file record.

For these matched individuals, we retrieved the complete original voter-file rows from the raw Statara data using their unique voter identifier. All matching and data-integration operations were implemented in R using DuckDB for secure in-place SQL processing, due to the large dataset size. All operations were conducted within Harvard's Faculty of Arts and Sciences Secure Environment (FASSE).

Step 3. We attempt to collect tweets from these 17,792 users from 2013 onward using the X API Pro. Only tweets containing at least one of the following keywords were collected: "abortion", "tax", "inequality", "justice", "injustice", "immigration", "democracy", "gun", "trade", "climate", "supreme court", "policy", "government", "congress", "senate". These were classified by topic and emotion with the same methodology used throughout the rest of the paper. To filter out likely spam accounts, we excluded users whose total tweet count exceeded eight standard deviations above the mean. The final dataset contains 6,403,211 tweets from 15,493 unique users. Users not included in the final dataset are those whose tweets did not contain any of the specified keywords.

The remainder of this appendix reports descriptive summary statistics, assesses the validity of the inferred party assignment following Mosleh and Rand (2022), and presents the main behavioral results disaggregated by party affiliation, using party registration information from the voter dataset.

Tweets Summary Statistics Table A6 presents key summary statistics from the sample of tweets.

Table A6: Descriptive statistics for the matched voter tweet panel

Total tweets: 6,403,211
Total unique users: 15,493
Average sentences per tweet: 1.43
Coverage window: 2013-01-01 – 2025-11-30

	Mean	*Median*	*P25*	*P75*	*Min*	*Max*
Activity						
Tweets per user	413.30	87	14	382	1	26,698
Retweet engagement						
Retweet count	10.59	0	0	1	0	134,942
User characteristics						
Followers	35252.96	3,080	920	11,807	0	7,972,224
Following	4985.70	1,877	728	4,425	0	525,960
Number of tweets (lifetime)	103591.09	54,849	23,526	120,883	2	2,063,903
Account age (years)	7.72	7.54	4.48	10.83	0.00	18.95

Notes. Tweets with dates prior to 2013-01-01 are excluded. Tweets-per-user statistics are computed across unique users; retweet statistics are computed at the tweet level.

Demographics Summary Statistics Table A7 presents the summary statistics of the constructed panel vis-à-vis the entire population of voters. The demographic comparison indicates that the Twitter sample is more heavily White, and more likely to have higher levels of educational attainment than the electorate as a whole. It also contains a greater share of urban residents and individuals with committed or frequent voting histories. These differences reflect well-documented selection into Twitter usage and into matching processes.

Table A7: Descriptive statistics for voter panel

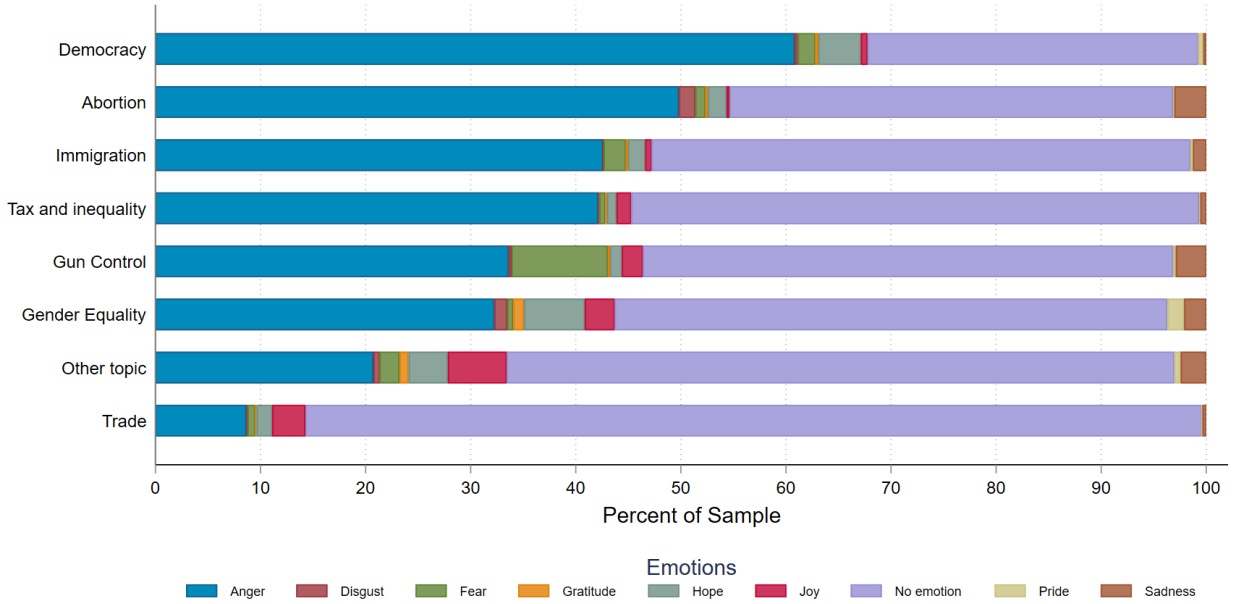
Category / Level	Share (Tweet sample)	Share (All voters)
Age range		
18-29	5.3%	13.6%
30-39	16.7%	14.9%
40-49	18.9%	13.9%
50-64	29.1%	21.2%
65-74	15.6%	13.3%
75+	8.0%	12.2%
Unknown	6.3%	10.9%
Gender		
Female	37.2%	50.4%
Male	61.2%	47.4%
Unknown	1.6%	2.2%
Race (main buckets)		
White	82.4%	69.4%
Black	6.9%	10.5%
Hispanic	4.3%	12.4%
Asian	3.8%	4.6%
Other/Unknown	2.6%	3.2%
Homeownership		
Homeowner	67.1%	65.4%
Renter	6.3%	7.0%
Unknown	26.6%	27.6%
Children present		
No children	36.2%	39.8%
Children present	63.8%	60.2%
Education		
Completed High School	25.8%	50.6%
Some College or Higher	4.5%	5.6%
Completed College	47.1%	32.2%
Completed Graduate School	20.2%	9.0%
Attended Vocational/Technical	0.8%	0.7%
Unknown	1.6%	2.0%
Urbanicity (Rural/Suburban/Urban)		
Rural	20.8%	29.8%
Suburban	35.7%	36.8%
Urban	42.4%	32.1%
Unknown	1.1%	1.4%
Registration status		
Registered	85.2%	74.1%
Unregistered	14.8%	25.9%
Party registration		
Democratic	25.0%	15.3%
Republican	13.3%	12.6%
Other	61.7%	72.2%
Voter frequency		
Committed	27.0%	13.7%
Frequent	39.4%	27.8%
Occasional	15.8%	23.0%
Registered Non-Voter	3.0%	9.6%
Unregistered	14.8%	25.9%

Notes. The table reports the proportion of voters in each bracket for the panel constructed vis à vis the entire electorate present in the voter file.

A.6.2 Replication of the Results in the Citizens' Sample

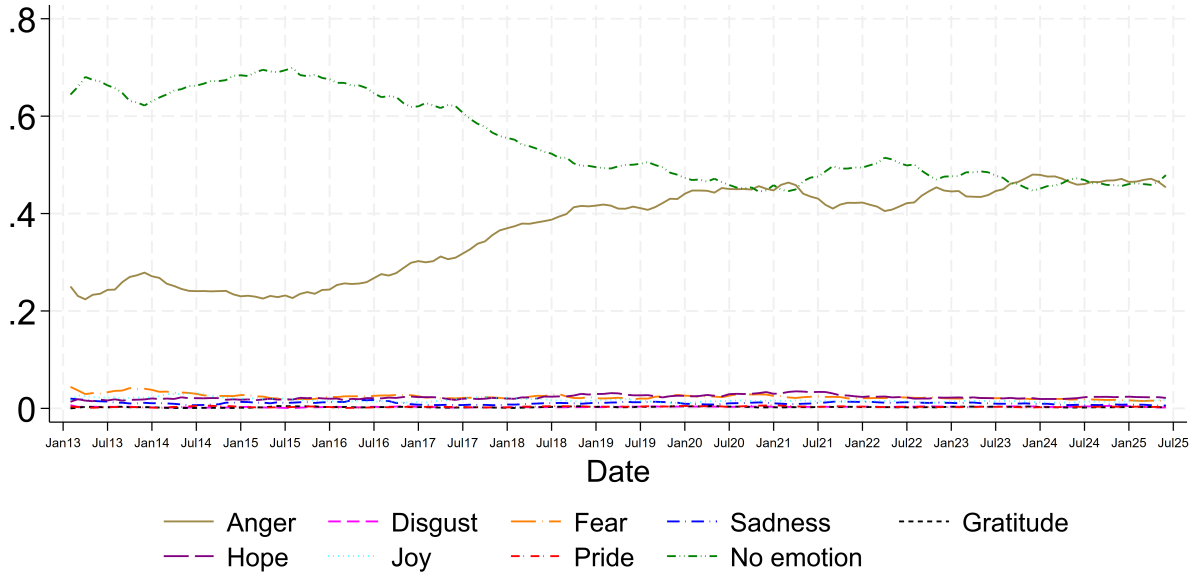
In this section, we replicate the core results from Section 3 using the random citizen dataset. Figure A4 shows the breakdown by emotion for each topic, excluding the category "other topics". Figure A5 shows the evolution of emotions over time.

FIGURE A4: EMOTIONS IN CITIZENS' TWEETS ON POLICY ISSUES 2013-2025



Notes. The figure shows the share of sentences across all tweets that contain a given emotion for the period 2013-2025.

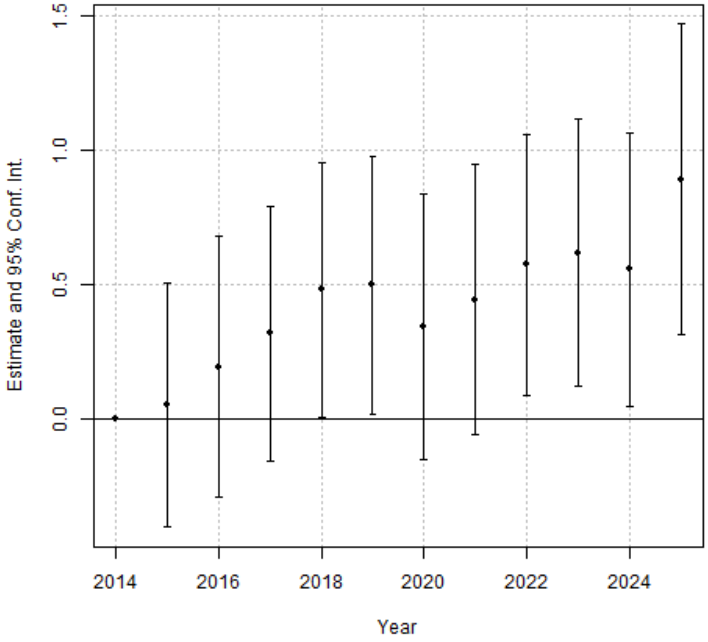
FIGURE A5: THE EVOLUTION OF EMOTIONS IN CITIZENS' TWEETS 2013-2025



Notes. The figure shows, for each month from January 2013 to October 2025, the share of sentences in tweets classified into each emotion. 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.

Within-user rise in anger. Figure A6 replicates the results of Figure 9 in the citizens' sample. While the core pattern is broadly aligned, estimates are noisy because it has not been drawn to be a panel, and thus we observe a limited number of repeated users.

FIGURE A6: WITHIN-USER RISE IN ANGER ON POLICY ISSUES 2013-2025



Notes. The figures show the coefficients on year fixed effects in a regression of anger on year fixed effects, user fixed effects, and topic fixed effects in the two datasets. The reference year is 2014. The regression model used is a fixed-effects Quasi-Poisson Generalized Linear Model (GLM). Error bars represent 95% confidence intervals.

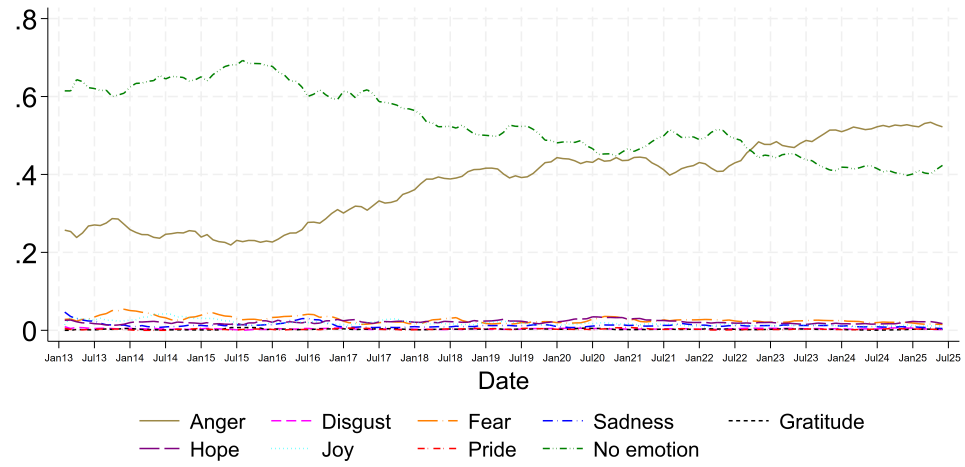
Bot detection exercise As noted in Section 3, tweets in the random citizen sample may have been posted by bots. To assess their prevalence, we exploit the newly available "About this Account" transparency features provided by X (rolled out in November 2025). This feature allows us to identify (i) the country associated with the account and (ii) whether the account is still active at the time of data collection.

We replicate the main time-series restricting the sample to accounts that are both identified as located in the United States and still active (Figure A7). We then implement a second specification restricting the sample only on account status (i.e., keeping accounts that are still active), reported in Figure A7b. While sample sizes decrease, patterns remain broadly unchanged.

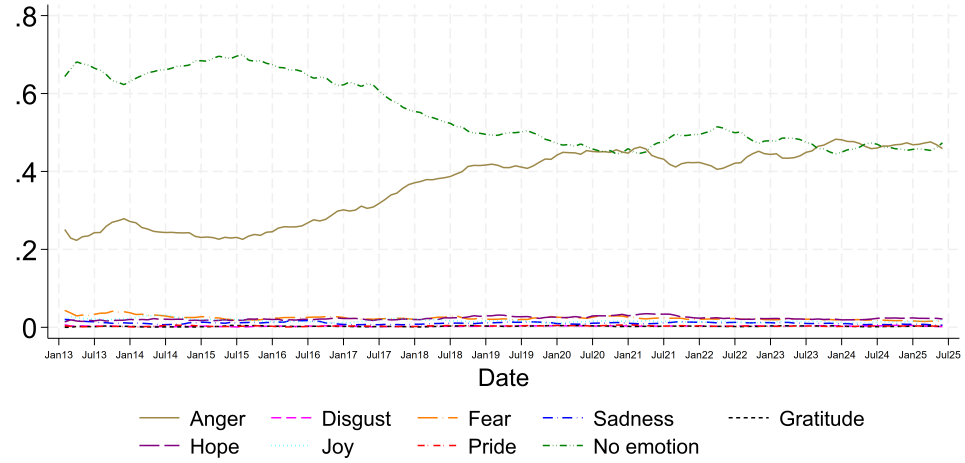
Removing reply tweets and tweets containing a link As an additional robustness check, we restrict the analysis to tweets that are neither replies nor contain hyperlinks. This restriction is motivated by measurement concerns: emotion classification is less precise for replies and link-containing tweets because the LLM evaluates emotion based solely on the text of the tweet itself. It cannot observe the content of the original tweet being replied to or access the material contained in shared hyperlinks, both of which may be necessary to accurately infer emotional tone. We replicate the main time-series analyses under this restriction for both the citizens and voters datasets (Figure A8)). Although the sample size declines, the overall patterns remain consistent with the baseline results.

Figure A7: Robustness to Bot Detection: Transparency Restrictions

(a) US based and Active Accounts



(b) Active Accounts Only

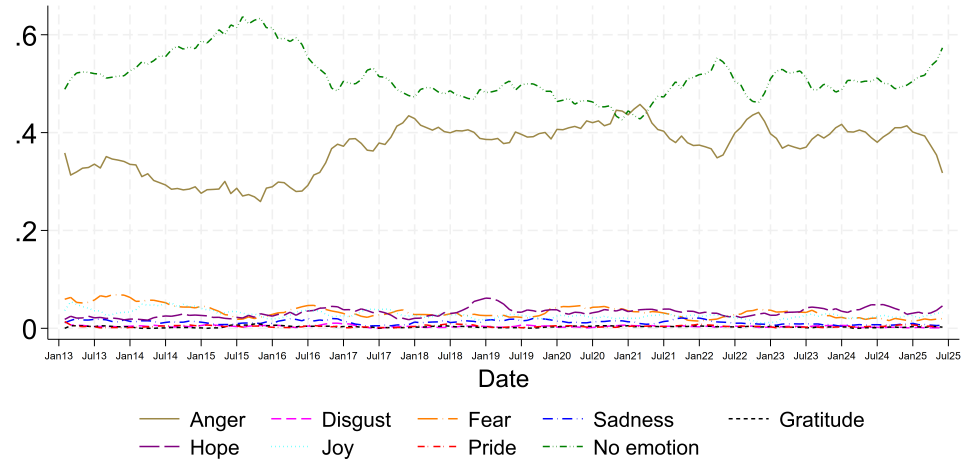


Notes. The figure shows, for each month from January 2013 to October 2025, the share of sentences in tweets classified into each emotion. For readability, the graph displays a 6-month moving average of monthly percentages. The sample is restricted to tweets whose primary topic is one of the following: 'abortion', 'democracy', 'gender equality', 'gun control', 'immigration', 'tax and inequality', or 'trade'. The category 'other topic' is excluded.

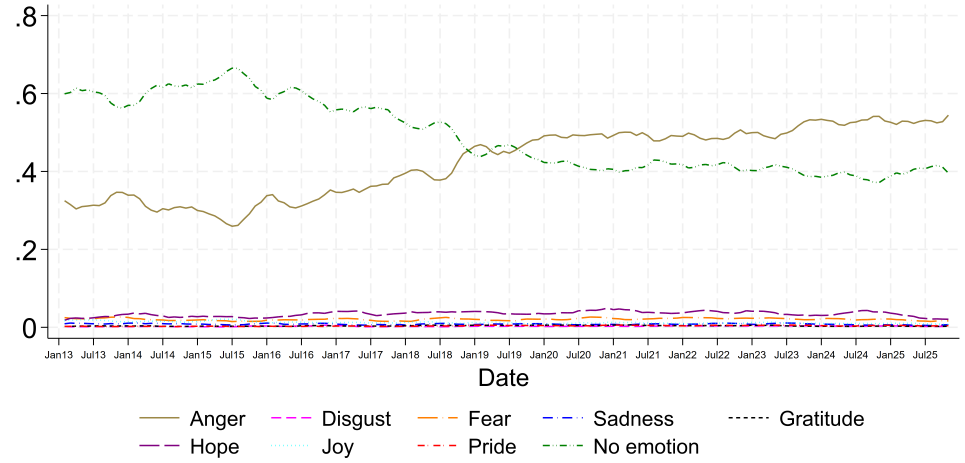
Panel (a) restricts the sample to accounts identified as located in the United States and still active at the time of data collection ($N = 239{,}998$, baseline $N = 791{,}425$). Panel (b) restricts the sample only to accounts that are still active ($N = 772{,}043$, baseline $N = 791{,}425$).

Figure A8: Robustness to Removing Replies and Tweets Containing Links

(a) Citizens



(b) Voters



Notes. The figure shows, for each month from January 2013 to October 2025, the share of sentences in tweets classified into each emotion. For readability, the graph displays a 6-month moving average of monthly percentages. The sample is restricted to tweets 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.

Panel (a) restricts the citizens dataset to tweets that are neither replies nor contain hyperlinks (N = 142,667, baseline N = 791,425). Panel (b) applies the same restriction to the voters dataset (N = 1,270,731, baseline N = 7,070,038).

A.6.3 Methodological note on the decomposition exercise

We decompose changes in the aggregate proportion of tweets classified as anger into two components: a *within component*, reflecting changes among continuing units, and a *selection component*, reflecting compositional changes due to entry and exit. The approach relies on a Shapley-value decomposition (Shorrocks, 2013), which ensures exact additivity and path independence.

Aggregate Proportion Let p_t denote the proportion of angry tweets in year t:

$$p_t = \frac{\sum_{i \in S_t} w_{it} a_{it}}{\sum_{i \in S_t} w_{it}}, \tag{1}$$

where S_t denotes the set of users active in year t, w_{it} represents the total number (or relative share) of tweets posted by user i in that year, and $a_{it} \in [0, 1]$ is the fraction of those tweets classified as angry. The ratio p_t therefore measures the weighted average share of angry tweets across all active users in our sample in year t. Our object of interest is the year-to-year change in this aggregate proportion,

$$\Delta p_t = p_t - p_{t-1}.$$

Define T_i^{first} and T_i^{last} as the first and last years in which user i is observed in the panel. For any adjacent pair of years $(t-1, t)$, we classify users as

$$E_t = \{i : T_i^{\text{first}} = t\}, \quad X_t = \{i : T_i^{\text{last}} = t-1\},$$

and let

$$C_t = \big(S_{t-1} \cup S_t\big) \setminus (E_t \cup X_t)$$

denote the set of continuing users. Thus, each user is counted as an entrant once, in the year of first appearance, and as an exiter once, in the year of last appearance; users who are intermittently inactive but later return are treated as continuers in all intermediate years.

Counterfactual States and Operators To isolate the contribution of different sources of change in the aggregate proportion, we construct a sequence of counterfactual states that progressively introduce the four possible transformations from period $t-1$ to period t. Each transformation can be viewed as an "operator" acting on the distribution of users, their tweet shares, and their emotional content.

Specifically, we distinguish four factors:

- E: the *entry* operator, which adds users whose first observed year of activity is t (panel-wide entrants);
- X: the *exit* operator, which removes users whose last observed year of activity is $t-1$ (panel-wide exiters);
- W: the *tweets per user* operator, which updates the weight w_{it} of continuing users, capturing the reallocation of tweet volumes across them;
- A: the *share of angry tweets* operator, which updates users' own emotional shares a_{it}, holding their relative tweet volumes fixed.

Intuitively, these four operators represent the distinct channels through which the aggregate proportion p_t can change over time: new users may enter (E), some may leave (X), continuing users may change how much they contribute (W), and they may also change *what* they contribute (A). By applying these operators sequentially, one can trace how p_t would evolve if each dimension of change were introduced in turn.

Formally, for each user i we define three elements: their activation status $s_i(E, X)$, their weight $w_i(W)$, and their emotional share $a_i(A)$. The activation status determines whether a user is counted in a given counterfactual state; the weight and emotional share determine how much the user contributes to the aggregate and with what content.

$$s_i(E, X) = \begin{cases} 1, & i \in S_{t-1} \text{ and not excluded by } X, \\ 1, & i \in E \text{ and } E = 1, \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

$$w_i(W) = \begin{cases} w_{i,t-1}, & W = 0, \\ w_{i,t}, & W = 1, \end{cases} \tag{3}$$

$$a_i(A) = \begin{cases} a_{i,t-1}, & A = 0, \\ a_{i,t}, & A = 1. \end{cases} \tag{4}$$

In the implementation, entrants are defined as users whose first observed year of activity in the panel is t, and exiters as users whose last observed year is $t-1$. Entrants are assigned zero weight in the baseline period ($w_{i,t-1} = 0$) and exiters zero weight in the current period ($w_{i,t} = 0$). The weight update operator W applies exclusively to continuing users, ensuring that reallocation in tweet volume is measured only among units that remain in the panel beyond their first and last appearance. Users who are intermittently inactive but later return are treated as continuers in all intermediate years, with zero tweet weight in years in which they do not post. The entry operator adds new users with their observed current weights ($w_{i,t}$), while the exit operator removes users with their baseline weights ($w_{i,t-1}$). To ensure that entry and exit effects are purely compositional, the emotional shares of these units are held constant across periods ($a_{i,t-1} = a_{i,t}$ for entrants and $a_{i,t} = a_{i,t-1}$ for exiters). Missing weights are treated as zero, and missing a_{it} values are replaced with the available counterpart.

Using these definitions, we can represent the proportion of angry tweets under any combination of changes as:

$$P(E, X, W, A) = \frac{\sum_i s_i(E, X)\, w_i(W)\, a_i(A)}{\sum_i s_i(E, X)\, w_i(W)}. \tag{5}$$

The function $P(E, X, W, A)$ therefore spans a family of 16 possible counterfactual states that range from the baseline configuration at $t-1$, $P(0, 0, 0, 0) = p_{t-1}$, to the final configuration at t, $P(1, 1, 1, 1) = p_t$. Each operator corresponds to moving along one dimension of this four-dimensional state space. For example, moving from $P(0, 0, 0, 0)$ to $P(1, 0, 0, 0)$ introduces entry only, while keeping all other dimensions fixed at their baseline levels.

Shapley Decomposition Because the aggregate p_t is a nonlinear function of all four factors, the marginal impact of each factor depends on the sequence in which changes are introduced. If, for instance, entrants are added before weights are reallocated, the resulting change may differ from the opposite order. To eliminate this path dependence, we employ the Shapley-value decomposition, which attributes to each factor its *average* marginal contribution across all possible orderings.

Let $\mathcal{F} = \{E, X, W, A\}$ denote the set of factors. For any $j \in \mathcal{F}$, define its Shapley contribution ϕ_j as:

$$\phi_j = \sum_{S \subseteq \mathcal{F} \setminus \{j\}} \frac{|S|!\,(4 - |S| - 1)!}{4!} \Big[P(S \cup \{j\}) - P(S) \Big], \tag{6}$$

where S denotes a subset of factors that are applied before j. The term in brackets measures the incremental effect of adding factor j given that the factors in S have already been applied, and the weighting term $\frac{|S|!\,(4-|S|-1)!}{4!}$ averages this contribution over the $4! = 24$ possible orderings.

The decomposition satisfies the additivity property:

$$p_t - p_{t-1} = \phi_E + \phi_X + \phi_W + \phi_A. \tag{7}$$

Each ϕ_j represents the unique and order-independent share of the total change Δp_t that can be attributed to factor j.

Interpretation The four terms correspond to distinct economic mechanisms:

$$\begin{aligned} \text{Entry} &: \text{composition effect from new entrants } (E), \\ \text{Exit} &: \text{composition effect from disappearing units } (X), \\ \text{Number of Tweets} &: \text{reallocation of weights among continuers } (W), \\ \text{Share of Angry Tweets} &: \text{change in } a_{it} \text{ among continuers } (A). \end{aligned}$$

In our context, the "entry" and "exit" components jointly capture *selection effects*—that is, how changes in the composition of active users contribute to the aggregate evolution of anger expression. The "number of tweets" and "share of angry tweets" components capture *within-user effects*, reflecting respectively (i) changes in users' tweet volumes and (ii) changes in the emotional content of their tweets among continuing users.

$$p_t - p_{t-1} = (\phi_W + \phi_A) + (\phi_E + \phi_X) = \text{Within component} + \text{Selection component} \tag{8}$$

A.6.4 Additional results by Political Affiliation

A.6.4.1 X Activity by Political Affiliation

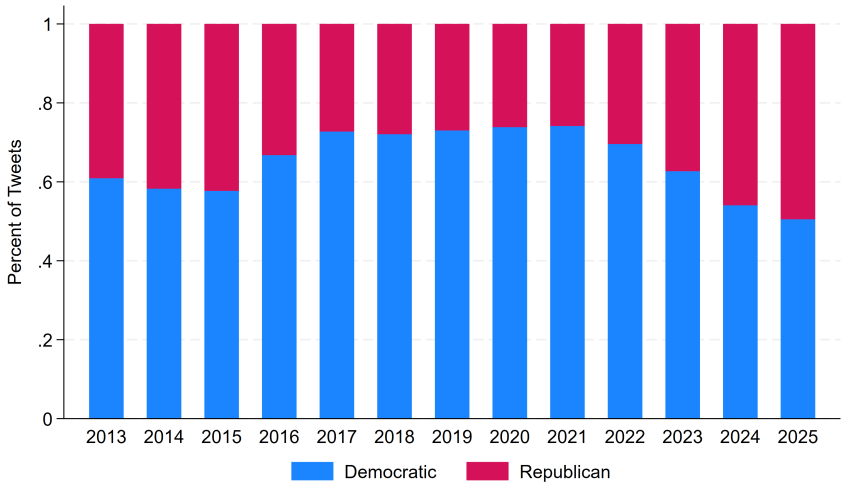
Figure A9 present results on volume of tweets using party registration in voters' tweets. Panel A9a demonstrates that, among users for whom party registration is observed, Democrats consistently account for the majority of tweets throughout the sample period. However, beginning in 2022—coinciding with Elon Musk's

acquisition of the platform—the share of tweets posted by Republicans begins to rise steadily.

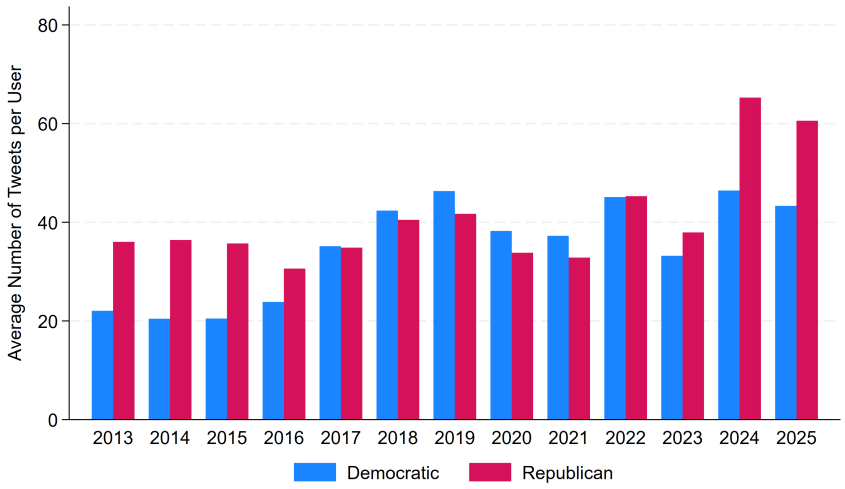
Panel A9b provides complementary evidence on user-level activity. Around the same period, Republicans exhibit a marked increase in engagement, measured by the average number of policy-related tweets per user. At the end of the sample period, Republicans post c. 40% more tweets on average.

FIGURE A9: EVOLUTION OF TWEETS BY POLITICAL AFFILIATION

(A) SHARE OF TWEETS



(B) AVERAGE NUMBER OF TWEETS



Notes. Panel (a) shows, for each year from 2013 to 2025, the share of tweets posted by each political group. Panel (b) shows the yearly average number of tweets posted by each political group over the same period. The sample is restricted to tweets by users whose party registration is available in the Voters' tweets dataset.

A.6.4.2 Political leaning and strength of partisanship in citizens' tweets

To replicate the results by political affiliation on the broader citizen sample, we infer a political leaning to each user since this information is not directly observed in that dataset. We follow the methodology of

Mosleh and Rand, 2022, which infers political orientation from the number and partisan leaning of accounts a user follows on X. [A4] Each user in our database is assigned a partisan score based on the list of partisan elites they follow on X. In Mosleh and Rand, 2022, a fixed set of prominent political elites was manually coded by party affiliation, assigning +1 to Republican-affiliated accounts and -1 to Democratic-affiliated accounts. A user's partisan score is then calculated as the average of the values associated with the elites they follow. This continuous measure ranges from –1 (following only Democratic elites) to +1 (following only Republican elites), with values near 0 indicating a more ideologically balanced followership pattern. We show heterogeneity in two dimensions below: by political leaning and by strength of partisanship. In the former, we divide people either into Democrats and Republicans or into a finer grouping ranging from Strong Democrats to Moderate Democrats, Moderate Republicans, and Strong Republicans. The coarser partition defines as Democrats users with a negative partisan score, while as Republicans users with a positive partisan score. The finer partition subdivides the partisan score range into four intervals: Strong Democrats have partisan scores in the range [-1, -0.5], Moderate Democrats in the range (-0.5, 0), Moderate Republicans in the range (0, 0.5), Strong Republicans in the range [0.5, 1]. Nonpartisan users are defined as those missing a partisan score, thus not following political elites.

To measure strength of partisanship, we can count the number of political elites that the user follows, which range from zero to 629 with a 25th percentile of 3; a median of 10, and a 75th percentile of 34.

To avoid misclassification, we only assign political leaning to users who follow at least two political accounts, but our results are robust to varying this threshold.

In our voters' tweets dataset, we observe party registration for those registered voters who report it. This information allows us to generate results based on verified party affiliation, which we present in the main text. We also show that the methodology used in our main analysis performs strongly relative to party registration–based classifications, as discussed in the subsequent paragraphs.

Evaluation of the Party Assignment Procedure We evaluate the performance of the constructed party compared to registration party in the voter dataset. Table A8 reports relevant performance metrics. Among users with known Democratic or Republican registration, classification accuracy reaches 0.888, indicating that the inferred measure correctly identifies nearly nine in ten users. Precision and recall are high for both parties, with somewhat stronger performance for Democrats than for Republicans.

[A4] We thank Mohsen Mosleh for providing the partisan scores used for each user in our dataset.

Table A8: Validation of Constructed Party Affiliation Against Registered Party

	Constructed Party		
Registered Party (Twitter users)	D	R	Total
Registered D	3096 (92.4%)	253 (7.6%)	3349
Registered R	303 (18.8%)	1309 (81.2%)	1612
Registered Other/Unknown	4297 (58.9%)	2995 (41.1%)	7292
Total	7696	4557	12253
Accuracy (D/R only)		0.888	N=4961
Precision — D / R		0.911 / 0.838	
Recall — D / R		0.924 / 0.812	
F1 — D / R		0.918 / 0.825	

Notes. The table reports a comparison between the constructed party indicator and the registered party affiliation among matched Twitter users in the voter panel. Cells show counts of users with corresponding labels, with row percentages in parentheses. "Constructed Party" refers to the inferred partisan leaning based on the sentiment and partisan-score features of users' tweets. "Registered Party" corresponds to the official party registration from voter records. Accuracy, precision, recall, and F1 scores are computed using only users whose registered party is Democratic or Republican.

Emotional Expressions of Voters by Political Affiliation and Strength of Partisanship We replicate the results obtained with party registration shown in 3.2 also in the citizens' sample, using the methodology described above.

Distribution of emotions by political affiliation. Figure A10 presents the distribution of tweets by emotional category by political leaning. As in Figure 6, we restrict the sample to tweets whose primary topic is one of the policy issues covered in Survey A. Only (22%) 33% of tweets by (strong) Republican-affiliated users and (27%) 34% of tweets by (strong) Democratic-affiliated users are classified as having no detectable emotion. Anger is by far the most common emotion: (73%) 63% of emotionally-charged tweets by (strong) Republicans express anger, compared to (67%) 60% among (strong) Democrats. Other emotions are relatively rare: disgust, fear, sadness, gratitude, joy, and pride each account for less than 1% of tweets in both groups. Hope appears in 3% of Democratic partisans' tweets. In Figure 12 we show the same results using the registration party obtained in voters' tweets, conditional on observing it. Proportions are broadly in line; a lower share of anger is detected in both parties, and compensated by higher shares of tweets classified as no emotions.

Emotions by partisan scores We deepen the analysis by examining the distribution of emotions within the citizens' sample as a function of the strength of their political leaning and partisanship. In Panel A of Figure A11, we group users into bins of 0.1 increments of their partisan score (see the definition above) and compute the mean anger score for each bin. We also overlay on the bar chart a distribution of partisan scores.

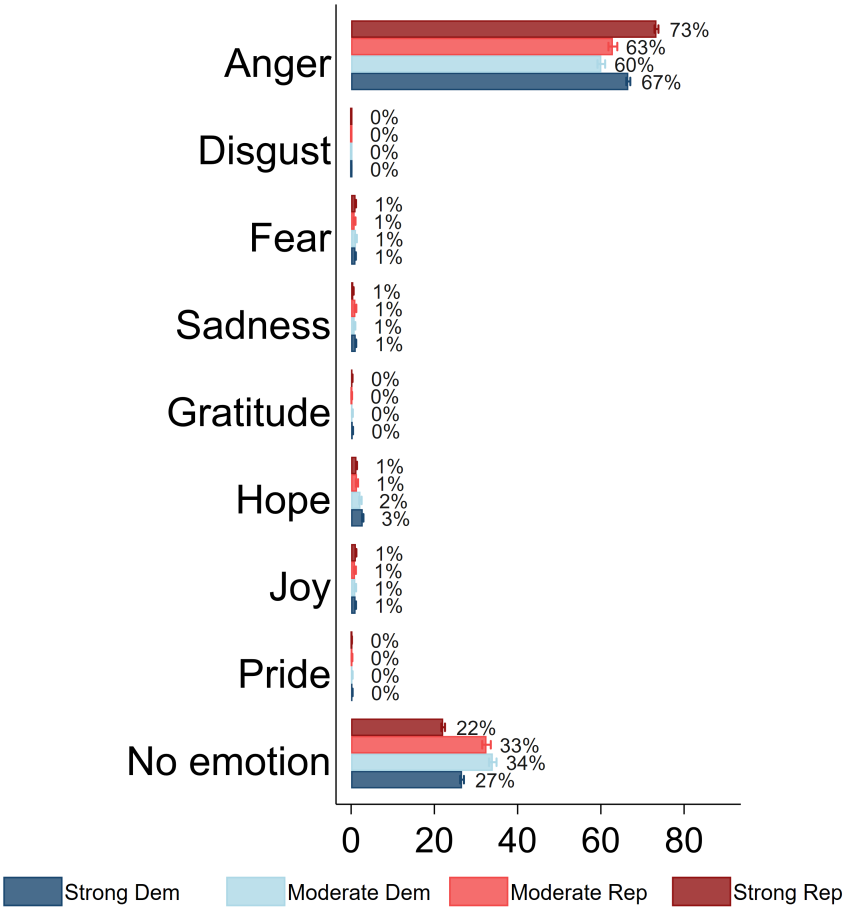
An interesting pattern emerges: the distribution of anger follows a U-shape, skewed to the right. In other words, users with stronger partisan identities (scores closer to –1 or +1) exhibit more anger than moderates, and strong Republicans (scores near +1) show even higher anger levels than strong Democrats (scores near –1 express). We find that 48% of the tweets of moderate or neutral users (scores near 0) are classified as

anger, while this proportion is around 58% for strong democrats and 64% for strong republicans. There is a dropoff in anger at the exact extremes (-1 and +1) driven by the sharp decrease in sample in these bins. Overall, our results suggest that being closer to the extreme ends of the political spectrum is associated with higher expression of anger, as is being more right-wing leaning.

Panel B complements the previous analysis by showing the relationship between mean anger and the number of partisan elite accounts followed, regardless of political leaning. We divide users into deciles based on the number of elite accounts they follow and calculate the mean anger score within each decile.

A clear pattern emerges: anger increases steadily with the number of political elites followed. Users who follow many elite accounts have nearly 60% of their tweets classified as angry (top decile - more than 60 accounts followed), compared to less than 40% for users who follow no elites at all. This suggests that greater engagement with partisan elites is associated with a higher propensity to express anger. This pattern highlights a positive correlation between the degree of partisan elite followership and the emotional intensity of users' discourse.

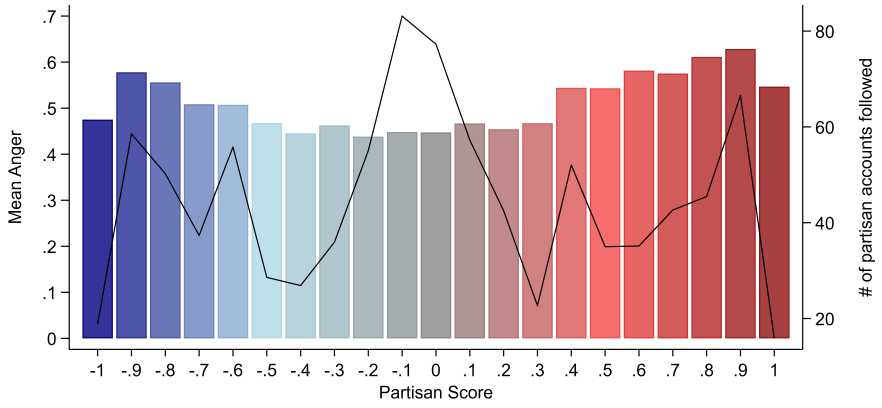
FIGURE A10: EMOTIONAL CONTENT OF CITIZENS' TWEETS BY POLITICAL AFFILIATION



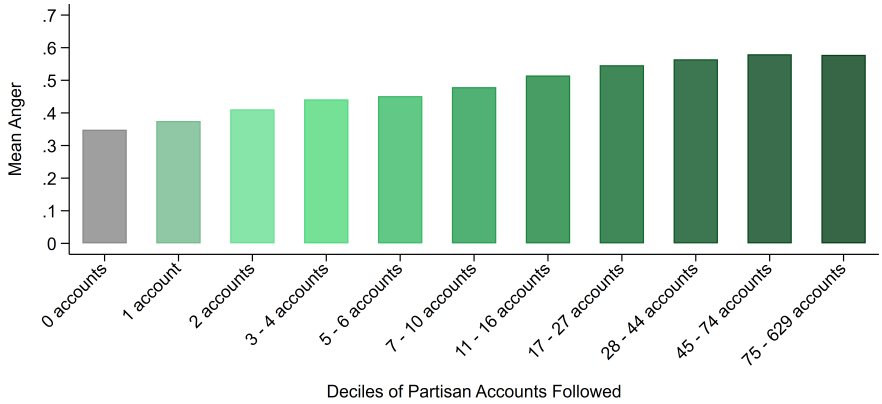
Notes. The figure shows, for each emotion, the share of tweets classified in a given emotional category by political affiliation. The numerator represents the number of tweets by X users within a given political affiliation classified in that emotion category, while the denominator is the total number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

FIGURE A11: DISTRIBUTION OF ANGER IN CITIZENS' TWEETS ON POLICY TOPICS

(A) BY PARTISAN SCORE



(B) BY NUMBER OF POLITICAL ELITES FOLLOWED



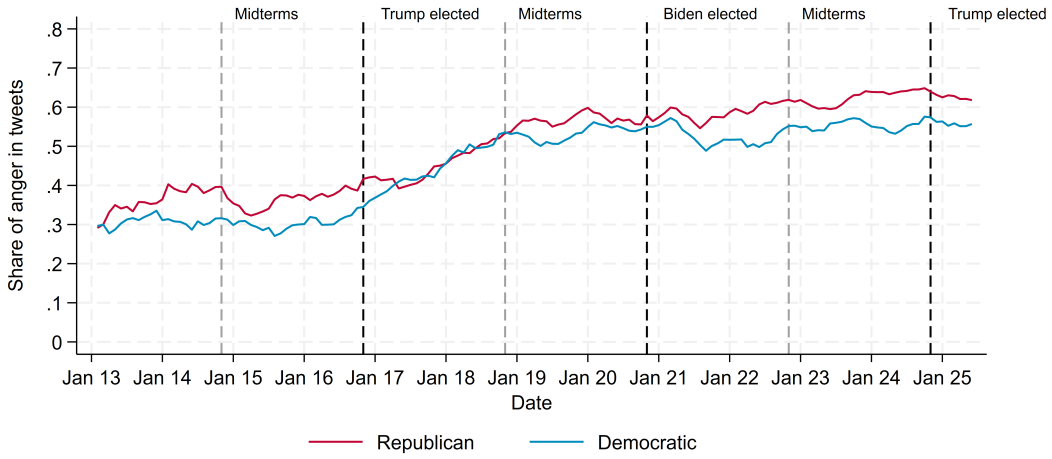
Notes. The figure shows the share of tweets classified as anger by partisan score and by deciles of the distribution of the number of accounts of political elites followed. The line in Panel A represents the average number of partisan account followed in each partisan score bin. The numerator represents the number of tweets by X users within a given group classified anger, while the denominator is the total number of tweets by X users in that group. 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.

Evolution of emotions by political leaning and partisanship. Figure A12 replicates the results of Figure 13.

Taking advantage of this methodology, Figure A13 shows the evolution more finely, distinguishing between the strength of political leaning (Panel A) and partisanship (Panel B). The same general upward trend in anger is observed. However, clear differences emerge in levels of anger: it is lowest among individuals who do not follow any political accounts or just one or two, and highest among those who follow the most accounts (more than 18), where anger reaches its peak. Similarly, anger is weakest among Non-Partisan users, becomes stronger among Moderate Democrats and Republicans and is strongest among Strong Democrats

and Republicans.

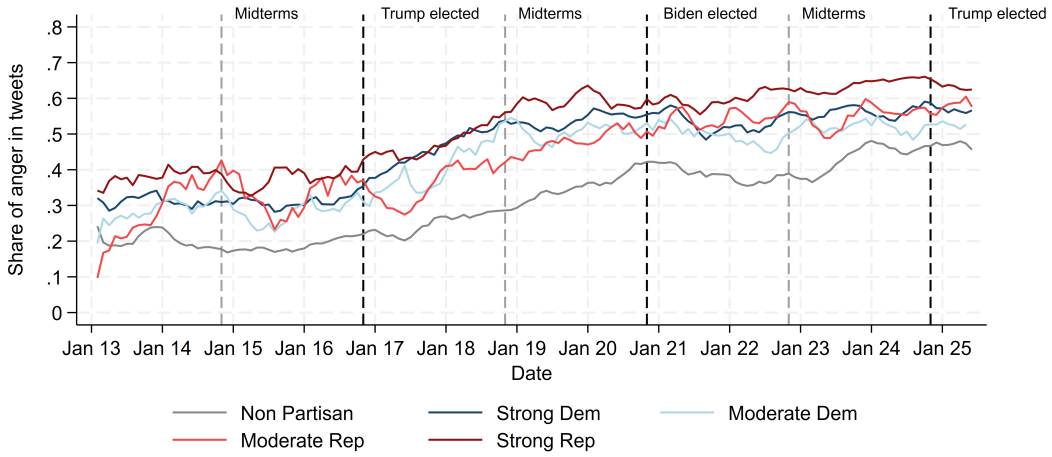
Figure A12: Evolution of Anger in Citizens' Tweets on Policy Topics by Party



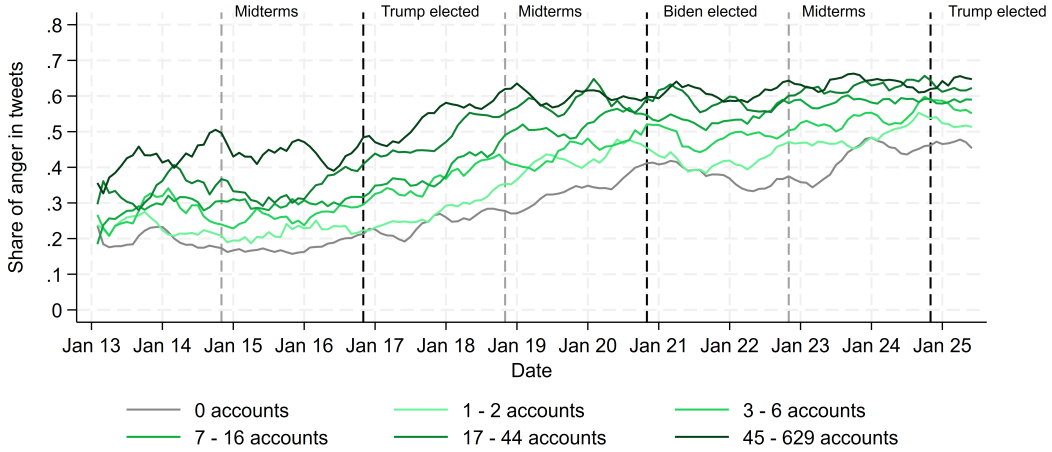
Notes. The figure shows, for each year, the share of tweets classified as anger by political affiliation and by quintiles of the distribution of the number of accounts of political elites followed. The numerator represents the number of tweets by X users within a given group classified anger, while the denominator is the total number of tweets by X users in that group. 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.

FIGURE A13: EVOLUTION OF ANGER IN CITIZENS' TWEETS ON POLICY TOPICS

(A) BY PARTISAN SCORE



(B) BY NUMBER OF POLITICAL ELITES FOLLOWED



Notes. The figure shows, for each year, the share of tweets classified as anger by political affiliation and by quintiles of the distribution of the number of accounts of political elites followed. The numerator represents the number of tweets by X users within a given group classified anger, while the denominator is the total number of tweets by X users in that group. 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. The category 'other topic' is excluded.

A.6.5 Further Heterogeneity in X Activity

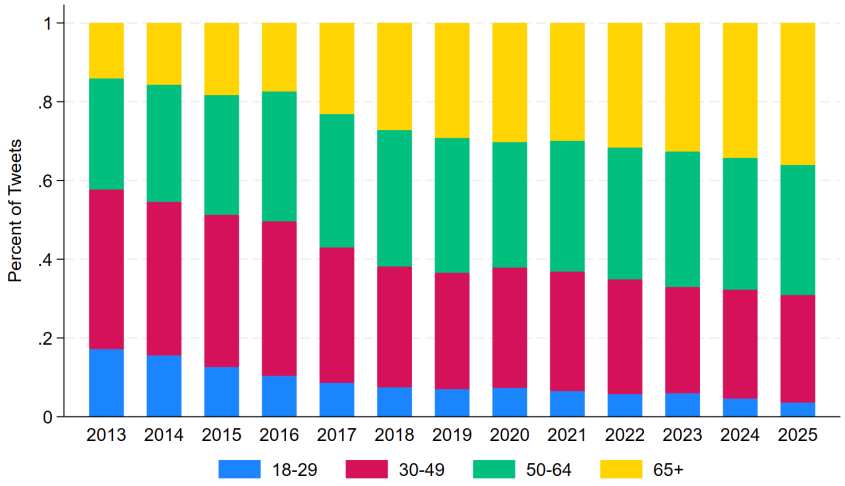
Figure A14 presents results on the volume of tweets by age group among users for whom age is observed. Panel A14a shows that, in the early years of the sample, individuals aged 30–49 account for the majority of

tweets. Over time, however, their relative contribution declines steadily. Beginning in the late 2010s, users aged 50–64 constitute an increasingly large share of total tweeting activity, indicating a gradual shift toward an older tweeting population.

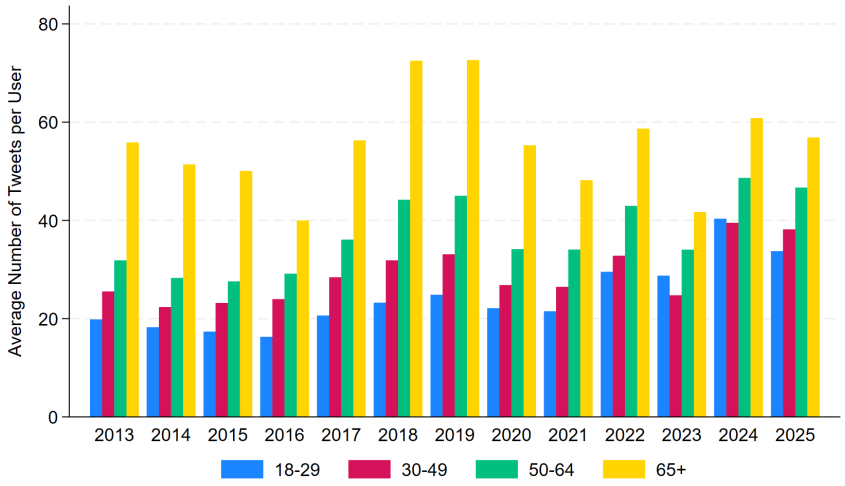
Panel A14b provides complementary evidence on user-level engagement. Older users consistently exhibit higher tweeting intensity, with especially elevated levels among those aged 50–64. While engagement peaks for most age groups around 2018–2019, the latter part of the sample is characterized by rising activity across all groups, with the most pronounced increases observed among users aged 65 and above.

Figure A14: Evolution of Tweets by Age

(a) Share of Tweets



(b) Average number of Tweets



Notes. Panel (a) shows, for each year from 2013 to 2025, the share of tweets posted by each age group. Panel (b) shows the yearly average number of tweets posted by each age group over the same period. The sample is restricted to tweets by users whose age is available.

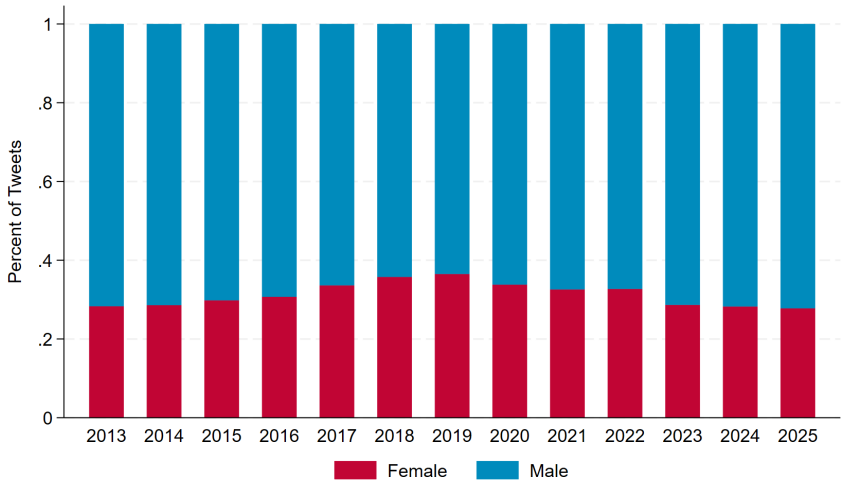
Figure A15 presents results on the evolution of tweeting activity by gender among users for whom gender

is observed. Panel A15a shows that men consistently account for a larger share of tweets throughout the sample period. While the gender composition remains relatively stable over time, the female share increases modestly during the late 2010s before declining slightly toward the end of the sample.

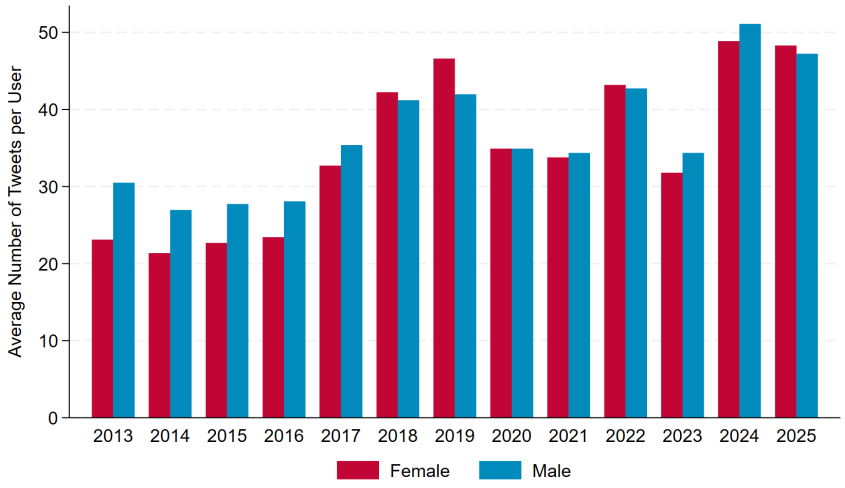
Panel A15b provides complementary evidence on user-level engagement. The gender gap in tweeting intensity varies over time. Both groups experience a decline around 2020, followed by a marked increase in activity after 2023.

Figure A15: Evolution of Tweets by Gender

(a) Share of Tweets



(b) Average number of Tweets



Notes. Panel (a) shows, for each year from 2013 to 2025, the share of tweets posted by each gender group. Panel (b) shows the yearly average number of tweets posted by each gender group over the same period. The sample is restricted to tweets by users whose gender is available.

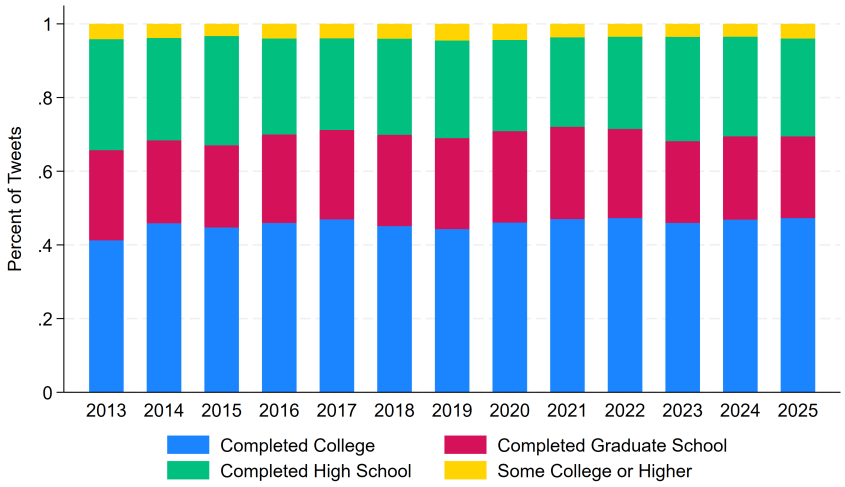
Figure A16 documents the evolution of tweeting activity by education level. Panel A16a shows that users with completed college education consistently account for the largest share of tweets, followed by users with

graduate education and those with high school education. The overall distribution across education groups remains relatively stable over time, with only modest shifts in composition.

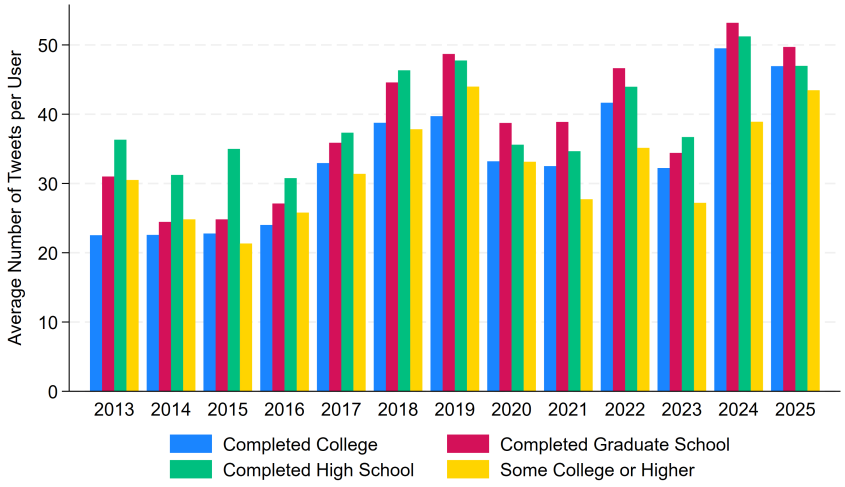
Panel A16b shows that users with lower levels of education exhibit greater tweeting intensity. In particular, individuals with graduate education post the highest average number of tweets throughout most of the sample. Tweeting activity rises for all education groups after 2023.

Figure A16: Evolution of Tweets by Education

(a) Share of Tweets



(b) Average number of Tweets



Notes. Panel (a) shows, for each year from 2013 to 2025, the share of tweets posted by each education group. Panel (b) shows the yearly average number of tweets posted by each education group over the same period. The sample is restricted to tweets by users whose education level is available.

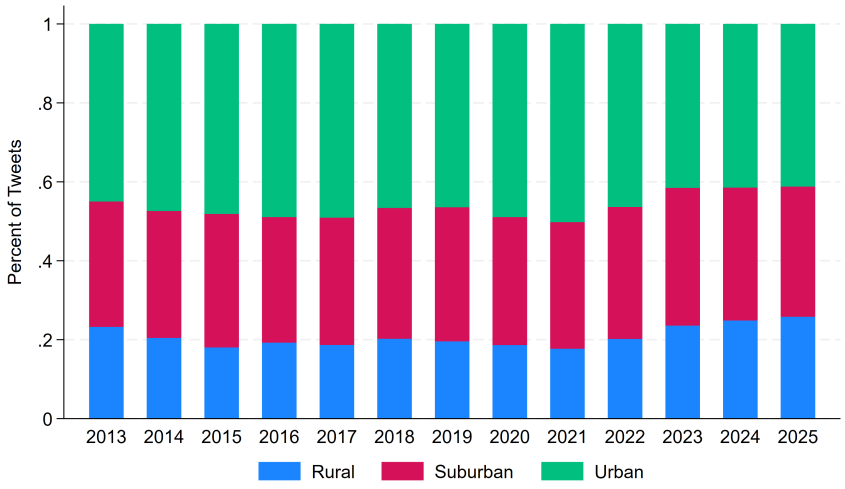
Figure A17 presents results on tweeting activity by urbanicity. Panel A17a shows that urban users consistently generate the largest share of tweets, followed by suburban users, while rural users account for a smaller but stable fraction of activity. Beginning in the early 2020s, the suburban and rural shares increase

modestly.

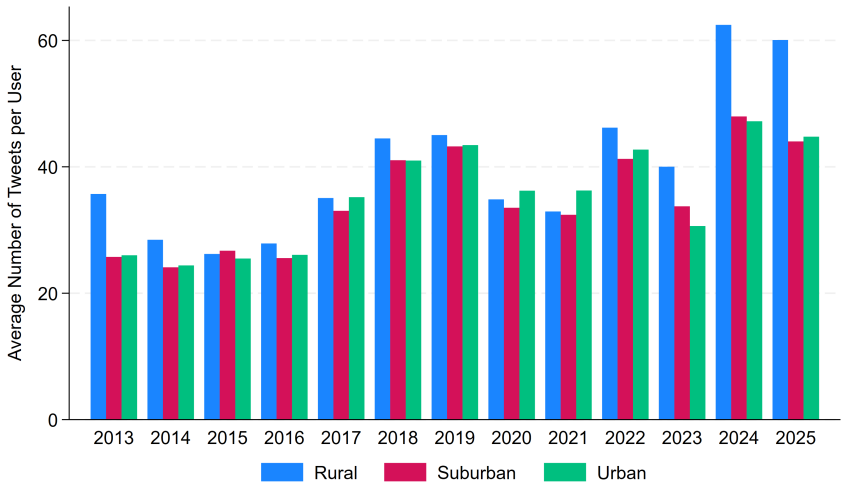
Panel A17b provides complementary evidence on user-level engagement. Rural users exhibit the highest average tweeting intensity in most years, particularly toward the end of the sample period. All urbanicity groups experience rising activity after 2023.

Figure A17: Evolution of Tweets by Urbanicity

(a) Share of Tweets



(b) Average number of Tweets

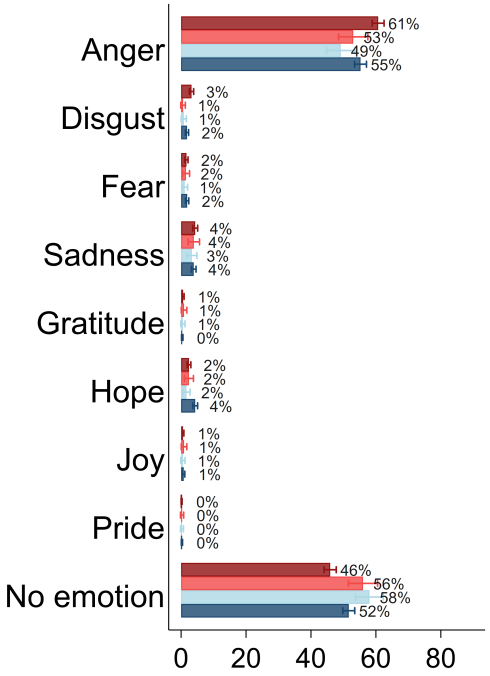


Notes. Panel (a) shows, for each year from 2013 to 2025, the share of tweets posted by each urbanicity group. Panel (b) shows the yearly average number of tweets posted by each urbanicity group over the same period. The sample is restricted to tweets by users whose urbanicity is available.

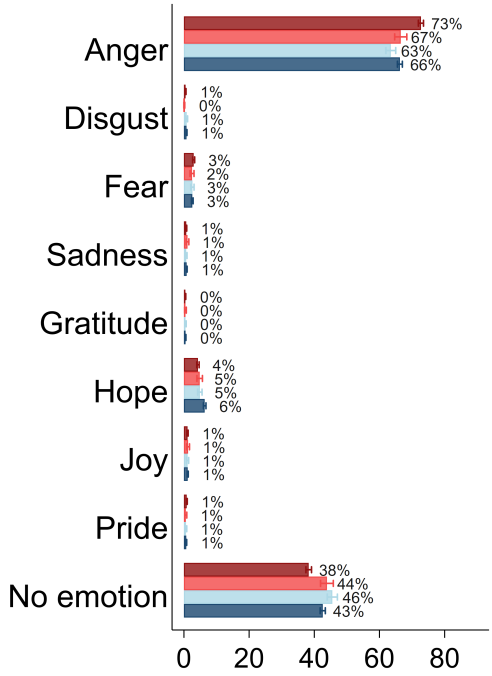
A.6.6 Additional Results on the Demand Side using Citizens' Tweets

Figure A18: Citizens' tweets on policy issues: emotions by political affiliation and topic

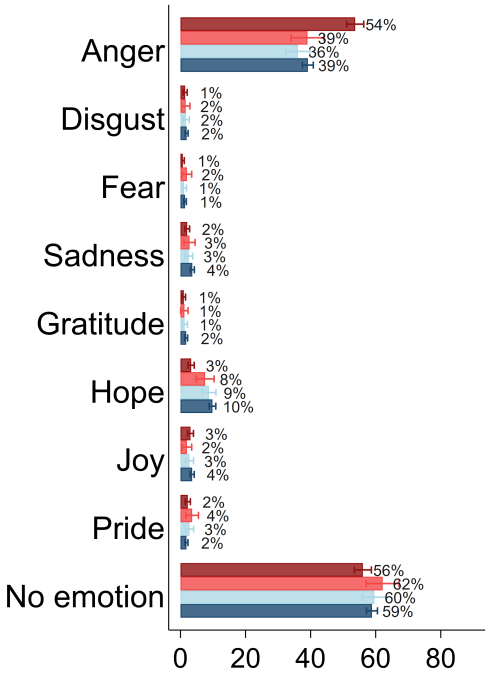
(a) Abortion



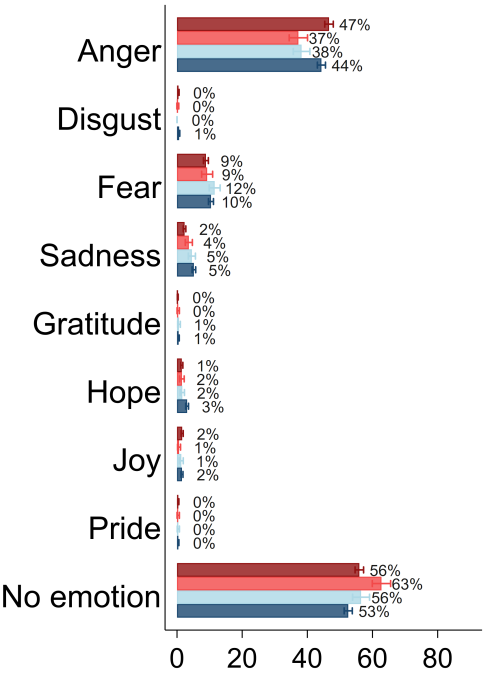
(b) Democracy



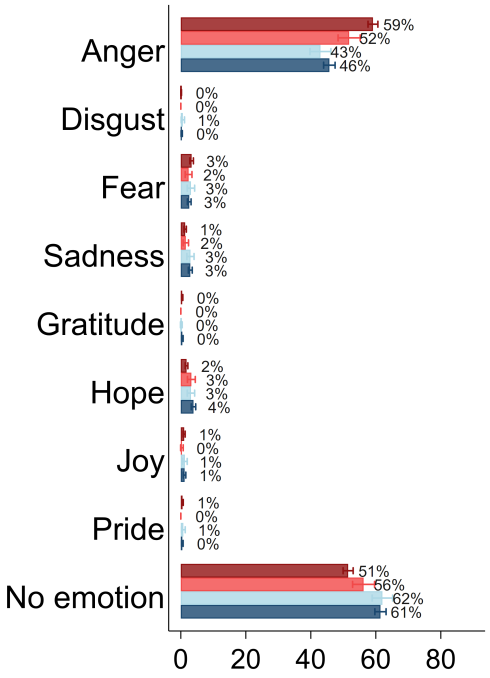
(c) Gender Equality



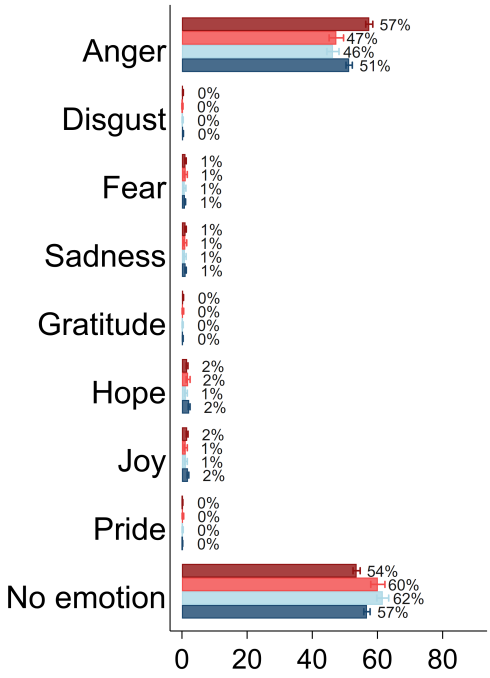
(d) Gun Control



(e) Immigration



(f) Tax and inequality



(g) Trade

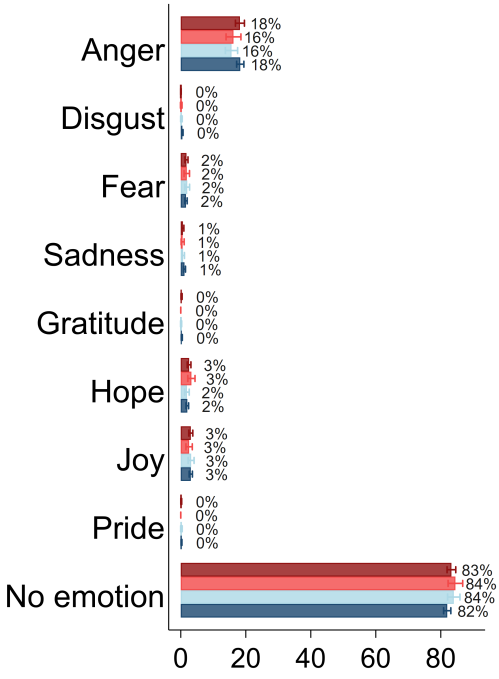
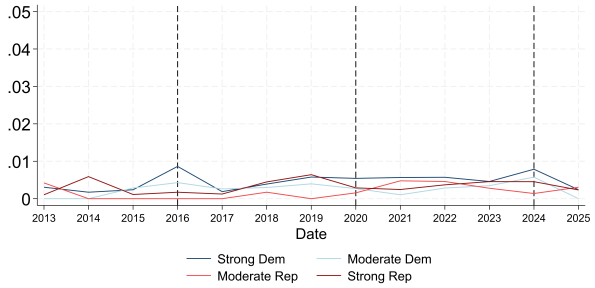
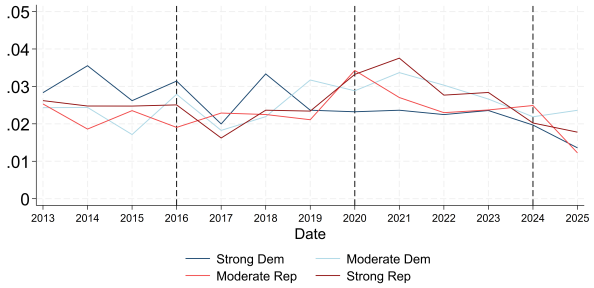


Figure A19: Evolution in Citizens' Tweets by Emotions and Degree of Partisanship

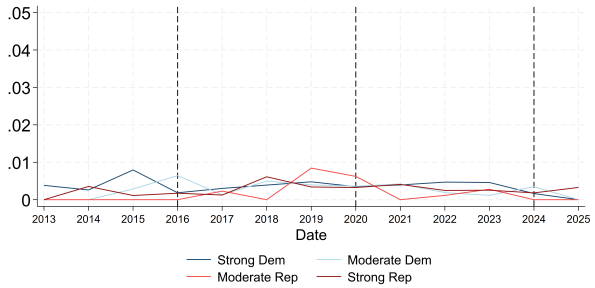
(a) Disgust



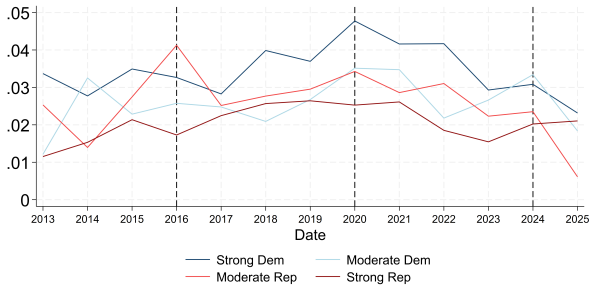
(b) Fear



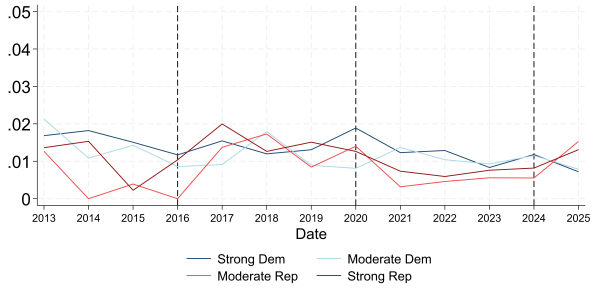
(c) Gratitude



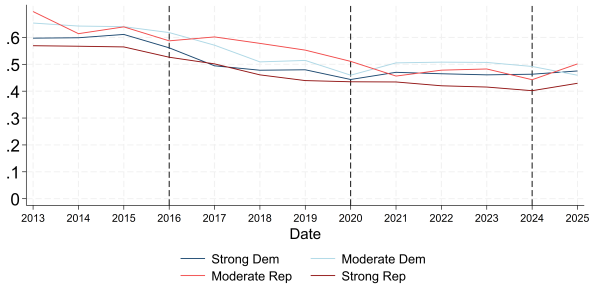
(g) Hope



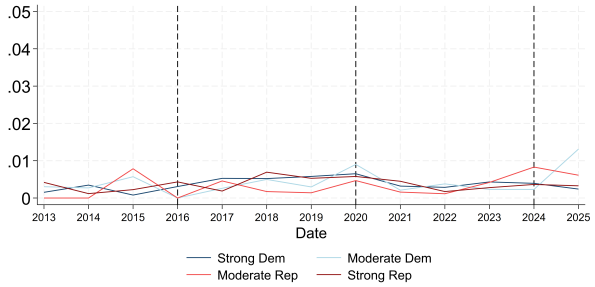
(h) Joy



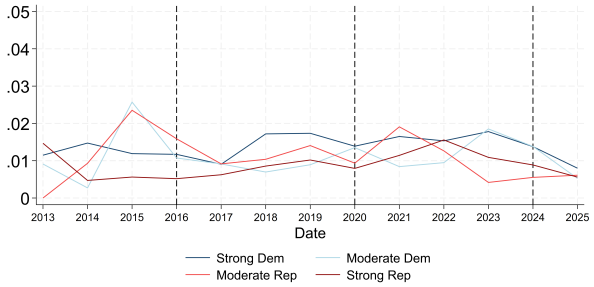
(i) No emotion



(p) Pride



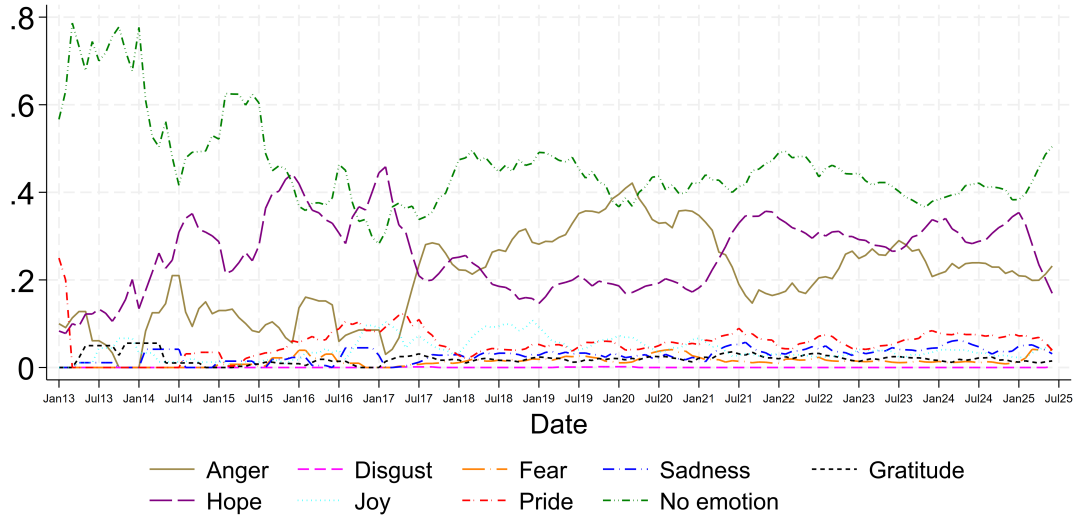
(q) Sadness



A.7 Additional Results on the Supply Side

FIGURE A20: EVOLUTION OF EMOTIONS IN OFFICIAL COMMUNICATION

(A) OTHER OFFICIAL ACCOUNTS



Notes. The figure shows, for each month from January 2013 to June 2025, the share of sentences in tweets classified into each emotion. The accounts displayed here are @POTUS, @FLOTUS, @VP (and respective archived accounts), and relevant accounts from the Cabinet @SecBlinken, @SecCardona, @SecGranholm, @SecMayorkas, @SecPompeo, @SecretaryPete, @DHS_Wolf, @EsperDoD. 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.

A.8 Survey A: Negative and Positive emotions - Individual components

Table A9: 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 A10: 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'.

Negative trade perception index

- Statement closest to view is "Trade entails winners and losers and it is impossible to compensate those who lose from it"
- Say "a great deal or a lot" when asked if trade causes unemployment
- Say "a great deal or a lot" when asked if trade increases inequalities

Table A11: 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 A9 for information on regression omitted categories and additional controls.

Anti-free trade index

- Say "strongly disagree or disagree" when asked "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.*"
- Say "not important at all" when asked "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?"
- Say "strongly oppose or oppose" when asked "Would you support or oppose raising tariffs on Chinese imports to at least 60 % ?"

Table A12: 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 A9 for information on regression omitted categories and additional controls.

Negative immigration perception index

- Say "immigrant's poverty is due to lack of effort" when asked "Which has more to do with why an immigrant living in the U.S. is poor?"
- Say immigration is a "very serious or somewhat serious" threat to the US economy
- Say immigration is a "very serious or somewhat serious" threat to the US culture

Table A13: 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 A9 for information on regression omitted categories and additional controls.

Anti-immigration index

- Say "decrease a lot or a little" when asked "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, or decreased a lot? "
- Say "strongly support or somewhat support" when asked "Would you support or oppose a large-scale deportation operation aimed at expelling millions of undocumented immigrants?"
- Say "strongly oppose or somewhat oppose when asked "Would you support or oppose spending U.S. funds on programs to address the root causes of migration from Central America?"
- Say "include mostly a stronger ideological screening for visa applicants" when asked " 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?"

Table A14: 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 A9 for information on regression omitted categories and additional controls.

Positive redistribution perception index

- Say "Circumstances beyond his or her control" when asked "Which has more to do with why a person is poor?"
- Say "People with higher incomes pay a lower share of their income in taxes than those with lower incomes" when asked "Do you think that people with higher incomes pay a higher or lower share of their total income in federal personal income taxes [...]?"
- Say "Raising taxes on wealthy people and corporations to expand programs for the poor" when asked "What do you think would ultimately do more to reduce the income differences between poor and rich families?"

Table A15: 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 A9 for information on regression omitted categories and additional controls.

Pro-redistribution index

- Rate government 5, 6 or 7 when asked to rate the government on a scale from 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.
- Say "Strongly support" or "Somewhat support" when asked "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%? [...]"
- Say "Strongly support" or "Somewhat support" when asked "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? [...]"
- Say "Strongly support" or "Somewhat support" when asked "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? [...]"

Table A16: 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 A9 for information on regression omitted categories and additional controls.

Pro-populism index

- Say "Fairly good" or "Very good" when asked "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?"
- Say "Fairly bad" or "Very bad" when asked "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?"
- Say "Fairly bad" or "Very bad" when asked "Do you think having a democratic political system is a good or a bad way of governing?"
- Say "Somewhat disagree" or Strongly disagree" when asked "Do you agree or disagree that elections in America are fair and each vote is counted fairly?"
- Say "They care about the interests of the rich and powerful" when asked "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?"

Table A17: 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 A9 for information on regression omitted categories and additional controls.

A.9 Survey B: Anger versus Fear - Individual component

Table A18: 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 A19: 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.

Climate policy views index 1/2

- Say "strongly support" or "support" when asked "Do you support or oppose the U.S. participating in the Paris Climate Agreement?"
- Say "strongly support" or "support" when asked "Do you support or oppose tax incentives for renewable energy projects, such as the installation of solar panels?"
- Say "strongly support" or "support" when asked "Do you support or oppose legislation to increase the proportion of electric cars sold from 10% today to 50% by 2035?"
- Say "strongly oppose" or "somewhat oppose" when asked "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."

Table A20: 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.

Climate policy views index 2/2

- Say "strongly support" or "support" when asked "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?"
- Say "strongly support" or "support" when asked "Would you pay 5% more on your monthly utility bill to get your electricity from renewable energy sources, like wind or solar?"
- Say "strongly support" or "support" when asked "Do you support or oppose a ban on combustion-engine cars?"
- Say "strongly support" or "support" when asked "Do you support or oppose a carbon tax with cash transfers?"

Table A21: 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.

Redistributive climate policy index

- Say "Strongly support" or "Somewhat support" when asked "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?"
- Say "Strongly support" or "Somewhat support" when asked "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?"

Table A22: 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.

Private action index

- Say "A lot" or "A great deal" when asked "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?"
- Say "A lot" or "A great deal" when asked "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?"
- Say "Everyone should reduce the number of flights they take" when asked "When it comes to climate action, what would you say should other people do, for instance with respect to taking flights?"

A.10 Robustness

A.10.1 Positive and negative emotions

Table A23: 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	0.10**	-0.02	-0.06	-0.04	0.11**	-0.04	-0.04	0.15	-0.09
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.17)	(0.08)
Panel B: Personal Characteristics									
Gender: Female	-0.00	0.03	-0.23***	-0.15***	-0.04	-0.01	-0.13***	-0.03	-0.38***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.14)	(0.07)
Age: 30-49 years old	0.08	0.06	-0.06	-0.08	0.16**	0.14**	-0.08	0.45**	-0.15
	(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**	-0.33***	-0.12*	-0.00	-0.04	-0.38***	-0.25	-0.46***
	(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***	-0.06	-0.09*	-0.08*	-0.18***	-0.11**	-0.49***	-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	-0.23***	-0.21***	-0.15***	-0.08	-0.19***	-0.29***	-0.14**	-0.91***	-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	-0.04	-0.12**	0.06	-0.03	-0.03	-0.14***	-0.12	-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***	-0.14***	-0.05	-0.10**	-0.11**	-0.16***	-0.39**	-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**	0.14***	-0.15***	-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	2309	2307	2306	2312	2307	2319	2318	2298	2300
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. The negative emotion index is composed of anger, fear, outrage and sadness. The positive emotion index is composed of joy and tranquility. See Table A9 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure A21: Effects of the treatments on indices

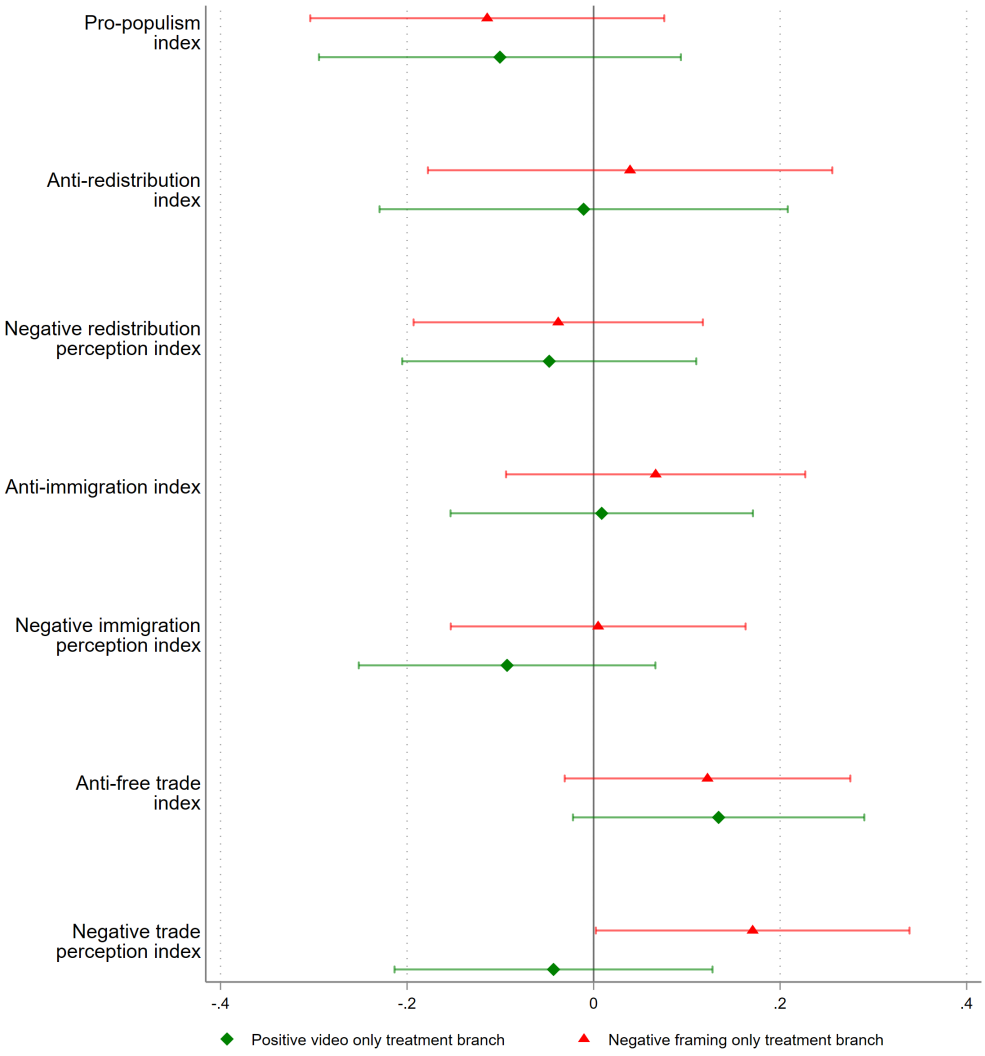


Table A24: All indices

	(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	-0.05	-0.01	-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	0.00	0.07	-0.04	0.04	-0.11
	(0.10)	(0.09)	(0.10)	(0.10)	(0.09)	(0.13)	(0.12)
Panel B: Personal Characteristics							
Gender: Female	-0.19**	-0.11	-0.10	-0.36***	0.20**	0.02	0.13
	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.11)	(0.10)
Age: 30-49 years old	0.06	0.01	0.22*	0.14	0.17	0.29	-0.04
	(0.14)	(0.12)	(0.13)	(0.13)	(0.13)	(0.19)	(0.16)
Age: 50-75 years old	-0.05	0.14	0.00	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	-0.23*	0.02	0.10	0.06	-0.68***	-0.38***	-0.21*
	(0.12)	(0.11)	(0.11)	(0.11)	(0.10)	(0.15)	(0.13)
Highest education level: some college and above	-0.06	0.17*	-0.20**	-0.12	-0.09	-0.15	-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***	-2.36***	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***	-0.06	-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	2328	2328	2328	2328	2328	2326	2328
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 A9 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A25: 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 A9 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A26: 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 A9 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A27: 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 A9 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A28: 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 A9 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A29: 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 A9 for information on regression omitted categories and additional controls. Standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A30: 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 A11 for information on regression omitted categories and additional controls. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A31: 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 A9 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 A32: 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 A9 for information on regression omitted categories and additional controls.*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

A.11 Questionnaire: Survey A

A.11.1 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.11.2 Socio-Demographics

A.11.2.1 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.11.2.2 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.11.2.3 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.11.2.4 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.11.3 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.11.4 Policy Issues

A.11.4.1 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.11.4.2 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.11.4.3 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.11.4.4 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.11.4.5 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.11.5 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.11.6 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.11.7 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.11.8 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.11.9 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.12 Questionnaire: Survey B

A.12.1 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.12.2 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.12.3 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.12.4 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.12.5 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.12.6 Policy Questions

A.12.6.1 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.12.6.2 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.12.6.3 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.12.6.4 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.12.6.5 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.12.7 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.12.8 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.12.9 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. ± 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.12.10 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.12.11 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.12.12 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.12.13 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.12.14 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.12.15 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.12.16 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.12.17 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.12.18 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.12.19 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.12.20 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.12.21 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.**

- 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.12.22 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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- 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.
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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.12.23 Feedback

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

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