The Political Divide: The Case of Expectations and Preferences

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Abstract

The divergence of attitudes towards their ideological extremes has become an identifying feature of political markets in the United States. Little is known about its source, how large it is, whether information can attenuate it, and its causal impact on civic behavior. We design a survey experiment that allows us to identify this results from misaligned perceptions rather than differences in preferences. We randomly introduce factual information and show that it corrects these misaligned beliefs, and further use this variation to estimate its effects on a suite of outcomes. For individuals who learn the government behaves worse than preferred, they become 0.35 s.d. less supportive towards the government, believe the government is less efficient by 0.42 s.d. and are less willing to compromise and trust by 0.43 s.d. We do not find any changes for those who learn the government behaves more in line with their preferences. This asymmetric response is consistent with the literature showing that negative information has a greater impact on attitudes and beliefs than does positive information.

JEL codes: D61, D72, D83, H20

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1 Introduction

In recent years, the United States and many countries around the globe have become defined by party politics and negative sentiments towards those on the other side of the aisle. Many studies document the diminishing ideological overlap between political parties, the rise in partisan animosity, an increase in anger towards the government, and an associated decline in trust (Pew Research Center, 2014; Newport and Dugan, 2017; Boxell et al., 2020; Neal, 2018; Webster, 2018; McCarty, 2016). These factors have led many to coin the the 21st century in the United States as one of the most polarized environments in its history.[1][2] On top of this, it also makes it more challenging to pass socially beneficial policy measures as individuals fail to agree on the actions needed to address economic and social issues. As for the sources responsible for these political changes, the timing of its growth mirrors that of the growth in technology and the Internet, making this coincidence a natural starting point. Theoretically, this relationship can work in either direction. While the Internet provides a near costless avenue to acquire real-time information instantly, it also enables users to self-segregate ideologically (Mullainathan and Shleifer, 2005).

In light of these facts, it is important to specifically identify the source of this divide as well as what can be done to attenuate its consequences. In this paper, we document people's feelings and perceptions towards the government. The government may behave in ways that individuals believe represents themselves or, rather, represents those on the other side of the political spectrum. In this sense, changes in perceptions and policy views affect how individuals behave and give way to two primary hypotheses related to the nature of division among a constituency. Division can be driven by different attitudes (i.e., preferences) towards

[1] It is important to acknowledge that polarization is an increasingly complex topic and may entail issues of identity, belonging to a social group, conformity, homophily in social networks, and that because of this complexity there is often not a uniform definition. However, polarization has traditionally been used to refer to a broad set of behaviors related to people's feelings towards those on the other side of the political spectrum, or to refer to differences in ideological positions, or to the intensity of partisan sorting (Boxell et al., 2017).

[2] For example of some of these claims, see CNN; Jennifer McCoy; Kolbert (2021); Murphy and Jolly; Thomas (2022).

policy issues, government, and society, implying that people are informed about policy and have more extreme preferences. Several studies show this to be the case for specific issues such as abortion, sexual morality, and war (DiMaggio et al., 1996; Fiorina et al., 2005; Shapiro and Bloch-Elkon, 2008). Alternatively, it can be driven by different perceptions (i.e., beliefs) about reality (Alesina et al., 2020). In this case, when people receive new information they may engage in *motivated reasoning*, distorting it in systematically biased and polarized ways towards that of their own preferences (Thaler, 2019; Flynn et al., 2017). Empirically, untangling which one is the driving force remains an open debate and, given very different policy prescriptions, is of first-order importance to address it. In a world of instant (mis)information, sound bites, and headlines, it is easy to form biases and opinions that may not be factually accurate, pushing individuals towards more extreme positions. We overcome this challenge by introducing purely objective and factual information about government spending receipts leaving little, if any, room for personal interpretation and distortions.

In this paper, we study the role of differences in preferences or differences in perceptions and how factual information affects perceptions and policy view formation. We document the results of a large-scale survey experiment on a community of active online U.S. individuals. We recruited a sample of 1,643 Amazon Mechanical Turk (MTurk) users and elicit their preferred spending allocation between two major federal expense categories (military and welfare) as well as their belief about the actual allocation. Democrats and Republicans have polar views on the willingness to support government programs (Oldendick and Hendren, 2018), and we exploit these differences to design a measure that represents the divide between preferences, beliefs, and reality and estimate the distribution between these differences.[3] Following this, we randomize the provision of factual information to identify whether misaligned perceptions can be corrected. Finally, we explore how factual information affects policy views and behaviors. We study how these changes impact individual

[3]On top of this, there is a literature showing that people are vulnerable to a wide range of heuristics and biases specifically for policies relating to public finance (McCaffery and Barron, 2006).

behavior across three main categories pertaining to civic engagement and the political process: i) political support, ii) views about government efficiency, and iii) the willingness to trust and compromise.

We contribute to the literature in a variety of ways. First, we find that misaligned perceptions (rather than preferences) are a source of divide among individuals. Using differences between an individual's expectations, preferences, and reality, we show that individuals have identical preferences related to government expenditure, but strikingly different perceptions about reality. This result builds on work that explores preferences of a single issue (DiMaggio et al., 1996; Fiorina et al., 2005; Shapiro and Bloch-Elkon, 2008; McCright et al., 2014) in the context of government spending allocations. We provide additional evidence that citizens are ill-informed on this issue (Kuklinski et al., 2000; Gilens, 2001). We also find consistent evidence with the theory that polarized views of the government are driven by people perceiving the same reality through a different lens (Alesina et al., 2020). This result suggests that one explanation for the drastic rise in polarization in the United States is not that preferences are approaching their polar extremes, but rather people form more extreme perceptions of the current state of affairs. Showing that differences in beliefs are a source of divide among individuals has important policy implications as providing accurate information could be a cost-effective way to close a 'mis-information' gap. This result also contributes to a broader political science debate regarding the source of increased partisanship in the general public. One hypothesis stems from the observation that the public is changing over and becoming more coherent in their preferences. A second hypothesis argues that preferences have remained stable, but the public splits into more extreme camps (Fiorina et al., 2005; Baldassarri and Gelman, 2008). Our analysis supports this latter hypothesis.

Our second contribution is to identify whether the provision of accurate information can act as a policy remedy to attenuate the total divergence. We show that providing factual information about actual government expenditures to individuals who have a less (more) favorable perception of the government than what they should, positively (negatively) impacts

this group's belief that the government represents their spending preferences by 13 points (12 points) on a scale of 0 to 100. These changes effectively close the mis-information gap. While prior beliefs can be shaped and influenced by many different factors, we show that providing this new lens encourages people to update their beliefs about the government in a Bayesian-like manner. This contribution of identifying Bayesian updating in response to information provision in of itself has been well documented across many situations (Lergetporer et al., 2018; Martinangeli and Windsteiger, 2019; Grigorieff et al., 2020). For example, political scientists use Bayesian models to assess changes in public opinion (Bartels, 1993; Gerber and Jackson, 1993; Grynaviski, 2006; Husted et al., 1995) as well as methods to evaluate how well citizens think of politics (Bartels, 2002; Gerber and Green, 1999; Tetlock, 1986). Perhaps most similar to our work, Gerber and Green (1999) develop a model that incorporates Bayesian updating and selective perception in the context of how voters learn. We overcome some of the challenges introduced in this model by controlling for a participant's prior preferences as well as their prior information allowing us to closely analyze the role of Bayesian updating in the context of voter learning.

Our final contribution is to provide comprehensive evidence describing how factual information can directly impact a broad set of policy views pertaining to civic engagement. Current research shows that polarization impacts a multitude of outcomes including the ability to reason (Gampa et al., fcm). More broadly, misinformation, misperceptions, and biases are prevalent in society and reducing these differences has significant impacts (Cruces et al., 2013; Tella et al., 2012; Karadja et al., 2017; Kuziemko et al., 2015; Roth et al., 2017; Alesina et al., 2018a,b; Nyhan and Reifler, 2010; Douenne and Fabre, 2020). In our experiment, we show that for individuals who learn the government is behaving closer to their preferences than they initially thought, there are no significant changes in civic engagement. For individuals who learn the government is behaving worse than what they expected, we find a significant reductions of 0.35 s.d. in support towards the government, 0.42 s.d. in beliefs about government efficiency, and 0.43 s.d. in the willingness to compromise or trust.

The difference in the responses between the two groups is consistent with the theory of motivated reasoning as agents possibly skew in the direction of the a priori policy views that they are motivated to hold (Thaler, 2019; Flynn et al., 2017; Fryer et al., 2018; Cook and Lewandowsky, 2016).[4] Also, beyond ensuring and testing for data quality, this asymmetric response suggests that experimenter demand effects do not drive results. If participants simply change their answers towards the direction of their intervention, then this would not lead to the asymmetries displayed by our data.

Overall, our results have important implications in political markets. The efficient provision of public goods and policies requires the alignment of voter's preferences with the trade-offs politicians face to access office. In the United States and in many other countries around the world, political polarization stemming from misinformed or ill-informed citizens threatens this alignment by making it more challenging to pass socially-beneficial policy measures by shifting civic engagement towards negative and extreme actions. However, there is a low-cost alternative to close these gaps. Our results suggest that providing accurate information can moderate these perceptions and close the gap in beliefs by moving 45% of the population closer to the middle. In terms of generalizability of our empirical results, we follow the List (2020) SANS conditions in our reporting. First, in terms of selection, our sample is a subset of actively online individuals from within the United States. In particular, MTURK is a crowd-sourcing website allowing us to sample from remotely located "crowd-workers" from across the United States to complete discrete on-demand surveys.[5] In terms of attrition, we have near perfect compliance (91.5%) indicating that nearly everyone who started the survey also completed it.[6] Considering naturalness of the choice task, setting, and time frame, we use a survey experiment, thus our setting is one in which our subject pool

[4]This result is also consistent with an emerging literature showing asymmetric responses between positive and negative information, where negative information has a greater impact on attitudes and beliefs than does positive information (Soroka, 2006; Sunstein et al., 2017). While Eil and Rao (2011) show the opposite result, our treatment is of a different nature where we show subjects either good news or bad news about an entity that is not personal.

[5]See Appendix Figure A.1 for a distribution of geocoded responses as determined by an individual's IP address.

[6]For those who did not complete the survey, attrition is not related to any observable characteristics.

are engaged in a natural and familiar task and are not placed on artificial margins.[7] Finally, in terms of scaling our insights to the larger US population, the signs and magnitudes of the unweighted and weighted results are by and large comparable.[8] However, it is important to note that we are only able to weight based on observable characteristics.

The rest of the paper is organized as follows. Section 2 overviews a conceptual framework explaining the primary theoretical components. Section 3 describes the experimental design. Section 4 discusses our estimation strategy used to identify both the impact of information on representation and the effect of fixing these on political beliefs. Section 5 documents our main results. Section 6 continues with robustness checks on our main findings. Section 7 concludes.

2 Conceptual Framework

In this section, we outline the various ways in which people turn marginal information into behaviors and views, and highlight testable implications. The literature gives way to two primary theories of this process. First, people update their views in light of new information in a Bayesian manner. Second, people engage in motivated reasoning, a process describing how people distort their inference of information towards the direction of beliefs that they are motivated to hold (Thaler, 2019; Flynn et al., 2017). We use a modified version of Alesina et al. (2020) to think about this process at large. Alesina et al. (2020) develop and test a model that translates signals and information into policy views through weighted perceptions. That is, people receive many signals, either costless or costly, which are then heterogeneously weighted into changes in perceptions - where perceptions are individual estimates of true parameters across many different topics. Then depending on the individual's prior levels of perceptions, the weight they place on the signal, and potentially endogeneity between signals and perceptions themselves, people will rationally update their perceptions - along

[7] See Harrison and List (2004).
[8] See Appendix Table A.8.

with their interactions - and form new policy beliefs. We formalize and modify this framework as described below.

Initially, people hold perceptions about different true parameters on a variety of subjects. In our case, people have a perception (belief) about the true allocation of government spending across multiple expense categories. That is, $P(Allocation) \in \mathbb{P}$. They will also hold perceptions about other parameters, such as wealth distribution and marginal tax rates. Importantly, each perception will have a true empirical counterpart. Individuals then decide how to behave using a function that translates perceptions into a policy view about topic i. Hence, $PolicyView_i = f(P_1, P_2, ..., P_N|\phi)$ where $P_1, P_2, ..., P_N \in \mathbb{P}$. For example, an individual's policy view regarding whether they believe government is wasteful might depend on their perception about the government's spending allocation, their perception about governmental employee salaries, among others. Note that there may be individual heterogeneity in both which perceptions along with their interactions that determine an individual's policy view. In the equation relating perceptions to policy views, we include an additional ϕ that will be discussed shortly.

Taking a step back, the way in which perceptions are formed depends on the process by which people learn from information. When new information is received, it is weighted by the individual into a change in perceptions. In general, information does not have the same impact on a person's perceptions, meaning that in the baseline, populations may have very different perceptions and misperceptions. Furthermore, marginal information allows people to update their perceptions. The literature supports two broad theories about how these perceptions are updated, either they are Bayesian or they are motivated reasoners.

To formalize the difference between the two theories, suppose agents have a prior perception $\Psi(\cdot)$, receive a piece of information, $x \in X$, and they infer a posterior perception $P(\cdot)$. According to Bayesian updating, their posterior perception is proportional to their prior times their belief that the information is true, $P(\cdot) \propto \Psi(\cdot) \cdot Pr(x|true)$. In the case of motivated reasoning, individuals distort this updating process by putting a higher weight on

the beliefs they are motivated to hold. According to a motivated reasoner, their updating process depends on their priors, their belief about whether information is true, and an additional motivated reasoning term $M(\cdot)^{\varphi(x)}$, where now $P(\cdot) \propto \Psi(\cdot) \cdot Pr(x|true) \cdot M(\cdot)^{\varphi(x)}$. In this case, the φ parameter is referred to as a susceptibility parameter capturing the weight agents place on information. In the case of $\varphi(x) = 0$, agents are Bayesian. When $\varphi(x) \geq 0$, agents are motivated reasoners. Furthermore, φ may depend on the information itself along with the perceived informativeness of the information.[9]

In this paper, we focus on signals and pieces of information that are factual and objective in the form of verifiable government spending receipts, increasing an individual's perception about the veracity of information, and hence, $Pr(x|true) \approx 1$. In light of this, we design a two-part experiment where we provide factual information regarding government tax receipts. In the first part, we rely on the verity and salience of this information to reduce the impact of motivated reasoning in the process of agents transforming signals into perceptions. We elicit from participants their baseline perception about government spending allocations, randomly provide a tax receipt treatment showing the allocation, and re-elicit their updated perception about government spending allocations. Given this, rational agents should update this belief in a Bayesian manner. In the second part of our experiment, we look more closely at the link between perceptions and policy views recognizing that people are complex. When it comes to developing policy views, this may entail issues of identity, belonging to a social group, conformity, homophily in social networks. This complexity goes beyond the simple function relating perceptions to policy views, and we use ϕ to capture a channel of motivated reasoning-like behavior. For example, when confronted by factual information in the first stage, rational agents have little to no room to misinterpret or skew information and form perceptions in any other direction than that of the signal. However, this does not necessarily translate in the second step since agents have more degrees of freedom in deciding the weights of each perception along with their interactions, as well as many other attributes represented

[9]For a full discussion, see Thaler (2019)

by ϕ. It is also important to note that in updating a policy view, agents possibly skew in the direction of the view that they are motivated to hold. Hence, even if perceptions directly related to a policy view are updated in a certain direction, agents have the flexibility to maintain their prior policy views and behaviors.

3 Experimental Design

3.1 Overview of Experiment

Our experimental design can be summarized in two steps. First, we recruited participants from an active online population (Amazon Mechanical Turk, i.e., MTurk) and directed them to an online survey. Second, in this survey, we recover an empirical distribution of preferences and beliefs that allows us to estimate how sizeable the gap between the two and reality is. Then, we randomly assign an information treatment to quantify how much information impacts an individual's gap between beliefs and reality. Our design allows us to difference out any changes in distribution patterns between individuals who either received or did not receive information. Finally, we exploit the exogenous variation in information to investigate the impact that it has on a suite of outcomes pertaining to civic engagement, including whether an individual's support for the government, an individual's willingness to compromise and trust others, and views on government efficiency, fraud, and waste.

3.2 Recruitment

Recruitment occurs in three waves. To test for statistical power, we ran a pilot wave ($n = 100$) in May 2019. Then, in July 2019, we run a second wave ($n = 446$). In these waves, we randomize treatment and estimate effects. Finally, we run a third wave ($n = 1,097$) beginning in September 2019 intended to detect smaller behavioral changes that individuals may report. In our main estimates, we pool all three waves ($n = 1,643$). We use Amazon's Mechanical Turk population (MTurk) in order to crowd-source responses from an active

online community. This also gives us a sample from across the United States throughout 2019.[10]

3.3 Survey Experiment

The first part of our experiment is designed to test the theoretical model developed in Alesina et al. (2020). Conceptually, we think of individuals as holding perceptions for a variety of topics. These perceptions are a function of various signals and information. Perceptions are dynamic and depend on updating and learning. People receive various signals and pieces of information which are ultimately weighted and translated into perceptions. When signals are costless, rational rules to update these perceptions depend on the prior level of all perceptions as well as their weights. Hence, this first part of our experiment can be thought of as a direct test of this model which identifies whether individuals update their perceptions in a Bayesian manner.

Upon starting the survey, participants are asked to consent followed by a variety of demographic questions, including gender, age, political orientation, and political representation.[11] After this, we take the standard question format in the information literature to elicit preferences and beliefs (Kuziemko et al., 2015; Alesina et al., 2018b) and sequentially ask participants two things for two different types of government spending.[12] First, for a given $100, how much they would prefer to have allocated between the two categories.[13] This provides a measure of an individual's preferred spending allocation, P_i. Second, how much they believe is being allocated to each category.[14] This gives a measure of an individual's expectations, E_i, capturing how she thinks the government is distributing between the two

[10] Appendix Figure A.1 reports geocoded responses by IP address.

[11] A full screen-by-screen copy of our experimental survey is documented in Appendix Section D.

[12] We randomize the ordering of this elicitation and test for any order effects. We do not find any significant differences.

[13] Specifically, participants are asked "Suppose you are responsible for planning the federal budget. The government receives $100 and asks you to distribute it between two categories. How would you like to distribute $100?"

[14] Specifically, participants are asked "Think about individuals in the executive and legislative branches responsible for planning the current federal budget. The government receives $100 and asks them to distribute it between two categories. How do you think they would distribute $100?"

categories. Panels (a) and (b) of Appendix Figure A.2 show the survey questions used to collect this information. In practice, the two categories that participants choose between are "Welfare and Government Assistance Programs" and "Military, Defense, and Homeland Security." We chose these categories because they draw extreme views across individuals with different political affiliations despite being funded similarly (Oldendick and Hendren, 2018).

With this base measure of differences between beliefs and reality, we are able to infer what would happen to participants had they known about the actual spending allocation between these programs (R). The difference between $|R - P_i|$ and $|E_i - P_i|$ provides an initial measure of how ill-informed someone is because, in this case, misinformation is the only reason why expectations on government expenditure allocations can differ from reality. Thus, if $|R - P_i|$ is smaller (greater) than $|E_i - P_i|$, then the individual should develop a better (worse) perception about the government.

After this, we randomly assign individuals into either a treatment or control group. The control group is showed their difference between P_i and E_i, as in Panel (c) of Appendix Figure A.2, and is then required to finish answering outcome questions. The treatment group is similarly showed their difference between P_i and E_i, but is also assigned an information intervention described below.

Our experimental design induces either an increase or a decrease in an individual's gap between beliefs and preferences. For concreteness, we refer to this gap as a perception gap. The directional change is dependent on the individual's initial beliefs and expectations regarding the allocation of government spending. We randomize an information intervention that reveals to treated participants the real allocation, R, between the two categories.[15] Panel (d) of Appendix Figure A.2 shows an example of how this information is revealed to

[15]In practice, the Congressional Budget Office reports that in 2017, for a given \$100, \$44 were allocated towards Welfare Programs and \$56 towards Military, Defense, and Homeland Security. This information corresponds to an average and provides a reference point for individuals to adjust their beliefs. While the questions participants answered were framed as allocating money to different expenditures, we do not find evidence that participants interpret this marginally (discussion in conclusion). We presented reality as an average to elicit a more robust response because there is evidence that individuals react stronger to average changes than to marginal changes (Ito, 2014).

participants. By doing so, depending on an individual's initial P_i and E_i, participants are treated with either a reduction of their perception gap, an increase, or no change. Figure 1 summarizes these conditions. In the case that $|P_i - E_i| > |P_i - R|$, treated individuals will experience a reduction in perception gap that is equal to $|P_i - E_i| - |P_i - R|$. If $|P_i - E_i| < |P_i - R|$, treated individuals will experience an increase in their perception gap equal to $|P_i - E_i| - |P_i - R|$. In cases when $E_i < P_i < R$ or $E_i > P_i > R$, an individual could be treated to either an increase or a decrease depending on the respective magnitudes of P_i and E_i. Finally, anytime $E_i = R$ an individual will not experience a change. With respect to an individual's perception about the government spending allocation, we take care to highlight the veracity of R give to little to no room to misinterpret or skew the information and form perceptions in any other direction than that of the signals described in Figure 1.

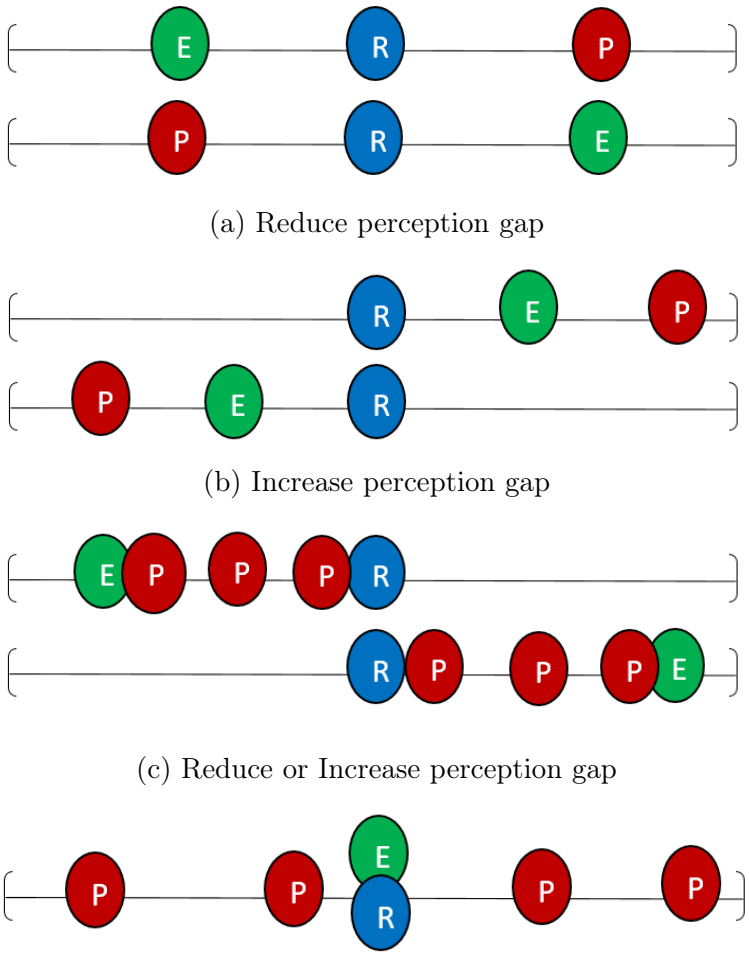
3.4 Outcomes Questionnaire

While the first part of our experiment tests whether individuals are Bayesian in regards to their perceptions, here in the second part we identify more broadly how changes in perceptions impact policy views pertaining to civic engagement and the political process. That is, we go beyond the theoretical predictions of Alesina et al. (2020) and test explicitly i) whether changes in perceptions impact behaviors, and ii) how these changes in perceptions impact behaviors.

All participants completed an outcome questionnaire that collects information on three categories: how well the government represents an individual's preferences and general feelings of approval and support towards the government, survey and behavioral measures of trust and compromise, and an individual's perception of how efficient the government is. A full description of each outcome question is in Appendix Section C.

We collected the following information across three main outcome categories. Our first main category captures beliefs about government representation and support. Before treatment, we elicited an individual's perspective on how well they think the government repres-

Figure 1: Treatment Descriptions



(a) Reduce perception gap

(b) Increase perception gap

(c) Reduce or Increase perception gap

(d) No Change in perception gap

Notes: Participants reveal their preferred distribution of spending, P_i, and what they currently expect the government to be allocating, E_i. This difference, $|P_i - E_i|$ captures a measure of one's perception gap. Treated individuals are revealed the actual distribution, R, which generates exogenous variation in the degree of perception. Illustrating an example, Panel (d) shows that if expectations match reality, then for any preference, denoted by different red dots, $|P_i - E_i| = |P_i - R_i|$, suggesting that treatment would not change government perceptions for this individual.

ents their preferences overall. After treatment, we re-elicit these preferences by asking the same questions. We also obtain additional post-treatment measures of political support. Our second main category captures views pertaining to government efficiency, fraud, and waste. After treatment, we obtained information about an individual's perceptions of government efficiency, fraud, and waste. Our final category looks to capture views on compromise and

trust. After treatment, we asked individuals a series of questions pertinent to compromise in the government as well as general feelings of trust. We also captured an individual's willingness to compromise and trust others by using both survey and behavioral measures. The behavioral measures included giving individuals the option to subscribe to different newsletters, to read a quote about a controversial issue made by a politician, and to write an email to their senators. We included links directing individuals to the alternatives, and we can track whether or not an individual selected a link in our survey. Upon completion of the survey, participants are thanked and promptly paid.[16]

3.5 Ensuring Data Quality

While recent research shows that experimenter demand effects are not likely to be a concern in survey experiments in general and MTurk survey experiments in particular (Mummolo and Peterson, 2019; de Quidt et al., 2018), we took several steps to ensure the best possible data quality. During the consent process, we provided general information about the survey without any direct mention of any objectives ("This survey will ask you questions about demographics, political preferences, and beliefs about the government"). After the section with background questions, we provided information about the budget process in the United States to nudge individuals to think about government spending. We strategically placed this information right before we elicit preferences and beliefs on government spending. For the questions that elicit preferences and beliefs, we constrain the answers to sum 100. In the outcome questionnaire, we introduce an attention check question to stimulate respondents to pay extra attention to the subsequent questions. Finally, there may be some concerns about lack of effort, lack of attention, and deception in MTurk that could affect the quality of the data that can be collected (Hauser et al., 2018; Kennedy et al., 2018; Dennis et al., 2019). To address this concern, we check if the results are robust to restricting the sample to participants who passed attention checks, who took more than 7 minutes to complete the

[16] All participants who successfully finish the experiment and pass "attention" checks are paid $1.00 for survey completion.

survey and deleted repeated IP addresses (GPS coordinates). We also checked two open-ended questions and found no evidence that these answers were generated by a computer algorithm. There are 255 participants who did not answer these questions. We check if the results are robust to excluding these participants.[17]

4 Estimation Strategy

To test the effect of information on perceptions, before treatment, we elicited an individual's perspective on how well they think the government represents their preferences for spending on welfare (or military) spending. After treatment, we re-elicit these preferences by asking the same questions.

To then study the impacts of perception changes on policy views relevant to the the political process, we construct indices that combine the outcome variables within each of the three categories. First, we orient outcome variables so that more positive values have the same meaning. Then, we demean each variable using the mean of the control group and convert it into an effect size by dividing it by the standard deviation of the control group. The index is the weighted average of the transformed outcomes, where the weights are derived from the inverse of the covariance matrix of the transformed outcomes (Anderson, 2008). These three indices are the primary outcomes for our treatment evaluation. As a robustness and consistency check, we also explore treatment effects on each outcome variable.[18]

[17] These checks are intended to provide evidence that participants engage with the survey and that similar results emerge irregardless of how potential sub-samples could be generated based on characteristics related to poor engagement or faulty data generation. It should still be cautioned that these are only observable checks and that unobserved concerns could still emerge. However, the lack of observable concerns is supportive of minimal unobservable concerns.

[18] The survey experiment also includes links to write to their senator, register to vote, and register on free newsletters from different media. Unfortunately, participants mostly skipped over these links, so we cannot test for effects on these outcomes.

4.1 Estimation

To examine the effects of information on perceptions, we exploit the fact that we asked individuals how well they think the government represents their preferences for spending on welfare (or military) both before and after treatment to estimate the effect of information using a difference-in-difference design. This specification increases the precision of the estimates and allows us to control for individual fixed effects as a robustness check. We estimate the following equation for both those who experience an increase or a decrease in their perception gaps:

$$y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Treated_i + \beta_3 Post_t \cdot Treated_i + \varepsilon_{it} \tag{1}$$

where $Post_t$ is a dummy variable that controls for any changes that occur between answering questions and $Treated_i$ indicates if individual i was randomly assigned to the information intervention. β_3 is the coefficient of interest. Individual fixed effects are included and control fixed individual covariates. We cluster standard errors at the individual level.

To examine the effects of perceptions on policy views, we estimate the effects on the three indices described above. Random assignment implies that we can compare treated individuals, who experience a reduction (increase) in their perception gap to individuals in the control group who would have experienced a similar reduction (increase) in their perception gap had they been treated. For these outcomes, we estimate the following equation for both those who experience an increase or a decrease in their perception gaps:

$$y_i = \beta_0 + \beta_1 Treated_i + \varepsilon_i \tag{2}$$

where $Treated_i$ indicates if individual i is randomly assigned to the information intervention. β_1 is the coefficient of interest. We use heteroskedastic robust standard errors because treatment is randomly assigned at the individual level with no clustering in sampling nor in

treatment assignment (Abadie et al., 2017).

For both the effects of information on perceptions and the effects of perceptions on policy views, we also test for effects on the distribution of outcomes. We use Kolmogorov-Smirnov based statistics to non-parametrically test for equality of the distributions, as well as first and second-order stochastic dominance of treatment over control (Abadie, 2002).[19]

5 Results

5.1 Distribution of Misperceptions

We recruited a sample of 1,643 participants using Amazon's crowdsourcing marketplace, Mechanical Turk (MTurk). As mentioned above, we define a "perception gap" as the difference between people's preferences for distributing government spending (P_i) and their beliefs about how the government is actually distributing its spending (E_i). To measure this gap, we asked participants two questions.[20] First, for a given \$100, we elicited how much they would prefer to have allocated between Welfare Programs and Military, Defense, and Homeland Security. This question measures P_i. Second, we asked participants what they believe the government is allocating between the two categories giving us a measure of E_i.

With a base measure of how ill-informed someone is, we inferred what would happen to the gap between preferences and expectations if participants learn about the actual spending allocation between these programs (R). The Congressional Budget Office reports that in 2017, for a given \$100, \$44 were allocated towards Welfare Programs and \$56 towards Military, Defense, and Homeland Security. As predicted by the Hotelling-Downs model of median voters and the partisan budget deliberation process, spending across these categories is stable over time and administrations from different parties (Hotelling, 1929; Downs,

[19] To test for distribution equality, let $F_{(1)}$ be the distribution of outcome y_{it} for the treated group and $F_{(0)}$ be the distribution of the control group. According to Abadie (2002), we define $F_{(1)}$ first order stochastic dominates $F_{(0)}$ if $\int_0^x dF_{(1)}(y) \leq \int_0^x dF_{(0)}(y)\ \forall x \geq 0$ and $F_{(1)}$ second order stochastic dominates $F_{(0)}$ if $\int_0^x \left(\int_0^z dF_{(1)}(y) \right) dz \leq \int_0^x \left(\int_0^z dF_{(0)}(y) \right) dz\ \forall x \geq 0$

[20] See Appendix Figure A.2 for an example of these questions.

Table 1: Summary Statistics

	(1)	(2)	(3)	(4)
	Full Sample	Better Perception	Worse Perception	U.S. Population
Income Below 50K (%)	0.45	0.45	0.44	0.42
	(0.5)	(0.5)	(0.5)	
4-Year College (%)	0.56	0.54	0.59	0.29
	(0.5)	(0.5)	(0.49)	
Male (%)	0.49	0.45	0.53	0.49
	(0.5)	(0.5)	(0.5)	
White (%)	0.82	0.83	0.81	0.74
	(0.38)	(0.37)	(0.4)	
Age (Years)	35.57	35.34	35.86	37.2
	(11.18)	(11.18)	(11.18)	
Married (%)	0.42	0.39	0.46	0.48
	(0.49)	(0.49)	(0.5)	
Republican (%)	0.25	0.19	0.32	0.26
	(0.43)	(0.4)	(0.47)	
Democrat (%)	0.47	0.51	0.42	0.2
	(0.5)	(0.5)	(0.49)	
Social Views (0 Lib. - 100 Cons.)	38.3	33.19	44.61	
	(31)	(29.86)	(31.23)	
Econ. Views (0 Lib. - 100 Cons.)	45.4	40.88	50.98	
	(31.47)	(30.88)	(31.32)	
Daily Facebook Minutes	55.76	50.04	62.71	
	(59.7)	(56.86)	(62.31)	
Daily Online Minutes	142.32	146.07	137.76	
	(58.99)	(57.8)	(60.14)	
Facebook News Freq. (0-100)	30.75	28.35	33.66	
	(31.44)	(30.02)	(32.87)	
Cable News Freq. (0-100)	34.09	32.07	36.54	
	(32.5)	(32.77)	(32.03)	
News Bias (0 Lib. - 100 Cons.)	44.6	41.9	47.88	
	(25.4)	(23.96)	(26.7)	
Preference Welfare (0-100)	60.19	62.61	57.19	
	(23.97)	(22.36)	(25.52)	
Expected Welfare (0-100)	40.9	29.69	54.75	
	(24.67)	(20.32)	(22.46)	
Gov. Represent (0 Bad - 100 Good)	31.96	26.2	39.09	
	(29.15)	(26.14)	(31.05)	
N	1,643	908	735	

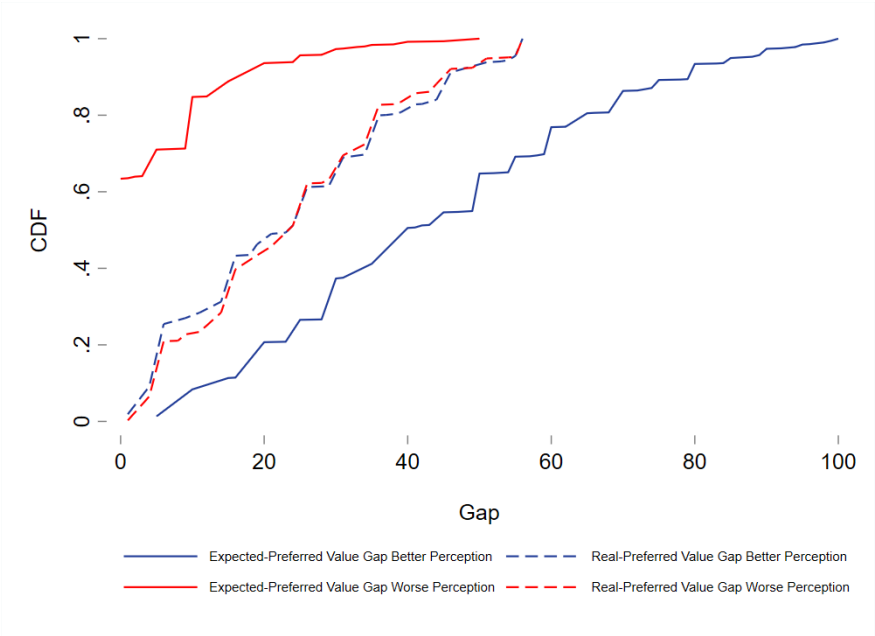
Notes: This table presents summary statistics for the full sample (1), the group treated to a better perception (2), the group treated to a worse perception (3), and demographics of American adults (4). The top six numbers of (4) are from the 2017 American Community Survey (United States Census Bureau 2017) and the Republican and Democrat shares are from the 2016 American National Election Study (American National Election Studies 2016). Standard deviations in parenthesis.

1957).[21, 22] After learning R, if $|R - P_i|$ is smaller (greater) than $|E_i - P_i|$, then the individual

[21] Appendix Table A.1 shows the distribution of spending across major federal expenses over time.

[22] The Hotelling-Downs model predicts that in a two-candidate election, each candidate should take the positions of the median voter to increase their respective probability of winning (Downs, 1957; Hotelling,

Figure 2: Differences Between Allocation Preferences, Expectations, and Reality



Notes: This figure plots the CDFs of the difference ("Gap") between an individual's preferred allocation and their expected allocation, as well as the difference between an individual's preferred allocation and the real allocation. This is displayed for both groups who are either treated to a better or worse perception towards the government.

should develop a better (worse) perception about the government, as described in Figure 1. Estimating these gaps, 55 percent of the sample should develop a better perception, indicating that a higher fraction of the population believes that government spending is further away from their preferences than it really is. The two groups do not differ on gender, age, income, education, and race, but individuals who should develop a worse perception are more likely to be Republican, express conservative views on social and economic issues, and spend more time on social media. This is summarized in Table 1. Our sample is qualitatively similar to the U.S. population in terms of characteristics like income, gender, race, and age, but varies slightly on metrics like education and percent democrat.

Figure 2 presents the distribution of $|E_i - P_i|$ and of $|R - P_i|$ for both types of individuals.

1929). This result is robust under a few conditions, namely, that voter preferences are single-peaked and that the number of candidates does not exceed two (J. Osborne, 1995). Furthermore, theory also predicts that candidates take on the positions of the median voter of the entire population even if the median voter of their respective party changes. For example, in U.S. elections, a change in preferences of the party's median voter but not in the general median voter results in candidates first taking more extreme positions in the party vote, but then adopting the positions of the general median population in the general election.

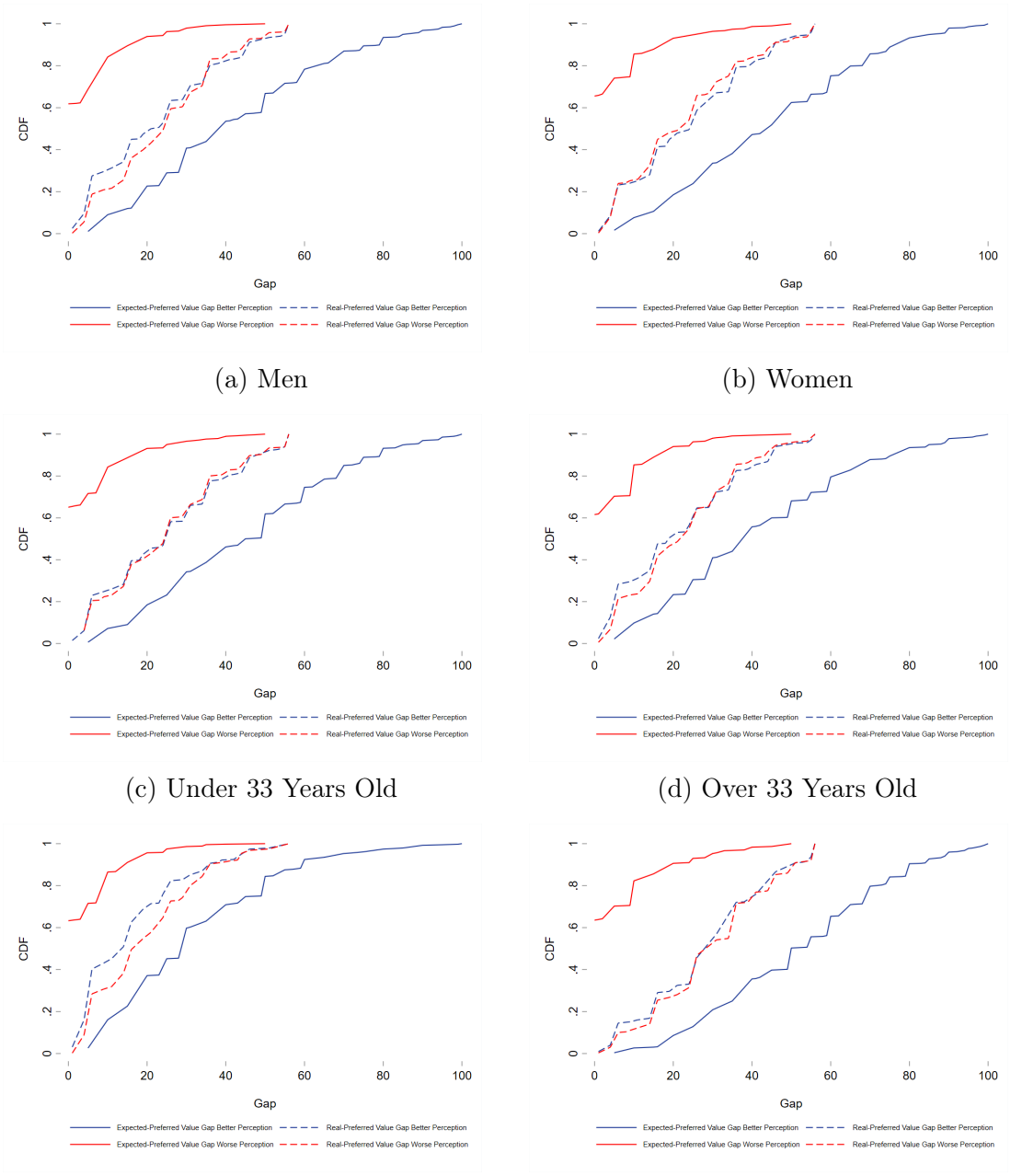
Individuals who should develop better perceptions have large gaps between their expectations and preferences on government spending. Individuals who should develop worse perceptions have substantially smaller gaps. These first two features of the distribution, but not necessarily their magnitudes, are by definition of how the groups are constructed. However, the distributions of $|R - P_i|$ are identical for both groups (Kolmogorov-Smirnov $p = 0.259$, Wilcoxon $p = 0.551$). This second result is not by construction but rather captures the observation that both groups have identical spending preferences.[23] Similarly, according to Table 1, individuals in the better perception group have a spending preference of \$62.61 for welfare but an expectation of only \$29.69. On the other hand, individual's in the worse perception group have a spending preference of \$57.19 for welfare but an expectation of \$54.75.

We find the same results across different subgroups defined by demographics and political orientation. Heterogeneity of the distribution of perception gaps for various subgroups is reported in Figure 3. We also look at how these gaps differ along partisan lines. While conservatives have smaller gaps than liberals, within both political groups, some individuals could develop better or worse perceptions depending on their individual preferences and beliefs. However, across all subgroups, the distributions of preferences are identical.[24] These results suggest that the divergence between people in a broader sense is being driven by changes in beliefs rather than preferences. Given this, it is an important policy question to identify whether and by how much information can increase or decrease the gap between preferences and beliefs by allowing individuals to update their beliefs according to a real benchmark. We address this question in the next section.

[23]One concern would be if expectations are independently distributed from preferences. This not the case in this setting. Overall, the distribution of preferences and expectation has a correlation coefficient of 0.083, significant at the one percent level ($p = 0.0007$). For those who should develop better perceptions the correlation between preferences and beliefs is -0.6015 ($p < 0.0001$), and for those who develop worse perceptions the correlation between preferences and beliefs is 0.9123 ($p < 0.0001$).

[24]See Appendix Table A.2.

Figure 3: Heterogeneity in the Distribution of Perceptions



(a) Men

(b) Women

(c) Under 33 Years Old

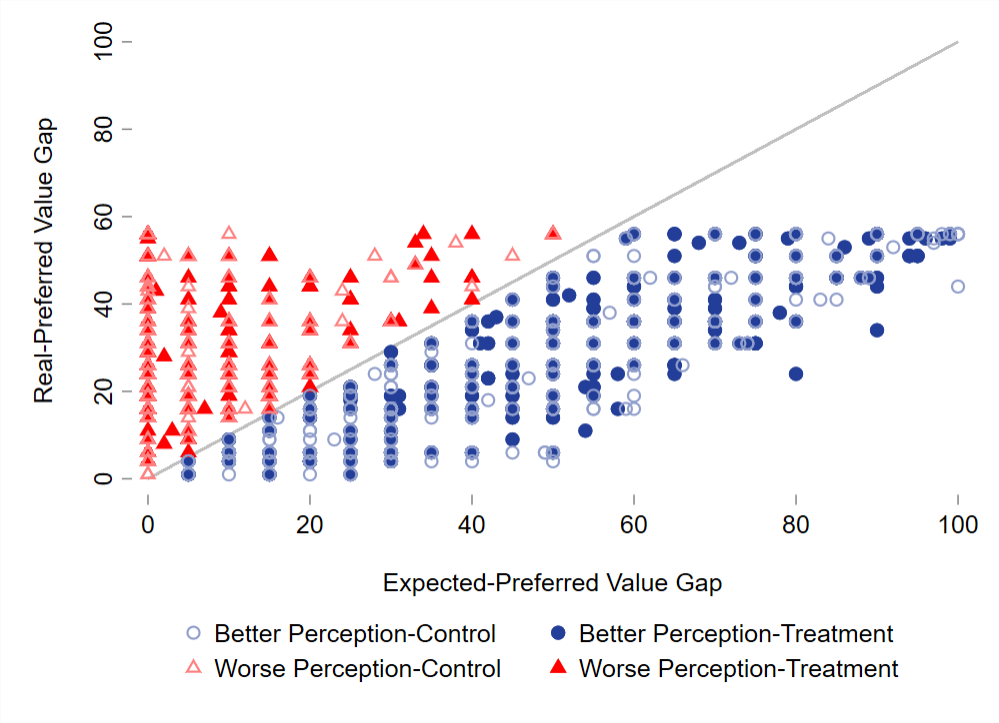
(d) Over 33 Years Old

(e) Conservative

(f) Liberal

Notes: This figure plots the CDFs of the difference ("Gap") between an individual's preferred allocation and their expected allocation, as well as the difference between an individual's preferred allocation and the real allocation. This is displayed for both groups who are either treated to a better or worse perception towards the government. Thirty three years is the median age in the sample (panels c and d).

Figure 4: Random Assignment to Information about the Real Expenditure Allocation



Notes: This figure compares $|R - P_i|$ and $|E_i - P_i|$ between individuals who either received or did not receive information. The group who should develop an improved perception has $n = 908$ (450 treated, 458 not treated), and the group who should develop a worsened perception has $n = 735$ (371 treated, 364 not treated).

5.2 Information Provision and Perceptions about the Government Spending Allocation

We estimate the effect of information on the gap between preferences and beliefs by identifying whether providing the actual spending allocation, R, leads individuals to reassess their prior beliefs and then adjust their perceptions of the government. We randomly revealed R to a subset of participants. As discussed above, the effect of treatment depends on the size of $|R - P_i|$ relative to $|E_i - P_i|$. After learning R, some individuals will develop better perceptions and other will develop worse perceptions. By randomly revealing R, we can compare outcomes between individuals who have similar initial beliefs about P_i and E_i but vary on treatment status.

Figure 4 summarizes our identification strategy. Individuals falling below the line cor-

respond to the "better perception" group (people who develop an improved perception if treated relative to the control, n=908), whereas individuals above the line correspond to the "worse perception" group (people who develop a worsened perception if treated relative to the control, n=735). We compare treated individuals (dense figures) to control individuals (hollow figures) within each group to estimate the effects of information on these perception gaps. Covariates across treatment status are balanced for the entire sample as well as within each group. This is reported in Appendix Table A.3.

We estimate the effect of information on how individuals perceive the government represents their preferences. We asked participants, "how well do the current president, congressmen, and senators represent your spending preferences" for both spending categories, as well as in totality, both before and after treatment to estimate the effect of information on the change of this measure.[25] We estimate the treatment-on-the-treated effect and test for effects on the distribution of preference representation as described in Section 4.

Figure 5 presents these results. For an individual who should develop an improved perception, learning the actual spending allocation, R, increases their belief that the government represents their spending preferences by 13 points on a scale of 0 to 100. Conversely, for an individual who should develop a worsened perception, learning the actual spending allocation, R, decreases their belief that the government represents their spending preferences by 12 points. We cannot reject that the magnitudes of these effects are the same. These results are robust to various specifications, including individual fixed effects and checks for inattention and lack of effort.[26] We find that treatment does not have heterogeneous effects across different population subgroups defined by demographics and political orientation.[27]

Learning the actual spending allocation, R, not only affects the mean but shifts the

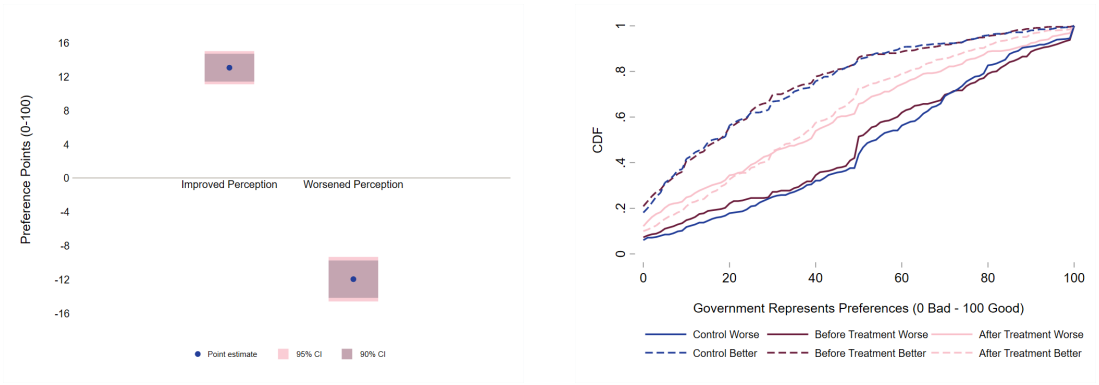
[25]This question is constructed to immediately and directly asses whether participants incorporate new information into their beliefs. Rational agents who were misinformed about the real allocation before treatment have little to no room to skew answers to questions of this granular nature.

[25]These estimates do not change with political affiliation. Interaction terms of treatment effect with political affiliation are one order of magnitude smaller and insignificant.

[26]See Appendix Figure A.3, and Appendix Table A.4 for main results displayed in a table across various specifications

[27]See Appendix Figure A.4, and Appendix Table A.5 for tabular heterogeneous results.

Figure 5: The Impact of Information on Government Representation



(a) Mean Effects

(b) Distributional Effects

Notes: Panel (a) of this figure presents the treatment-on-the-treated effects on information and whether an individual thinks the government represents their spending preferences. Both 95 percent and 90 percent confidence intervals are displayed. Panel (b) shows effects at the distribution level.

entire distribution of belief that the government represents their spending preferences (panel (b) of Figure 5). Treated individuals develop improved perceptions now state that they believe the government represents their preferences better, while treated individuals who develop worsened perceptions now state that they believe the government represents their preferences worse. After treatment, both groups have the same distribution of beliefs. Using Kolmogorov-Smirnov tests, we cannot reject that the post-treatment distributions are the same ($p = 0.152$), that there is no first-order stochastic dominance ($p = 0.229$), and that there is no second-order stochastic dominance ($p = 0.325$).

These results provide further evidence that differences in beliefs are at least part of the driving force behind misaligned perceptions. Moreover, they show that reporting accurate information causes both groups to converge to comparable levels of beliefs, closing the perception gap. This alignment can help facilitate the political process by making it easier to pass socially beneficial policy measures. In the next section, we further use the experimental change in beliefs to document its consequences on policy views that affect the political process by estimating its effects on government support, perceptions about government efficiency, and the willingness to trust and compromise.

5.3 The Impact of Perceptions on Policy Views and Civic Behavior

When an individual forms more extreme positions either in favor of or against a government, it is important to consider how this divergence manifests in policy views that affect the political process. We exploit our exogenous information intervention to document the impact of changes in perceptions across three outcomes: government support, views about government efficiency, and the willingness to trust and compromise. We asked participants several questions related to each outcome and combined them into three indices.[28] We estimate the effect of information on each index and test for effects on their respective distributions as described in Section 4.

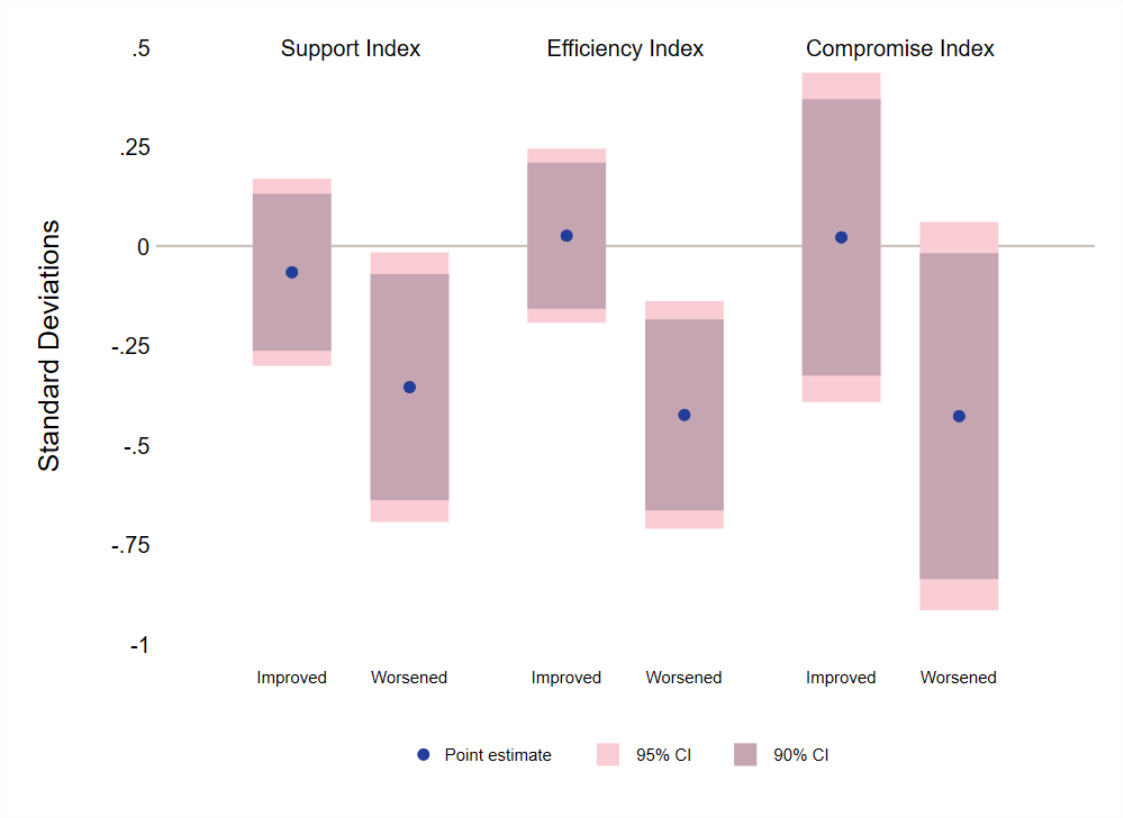
As presented in Figure 6, revealing the allocation spending allocation R to individuals who should develop better perceptions does not result in any change across any of the primary indices. The point estimates are small and close to zero. However, individuals treated with a worsened perception are 0.35 standard deviations ($p = 0.040$) less supportive towards the government, feel as though the government is less efficient by 0.42 standard deviations ($p = 0.003$), and experience a 0.43 standard deviation decrease in the willingness to compromise and trust ($p = 0.086$). These results indicate that individuals who initially believe the government represents their preferences well, upon learning that the government is behaving worse than they expected, state to be less supportive and believe that the government is less efficient. Similar results emerge for various heterogeneous groups, including conservatives and liberals.[29]

We find similar results in terms of the distributions of the three indices. Figure 7 reports treatment's effects at the distribution level for each index for both the improved and worsened perception groups. For those in the improved perception group, we find identical distributions for treated and control individuals across the three indices. Using Kolmogorov-Smirnov tests, we cannot reject that the distributions are the same ($p = 0.269$, $p = 0.421$, $p = 0.284$),

[28] The variables within each category and the associated question text is presented in Appendix Section C.

[29] See Appendix Figure A.5, and Appendix Table A.7 for a tabular decomposition across various groups.

Figure 6: Perceptions and Behaviors

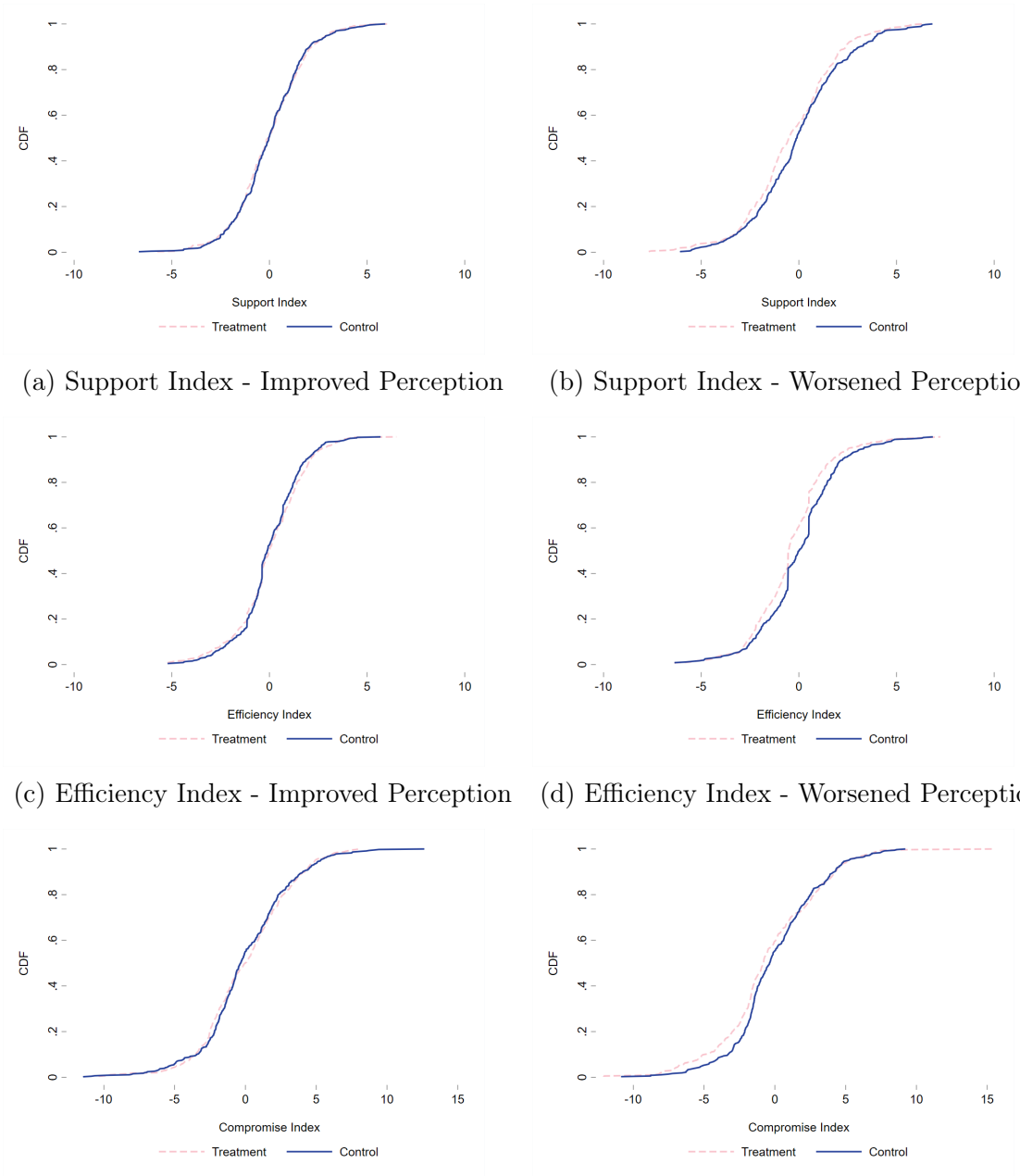


Notes: This figure presents the treatment-on-the-treated effects of perception changes on various indices on beliefs that affect the political process, including government support, views about government efficiency, and the willingness to trust and compromise. Both 95 percent and 90 percent confidence intervals are displayed.

that there is no first-order stochastic dominance ($p = 0.601$, $p = 0.226$, $p = 0.141$), and that there is no second-order stochastic dominance ($p = 0.802$, $p = 152$, $p = 0.536$). Conversely, for those in the worsened perception group, across the three indices, the distribution for treated individuals shifts to the left relative to the distribution of the control group. There is evidence that for each index, the distribution of the control group first-order stochastic dominates the distribution of the treatment group ($p = 0.024$, $p = 0.000$, $p = 0.012$). Again, these results suggest that when individuals are treated with information that make them more aware that the government is behaving further away from their prior beliefs, they state to become less supportive, believe that it is less efficient, and experience a reduction in their willingness to trust and compromise.

The information treatment provides a new lens for participants to view the government

Figure 7: Distributional Effects of Perceptions and Behaviors



(a) Support Index - Improved Perception (b) Support Index - Worsened Perception

(c) Efficiency Index - Improved Perception (d) Efficiency Index - Worsened Perception

(e) Compromise Index - Improved Perception (f) Compromise Index - Worsened Perception

Notes: This figure presents the treatment-on-the-treated effects of perception changes on indices pertaining to individual beliefs, including government support, views about government efficiency, and the willingness to trust and compromise. The effects are displayed at the distribution level for each index.

and update their priors as well as any other associated belief towards the government. Figure 5 shows that both groups update prior beliefs about the government representing their

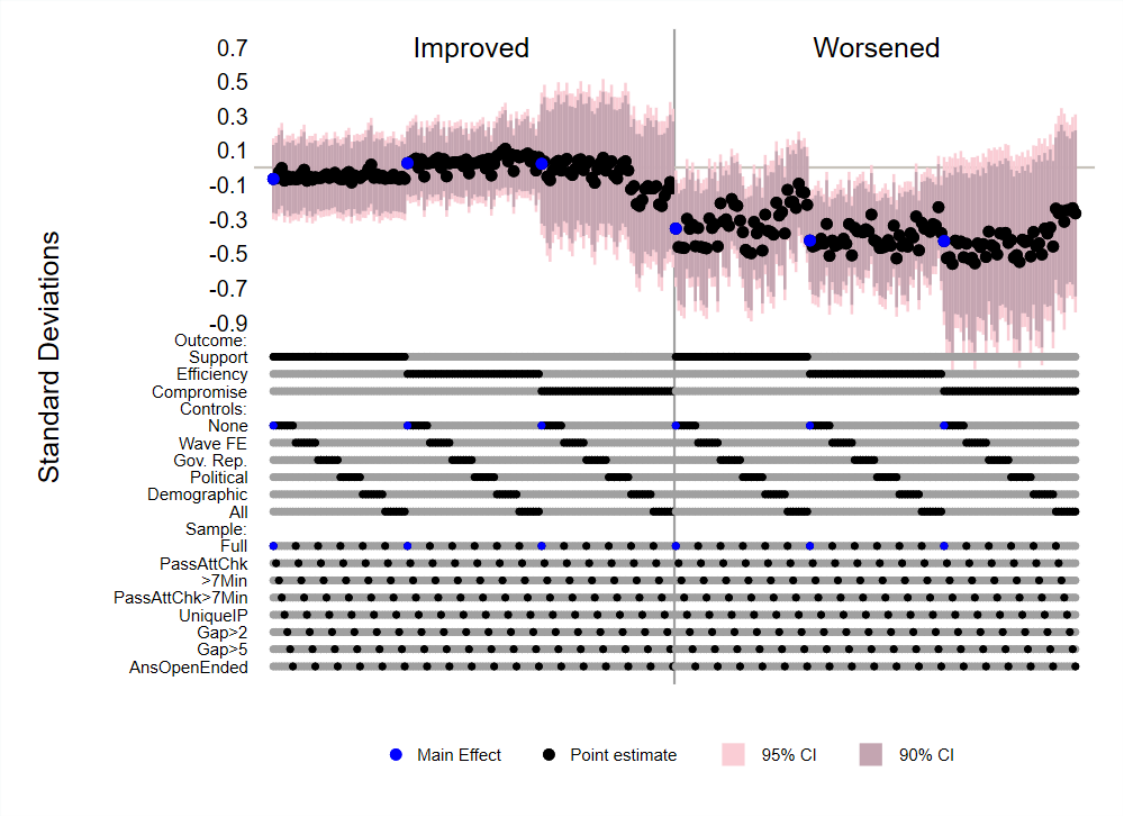
preferences in a Bayesian manner. However, Figure 6 indicates that only those who have a worsened perception further update any associated policy views. This asymmetry between groups' responses is consistent with motivated reasoning (Thaler, 2019; Flynn et al., 2017). In the first part, we tested the effect of factual information on beliefs about the government, information salience gave participants little to no room to misinterpret or skew it and form perceptions in any other direction than that of the signal. However, this does not necessarily translate in the second step since participants have more degrees of freedom in deciding the weights of each perception. In this context, in updating a policy view, agents possibly skew in the direction of the view that they are motivated to hold. The asymmetric response is also consistent with a growing literature showing asymmetric responses between positive and negative information, where negative information has a greater impact on attitudes and beliefs than positive information (Soroka, 2006; Sunstein et al., 2017). In our case, treatment tells the worsened perception group that the government is performing worse than they thought and tells the improved perception group that the government is performing better than they thought. Furthermore, this asymmetric response is also evidence against the notion that experimenter demand effects drive results. If participants simply change their answers towards the direction of their intervention, then this behavior would not lead to the asymmetric pattern documented by our data.

6 Robustness Checks

The previous results are robust to a variety of checks. Various robustness checks are presented in Figure 8.[30] We address any minor imbalances in sample composition by controlling for representation before treatment, political identity, social media usage, and basic demographics. There may also be some concerns about lack of effort, inattention, and deception in MTurk that affect the quality of the data that can be collected (Hauser et al., 2018).

[30]Figure 8 provides robustness checks for results in Section 4.3. See Appendix Figure A.3 for a similar exercise for Section 4.2. Appendix Table A.6 presents robustness checks in a tabular manner.

Figure 8: Robustness Tests for Perceptions and Behaviors



Notes: This figure presents the treatment-on-the-treated effects of perception changes on various indices pertaining to individual beliefs, including government support, views about government efficiency, and the willingness to trust and compromise. Both 95 percent and 90 percent confidence intervals are displayed. Results are displayed for various robustness checks across the main index variables.

To address this concern, we restrict the sample to participants who passed attention checks, who took more than 7 minutes to complete the survey, deleted repeated IP addresses (GPS coordinates), and exclude participants who did not answer either of the open-ended questions and find almost identical results. We also drop individuals who experienced changes smaller than 5 points in their belief that the government represents their spending preferences and find no differences in the results.[31]

As a final consistency check, we estimate the effects of the information treatment on the

[31] We also estimate the effect using a least absolute deviations estimator to check if the results are robust to outliers. While the magnitudes are not comparable, the estimates' patterns match those from OLS presented in Figure 8. For individuals who should develop better perceptions, treatment does not result in significant change across any primary indices. For individuals treated with a worsened perception, the estimates are negative, larger in magnitude, and significant at conventional levels (except for the compromise index where the estimate is large but insignificant).

components of each index.[32] The estimates go in the same direction as in the general indices. For the "improved" group, the estimates are small, statistically insignificant, and tend to be positive. For the "worsened" group, the estimates are generally negative, larger, and have higher statistical significance.

In order to speak to how our results generalize from our sample to the general population, we use the 2018 population weights from the Census Bureau to construct weights of the frequencies between the interactions of Age, Gender, and Education. We use this to adjust our main results (Appendix Table A.8). The signs and magnitudes of the unweighted and weighted results are comparable.[33]

We can re-scale the treatment effects on beliefs that affect the political process by the effect of the treatment on how individuals perceive the government represents their preferences. This will estimate the effect of decreasing the gap between preferences and beliefs on policy views that affect the political process only if we assume that the treatment has no direct effect on these other views. Re-scaling the estimates, we find that if an individual increases their belief that the government represents their spending preferences by one point on a scale of 0 to 100 (decreases their gap), then support for the government increases by 0.03 standard deviation, perceptions of government efficiency increase by 0.035 standard deviations, and willingness to trust and compromise increases by 0.036 standard deviations. However, the plausibility of the assumption makes the re-scaled estimates only suggestive of a potential IV estimate.

7 Discussion and Conclusion

Our main results have several important policy implications. First, we document the distribution of the gap between preferences and beliefs using a novel measure between pref-

[32] See Appendix Figure A.6.

[33] There are some small changes in significance, which may be the result of using a smaller sample size for the weighted adjustments. This is largely a feature of our sample including 3 levels of gender (Male/Female/Other) whereas the Census only includes 2 (Male/Female). We drop observations that do not have a counterpart in the Census.

erences, expectations, and the actual spending allocation. In doing so, we document groups who share similar spending preferences, but have drastically different expectations about what they believe the government to be actually doing. This result is consistent with the theory that the misalignment of political views of the government is driven by people perceiving the same reality through a different lens (Alesina et al., 2020). Hence, part of the explanation for the rapid rise in polarization in the United States could be that people are forming more extreme perceptions of the current state of affairs, rather than preferences approaching polar extremes. In a world of instant (mis)information, sound bites, and headlines, it is easy to form biases and opinions through a lens that may not be factually accurate, pushing individuals towards these more extreme positions. Recent work shows that information content conveyed through the internet matters, turning the discussion towards skewed news, false information, and the role of biased coverage and social media (Gentzkow and Shapiro, 2010; Boxell et al., 2017; Allcott and Gentzkow, 2017). With the growth of social media and the associated concern about skewed and fake news, our results show significantly more profound consequences and suggest that it would be socially beneficial to limit exposure to news of this type (Mosquera et al., 2020; Allcott et al., 2020).

When it comes to interpreting results, it is worth pointing out that we asked participants how they would prefer to have $100 allocated. While participants could have interpreted this as preferences at the margin that depend on the current distribution of expenditures, we first note that all the estimated patterns are consistent with the unconditional counterpart. Second, the fact that we chose spending items that are similarly allocated attenuates this concern. Lastly, we administer an additional wave of surveys eliciting spending preferences and expectations under three different question wordings: 1) the question as worded in the experiment, 2) a modified version of the question to reflect average spending preferences and expectations, and 3) a modified version of the question to reflect marginal spending preferences and expectations.[34] We then compare if the different question wordings elicit different

[34]Specifically, to reflect averages, we ask "Suppose you are responsible for planning the federal budget. The government receives $100 and asks you to distribute it between two categories. On average, how would

responses. In comparison to our experimental wording, participants have a statistically significant different spending distribution when facing the marginal wording but, importantly, not when facing the average wording.[35] These results remain after adjusting for multiple comparisons as well as for outliers in the sample. Hence, this result helps demonstrate that our experimental wording does not elicit marginal preferences and expectations but rather those that are similar to their average counterparts.

Despite this concern, we show that providing a new lens in the form of accurate information can mend the divergence between misaligned individuals in terms of government spending representation. Providing factual information about actual government expenditures to individuals who have a less (more) favorable perception of the government than what they should positively (negatively) impacts this group's belief that the government represents their spending preferences by 13 points (12 points) on a scale of 0 to 100. This initial alignment can help facilitate the political process by making it easier to pass socially beneficial policy measures.

However, we also show that for associated policy views related to the political process, only those treated with a worsening perception adjust their behaviors according to the factual benchmark. For individuals who learn the government is behaving closer to their preferences than they initially thought, there are not any significant changes in behaviors. For individuals who learn the government is behaving worse, we find a significant reductions of 0.35 s.d. in support towards the government, 0.42 s.d. in beliefs about government efficiency, and 0.43 s.d. in the willingness to compromise or trust.

Returning to the theoretical model in Alesina et al. (2020) where individuals hold perceptions for a variety of topics and perceptions are a function of signals and information,

you like to distribute $100?" To reflect marginals, we ask "Suppose you are responsible for planning the federal budget. The government receives an additional $100 and asks you to distribute it between two categories. How would you like to distribute $100?"

[35] In a sample of 180 participants, relative to our experimental wording, the marginal wording elicited an education spending preference $9.56 higher (p-value = 0.03) and an education spending expectation $4.76 lower (p-value = 0.76). Relative to our experimental wording, the average wording elicited education spending preferences and expectations that were not statistically different from each other.

we show that providing accurate information affects perceptions, resulting in a complete translation in the function that relates perceptions to policy views. Reporting accurate information causes everyone to converge to comparable levels of beliefs, effectively closing the gap between them in this dimension. Importantly, we have the same response for both conservatives and liberals. However, the information intervention causes an asymmetric response in a secondary function that relates perceptions to policy views. Only the group treated with a worsening of perceptions responded. This is consistent with both motivated reasoning, where agents distort information content depending on the priors, and a behavioral response where negative information has a greater impact on attitudes and beliefs than positive information or where other perceptions about the government have higher weights than spending perceptions for the other group. Nevertheless, this result is Pareto efficient in of itself. Providing costless information about actual policy reduces the total divergence between individuals by moving 45% of the population closer to the middle.

Communication from a government to its people is a primary channel that fosters their relationship, as well as the relationship amongst individuals themselves. As an example, many countries provide itemized tax receipts to their constituents detailing how tax dollars are spent. While factual information can attenuate the divide amongst individuals and increase efficiency, this also suggests that biased rhetoric may increase the divide making it unnecessarily difficult to find common ground and pass socially beneficial policy measures that address fundamental economic and social issues.

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A Online Appendix Tables and Figures

Table A.1: Government Expenditures[36]

	1994	2004	2014	2018
Defense	14.3%	12.1%	13.9%	11.4%
Education	14.3%	18.2%	16.7%	14.3%
Health Care	14.3%	18.2%	19.4%	22.9%
Pensions	17.1%	15.2%	19.4%	20.0%
Welfare	8.6%	9.1%	8.3%	5.7%
Other	31.4%	27.2%	22.3%	25.7%

Notes: This table presents a breakdown of government expenditures across several major categories across time.

[36]Data from *https://www.usgovernmentspending.com/breakdown_2018USpt_19ps5n.*

Table A.2: Differences in the Distribution of Perception Gaps

	Kolmogorov-Smirnov	Wilcoxon
Full Sample	0.259	0.552
Women	0.193	0.203
Men	0.029	0.055
Less than 33 years	0.958	0.921
More than 33 years	0.235	0.266
Conservatives	0.001	0.000
Liberals	0.723	0.523
Low social media usage	0.237	0.399
High social media usage	0.583	0.546
Liberal news bias	0.515	0.243
Conservative news bias	0.012	0.025

Notes: This table presents results from various tests of differences in distributions for perception gaps for the full sample as well as for various heterogeneous subgroups.

Table A.3: Balance of Covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full Sample			***Improved Perceptions***			***Worsened Perceptions***		
	Treated	Not Treated	P-value	Treated	Not Treated	P-value	Treated	Not Treated	P-value
Income Below 50K (%)	0.44	0.45	0.78	0.44	0.46	0.67	0.44	0.44	0.95
	(0.5)	(0.5)		(0.5)	(0.5)		(0.5)	(0.5)	
4-Year College (%)	0.55	0.57	0.54	0.52	0.55	0.3	0.59	0.58	0.83
	(0.5)	(0.5)		(0.5)	(0.5)		(0.49)	(0.49)	
Male (%)	0.49	0.48	0.94	0.45	0.45	0.81	0.53	0.53	0.84
	(0.5)	(0.5)		(0.5)	(0.5)		(0.5)	(0.5)	
White (%)	0.8	0.84	0.09	0.82	0.85	0.2	0.79	0.82	0.28
	(0.4)	(0.37)		(0.39)	(0.36)		(0.41)	(0.38)	
Age (Years)	35.84	35.3	0.33	35.8	34.89	0.22	35.89	35.82	0.93
	(11.27)	(11.1)		(11.23)	(11.14)		(11.34)	(11.04)	
Married (%)	0.42	0.42	0.9	0.39	0.39	0.9	0.46	0.46	0.93
	(0.49)	(0.49)		(0.49)	(0.49)		(0.5)	(0.5)	
Republican (%)	0.26	0.24	0.35	0.21	0.18	0.26	0.32	0.31	0.89
	(0.44)	(0.43)		(0.41)	(0.38)		(0.47)	(0.46)	
Democrat (%)	0.47	0.48	0.6	0.5	0.52	0.56	0.42	0.42	0.94
	(0.5)	(0.5)		(0.5)	(0.5)		(0.49)	(0.49)	
Social Views (0 Lib. - 100 Cons.)	38.6	38	0.7	33.26	33.12	0.94	45.06	44.15	0.69
	(31.33)	(30.68)		(29.82)	(29.93)		(31.93)	(30.55)	
Econ. Views (0 Lib. - 100 Cons.)	45.75	45.05	0.65	40.87	40.9	0.99	51.67	50.29	0.55
	(31.75)	(31.21)		(31)	(30.8)		(31.67)	(30.98)	
Daily Facebook Minutes	55.63	55.89	0.93	50.51	49.58	0.81	61.83	63.59	0.71
	(59.41)	(60.03)		(55.98)	(57.79)		(62.84)	(61.86)	
Daily Online Minutes	144.34	140.29	0.18	149.12	143.04	0.13	138.57	136.94	0.72
	(58.11)	(59.83)		(56.15)	(59.3)		(59.96)	(60.4)	
Facebook News Freq. (0-100)	30.89	30.6	0.86	29.79	26.92	0.17	32.23	35.09	0.25
	(31.27)	(31.63)		(30.11)	(29.89)		(32.61)	(33.11)	
Cable News Freq. (0-100)	34.32	33.85	0.78	32.21	31.93	0.9	36.89	36.2	0.78
	(32.57)	(32.45)		(32.85)	(32.72)		(32.09)	(32.01)	
News Bias (0 Lib. - 100 Cons.)	45.44	43.77	0.2	42.62	41.19	0.39	48.85	46.91	0.34
	(25.7)	(25.09)		(24.18)	(23.75)		(27.07)	(26.33)	
Preference Welfare (0-100)	60.25	60.12	0.91	61.95	63.25	0.38	58.18	56.18	0.29
	(24.75)	(23.18)		(23.29)	(21.41)		(26.28)	(24.7)	
Expected Welfare (0-100)	41.66	40.14	0.21	30.26	29.14	0.41	55.49	53.99	0.36
	(25.15)	(24.18)		(20.88)	(19.76)		(22.87)	(22.04)	
Gov. Represent (0 Bad - 100 Good)	31.05	32.88	0.2	26.12	26.27	0.93	37.02	41.2	0.07
	(28.91)	(29.37)		(26.36)	(25.96)		(30.73)	(31.27)	
N	821	822		450	458		371	364	

Notes: This table presents covariate balance tests across treatment status. Columns (1)-(3) show balance across the full sample, (4)-(6) for those in the improved perception group, and (7)-(9) for those in the worsened perception group. P-value columns test differences in means between the two preceding columns. Standard deviations in parenthesis.

Table A.4: Robustness of Information and Representation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Improved Perception	13.05	13.05	13.40	13.26	13.81	14.04	13.54	12.99	14.11	13.31
	(1.00)	(1.00)	(1.58)	(1.03)	(1.04)	(1.04)	(1.02)	(1.00)	(1.08)	(1.06)
Worsened Perception	-11.98	-11.98	-12.57	-11.83	-11.42	-11.00	-11.45	-12.10	-13.04	-11.82
	(1.34)	(1.34)	(1.78)	(1.43)	(1.44)	(1.48)	(1.38)	(1.36)	(1.48)	(1.48)
Sample:										
Fixed Effects		X								
Military			X							
Pass Attention Check				X		X				
>7 Minutes					X	X				
Unique IP							X			
Gap>2								X		
Gap>5									X	
Open Ended										X
N	1642	1642	1642	1454	1293	1229	1556	1617	1415	1387

Notes: This table presents robustness tests of the treatment-on-the-treated effects on information and whether an individual thinks the government represents their spending preferences. Standard errors are presented in parentheses.

Table A.5: Heterogeneity of Information and Representation

	(1)	(2)
	Improved Perception	***Worsened Perception***
Main Estimate	13.05	-11.98
	(1.00)	(1.34)
Male	11.88	-13.03
	(1.31)	(1.75)
Female	14.33	-10.46
	(1.52)	(2.09)
Young	15.01	-10.93
	(1.44)	(1.86)
Old	10.90	-13.13
	(1.37)	(1.94)
White	13.51	-12.66
	(1.08)	(1.43)
NonWhite	10.98	-9.44
	(2.53)	(3.47)
No College	11.90	-13.47
	(1.54)	(2.09)
College	14.03	-11.00
	(1.30)	(1.75)
Low Income	12.82	-10.64
	(1.27)	(1.58)
High Income	14.01	-14.76
	(1.87)	(2.94)
Liberal	12.62	-12.87
	(1.34)	(2.34)
Conservative	13.62	-11.38
	(1.50)	(1.60)
Low SM Use	15.19	-12.45
	(1.33)	(1.99)
High SM Use	10.43	-11.56
	(1.49)	(1.82)
News Bias Lib.	13.46	-11.27
	(1.31)	(2.39)
News Bias Cons.	12.81	-12.14
	(1.69)	(1.67)

Notes: This table presents heterogeneity of the treatment-on-the-treated effects on information and whether an individual thinks the government represents their spending preferences across various subgroups of the sample. Standard errors are presented in parentheses.

Table A.6: Robustness of Index Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Improved Perception Group								
Support Index	-0.07	-0.06	-0.03	0.00	-0.08	-0.05	-0.07	-0.06
	(0.12)	(0.13)	(0.13)	(0.13)	(0.12)	(0.12)	(0.13)	(0.13)
Efficiency Index	0.03	0.03	0.04	0.05	0.00	0.05	-0.05	0.02
	(0.11)	(0.12)	(0.12)	(0.13)	(0.11)	(0.11)	(0.12)	(0.13)
Compromise Index	0.02	0.03	-0.05	-0.07	-0.02	0.03	0.04	-0.02
	(0.21)	(0.23)	(0.23)	(0.24)	(0.22)	(0.21)	(0.23)	(0.23)
Worsened Perception Group								
Support Index	-0.35	-0.46	-0.47	-0.47	-0.30	-0.36	-0.33	-0.46
	(0.17)	(0.19)	(0.20)	(0.21)	(0.18)	(0.17)	(0.18)	(0.19)
Efficiency Index	-0.42	-0.46	-0.45	-0.44	-0.41	-0.44	-0.33	-0.51
	(0.15)	(0.17)	(0.18)	(0.19)	(0.15)	(0.15)	(0.15)	(0.17)
Compromise Index	-0.43	-0.53	-0.52	-0.56	-0.43	-0.44	-0.43	-0.52
	(0.25)	(0.29)	(0.30)	(0.31)	(0.26)	(0.25)	(0.27)	(0.30)
Sample:								
Pass Attention Check		X		X				
>7 Minutes			X	X				
Unique IP					X			
Gap>2						X		
Gap>5							X	
Open Ended								X
N	1642	1451	1290	1226	1553	1614	1412	1384

Notes: This table presents robustness tests of the treatment-on-the-treated effects of perception changes on various indices on beliefs that affect the political process, including government support, views about government efficiency, and the willingness to trust and compromise. Standard errors are presented in parentheses.

Table A.7: Heterogeneity of Index Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Improved Perception			***Worsened Perception***		
	Support	Efficiency	Compromise	Support	Efficiency	Compromise
Male	-0.18	0.01	0.11	-0.55**	-0.66***	-0.65*
	(0.16)	(0.16)	(0.30)	(0.23)	(0.19)	(0.33)
Female	0.05	0.04	-0.08	-0.07	-0.09	-0.13
	(0.18)	(0.16)	(0.30)	(0.27)	(0.23)	(0.37)
Young	0.01	0.14	0.21	-0.29	-0.41*	0.00
	(0.16)	(0.16)	(0.28)	(0.24)	(0.21)	(0.32)
Old	-0.19	-0.11	-0.16	-0.42*	-0.45**	-0.89**
	(0.18)	(0.16)	(0.31)	(0.25)	(0.20)	(0.38)
White	-0.08	-0.05	0.08	-0.45**	-0.40**	-0.54*
	(0.13)	(0.12)	(0.23)	(0.20)	(0.16)	(0.28)
NonWhite	0.03	0.39	-0.37	0.10	-0.50	-0.08
	(0.28)	(0.28)	(0.49)	(0.34)	(0.35)	(0.56)
NoCollege	-0.12	0.04	0.00	-0.41	-0.52**	-0.81**
	(0.19)	(0.18)	(0.31)	(0.29)	(0.22)	(0.34)
College	-0.03	0.03	0.04	-0.33	-0.37*	-0.19
	(0.15)	(0.14)	(0.29)	(0.21)	(0.19)	(0.34)
Low Income	-0.26*	0.03	-0.17	-0.13	-0.27	-0.27
	(0.15)	(0.14)	(0.26)	(0.22)	(0.18)	(0.30)
High Income	0.51**	0.04	-0.03	-0.73**	-0.79***	-0.69
	(0.24)	(0.22)	(0.40)	(0.30)	(0.28)	(0.49)
Liberal	-0.22*	0.04	-0.24	-0.30	-0.11	-0.45
	(0.13)	(0.14)	(0.26)	(0.23)	(0.22)	(0.38)
Conservative	0.13	0.01	0.39	-0.40*	-0.64***	-0.41
	(0.22)	(0.18)	(0.34)	(0.24)	(0.19)	(0.33)
Low Social Media Use	-0.03	0.15	0.07	-0.36	-0.29	-0.45
	(0.16)	(0.17)	(0.28)	(0.25)	(0.21)	(0.33)
High Social Media Use	-0.06	-0.08	0.02	-0.32	-0.54***	-0.37
	(0.18)	(0.14)	(0.31)	(0.24)	(0.20)	(0.36)
News Bias Lib.	0.05	0.23	-0.24	-0.21	-0.55**	-0.67*
	(0.14)	(0.15)	(0.28)	(0.23)	(0.22)	(0.37)
News Bias Cons.	-0.21	-0.18	0.07	-0.40	-0.33	-0.17
	(0.22)	(0.18)	(0.34)	(0.25)	(0.20)	(0.36)

*Notes: This table presents heterogeneity of the treatment-on-the-treated effects of perception changes on various indices on beliefs that affect the political process, including government support, views about government efficiency, and the willingness to trust and compromise across various subgroups of the sample. Columns (1)-(3) present these for the Improved Perception Group, (4)-(6) for the Worsened Perception Group. Standard errors are presented in parentheses. *** depicts significance at 1%, ** at 5%, * at 10%.*

Table A.8: Weighting Adjustments

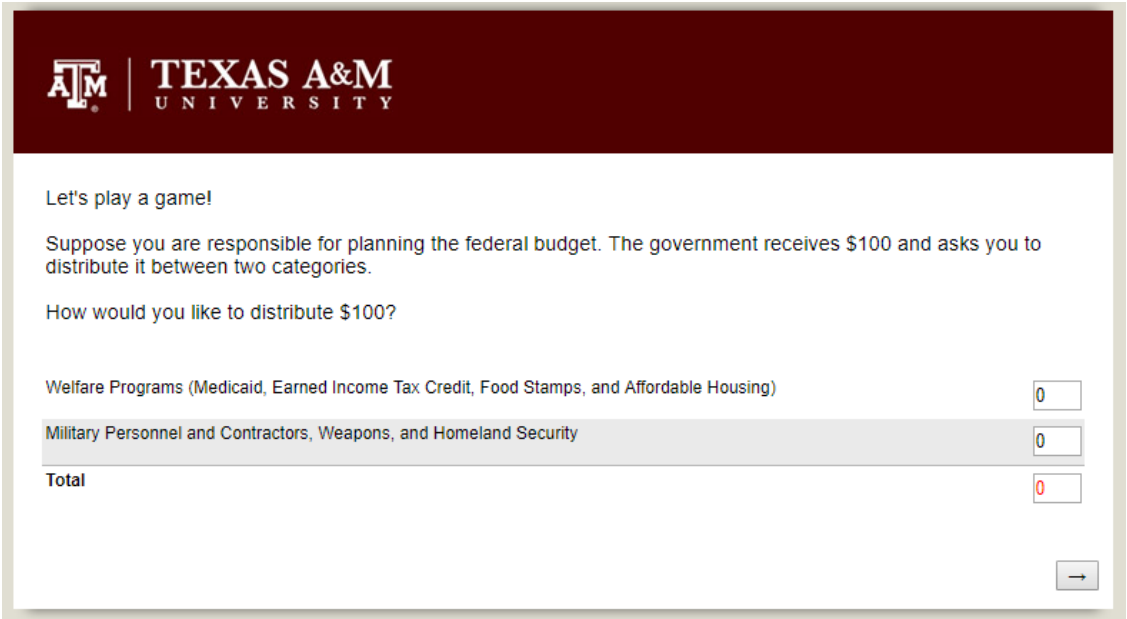
	(1)	(2)	(3)	(4)
	Worsened Perception		***Improved Perception***	
	Unweighted	Weighted	Unweighted	Weighted
Panel A: Information and Government Representation				
Government Representation	-11.98***	-13.03***	13.05***	11.41***
Panel B: Political Perceptions				
Support Index	-0.39**	-0.41	-0.02	-0.08
Efficiency Index	-0.43***	-0.50***	-0.03	-0.08
Compromise Index	-0.43*	-0.75**	-0.02	-0.18

*Notes: This table compares the main results with the weight-adjusted estimates. We use the 2018 Census to obtain population frequencies for the interaction of Age by Gender by Education crosstabs in order to construct our weights. Panel A presents results for the treatment-on-the-treated effects of information on whether an individual feels like the government represents their spending preferences. Panel B for the treatment-on-the-treated effects of perception changes on the three primary outcome indices. *** depicts significance at 1%, ** at 5%, * at 10%..*

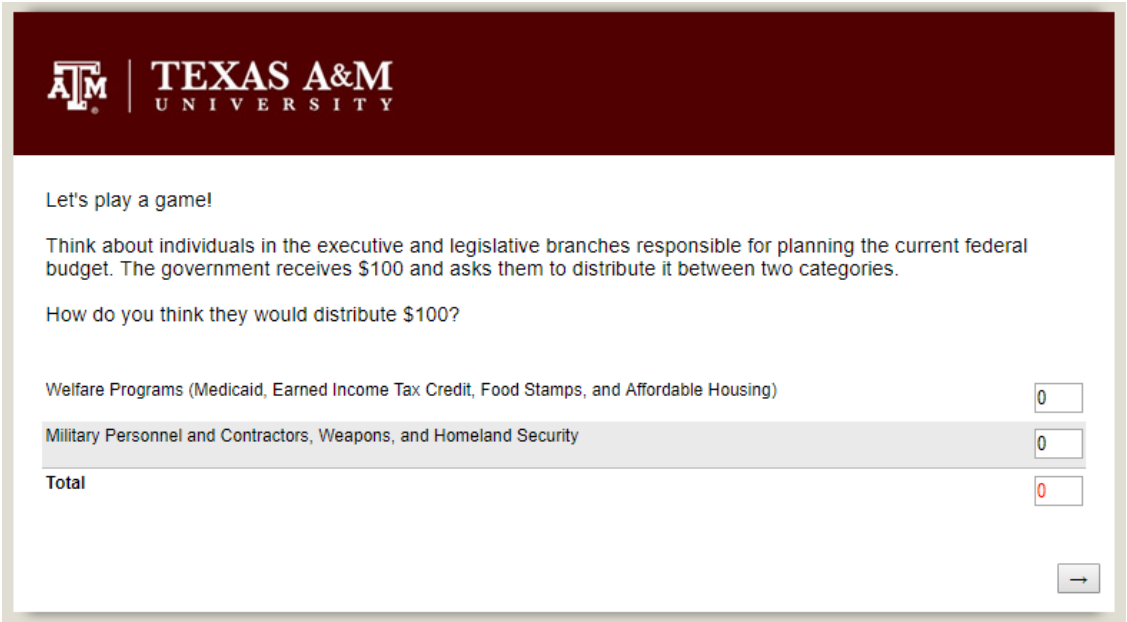
Figure A.1: Location of Survey Respondents

Notes: This figure presents the geo-located latitude/longitude pairs of all survey respondents based on a participant's IP address. This information is automatically collected by Qualtrics.

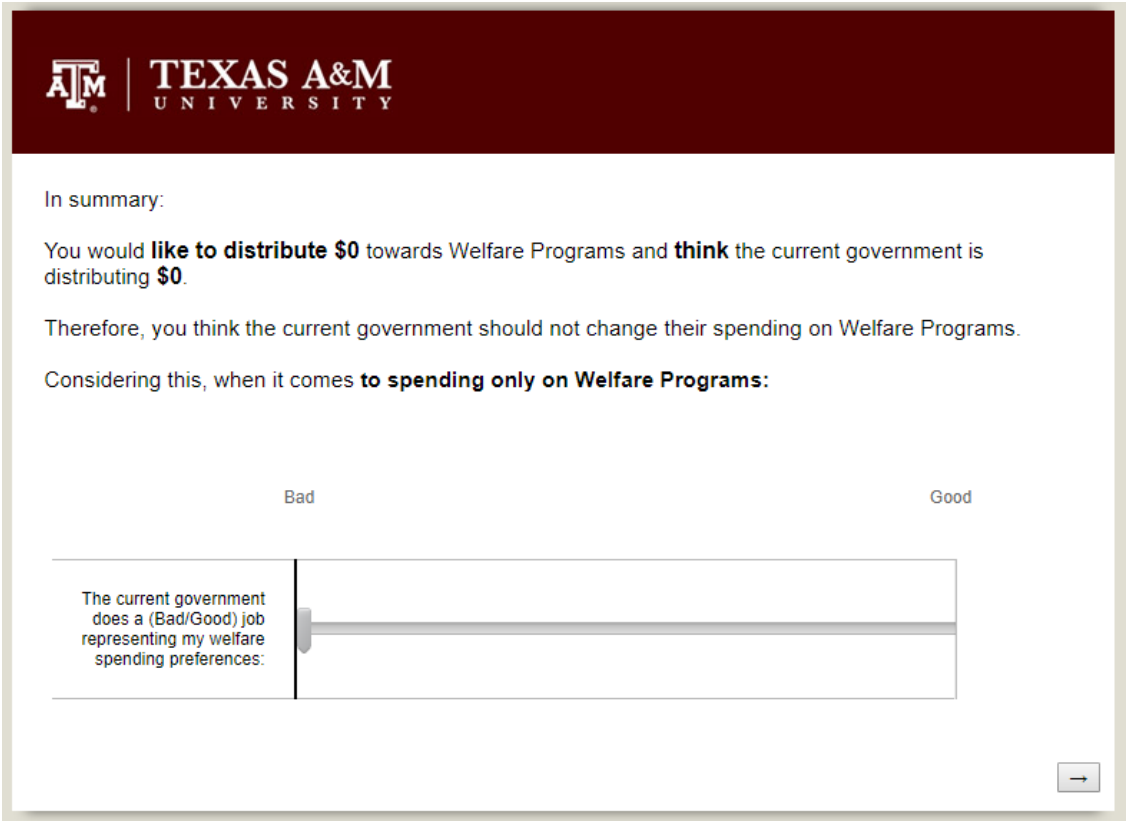
Figure A.2: Elicitation Questions and Treatment/Control Text



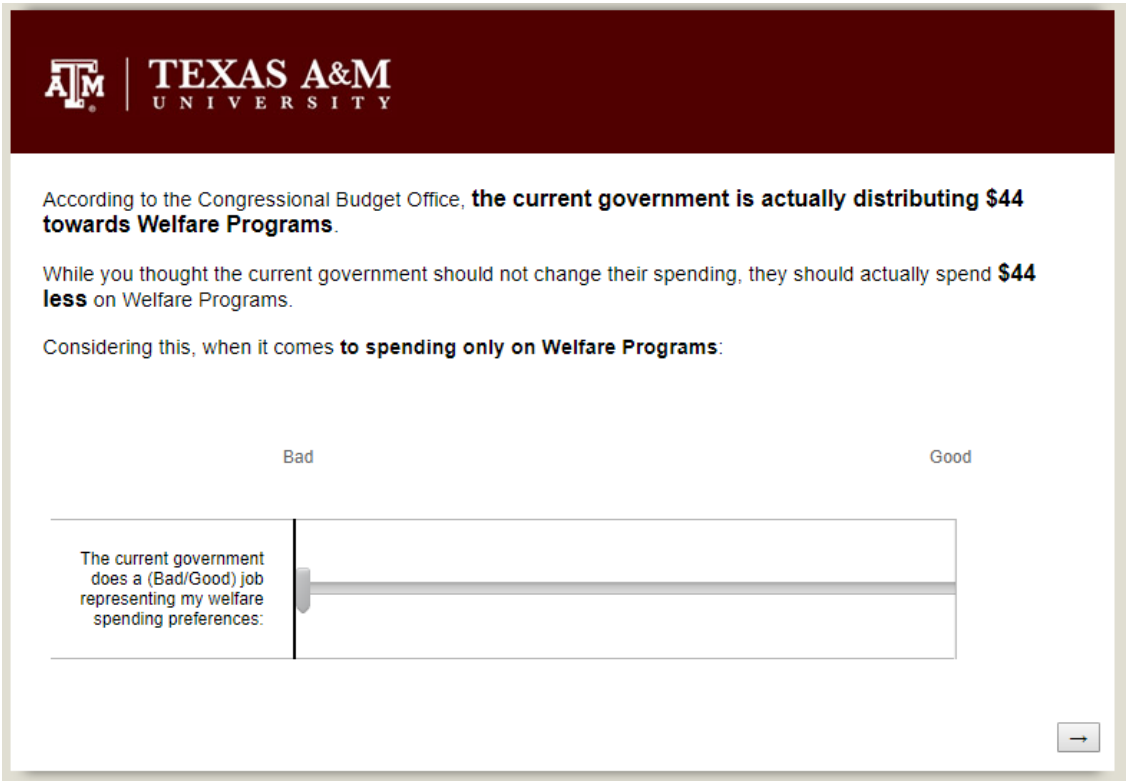
(a) Preference Elicitation



(b) Expectation Elicitation

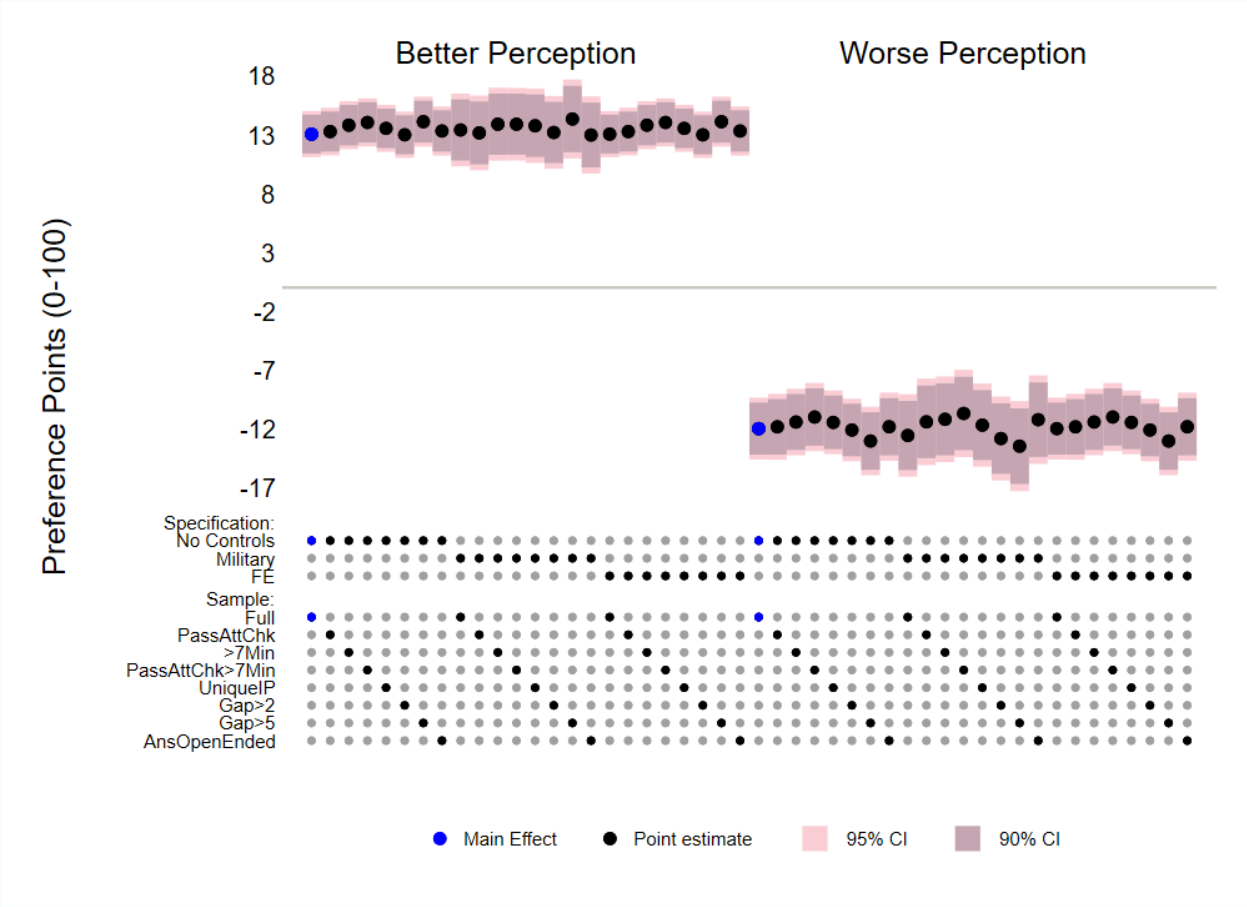


(c) Summary of Preferences and Expectations



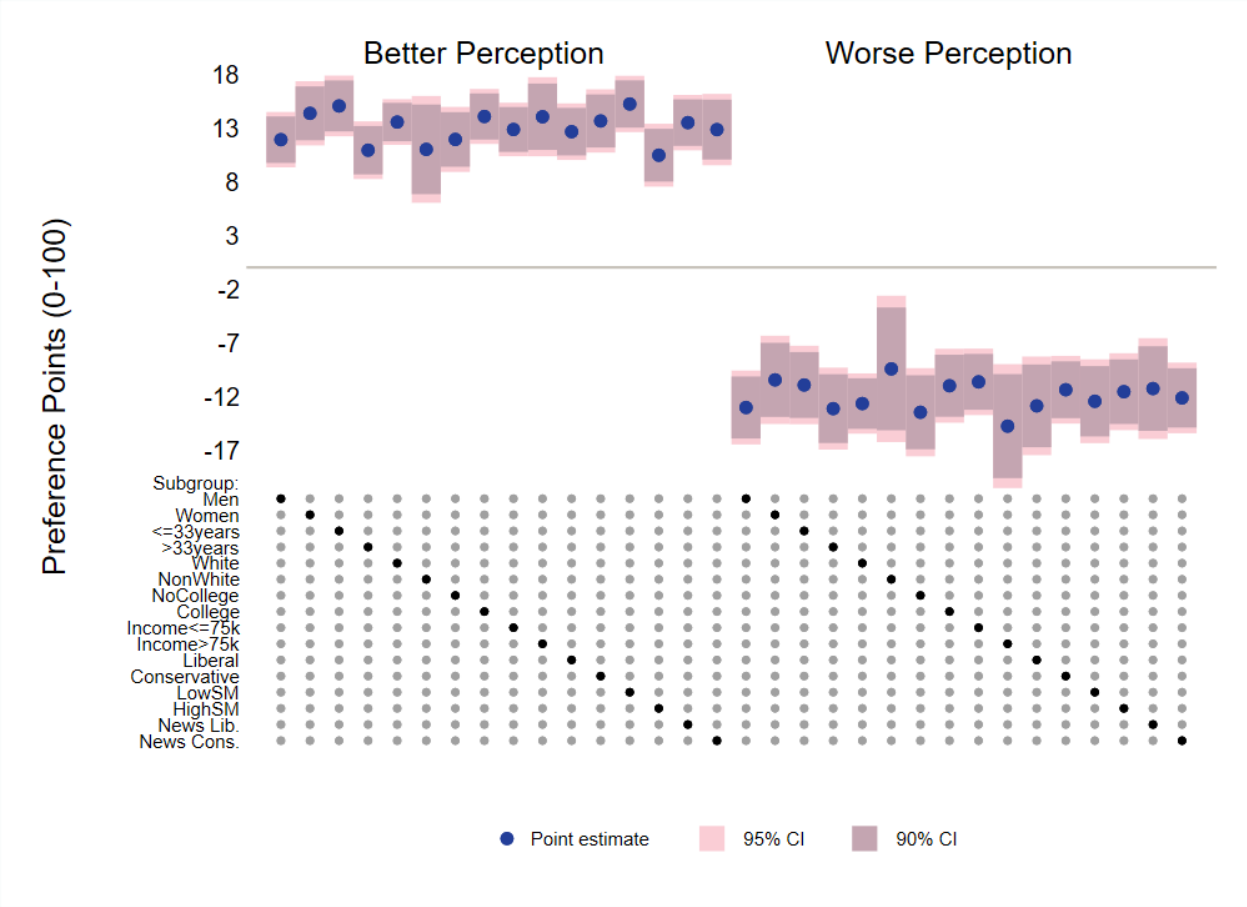
(d) Treatment Information

Figure A.3: Robustness of Information and Representation



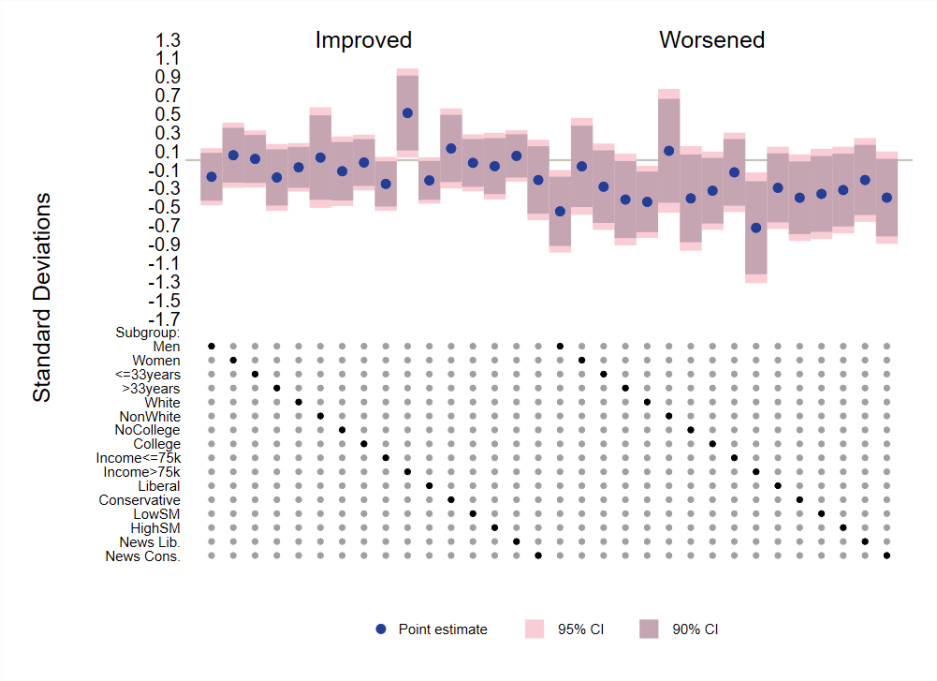
Notes: This figure presents the treatment-on-the-treated effects on information and whether an individual thinks the government represents their spending preferences. Both 95 percent and 90 percent confidence intervals are displayed. Results are displayed under various robustness checks.

Figure A.4: Heterogeneity of Information and Representation

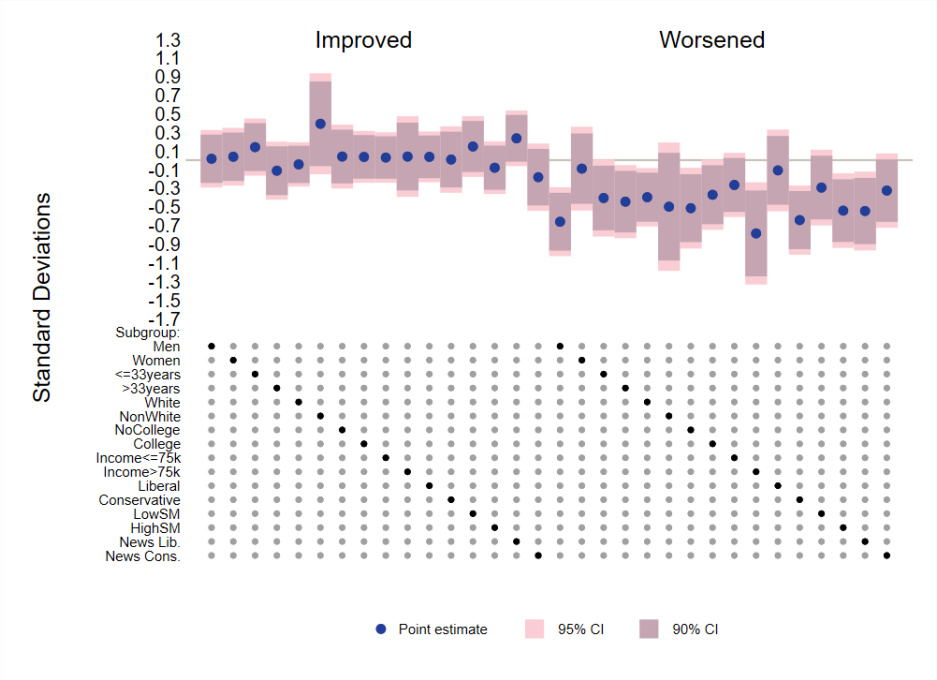


Notes: This figure presents the treatment-on-the-treated effects on information and whether an individual thinks the government represents their spending preferences. Both 95 percent and 90 percent confidence intervals are displayed. Results are displayed for various heterogeneous samples.

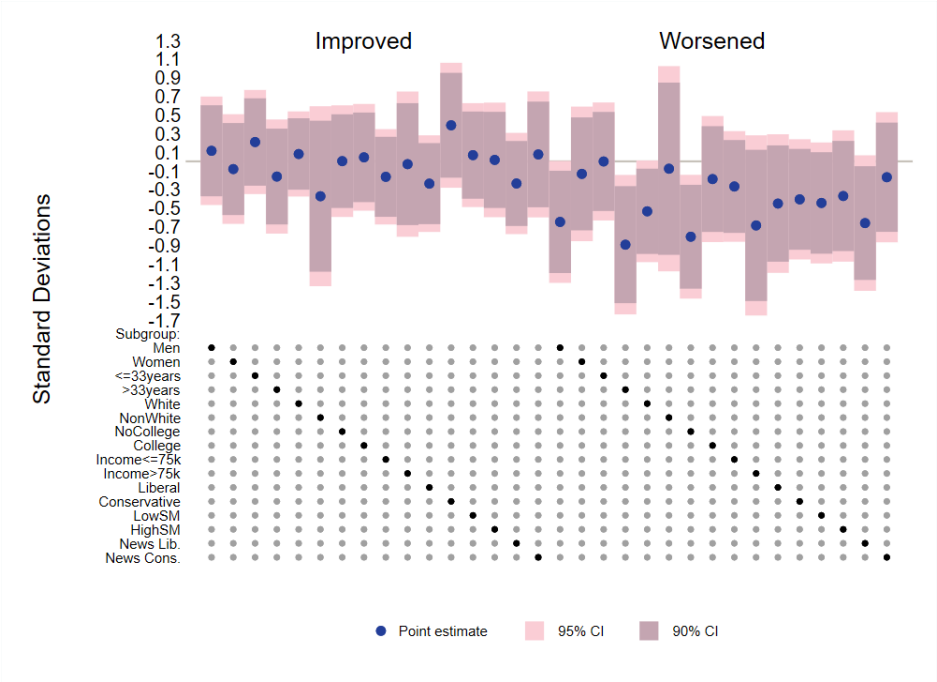
Figure A.5: Heterogeneity of Perceptions and Beliefs



(a) Support Index



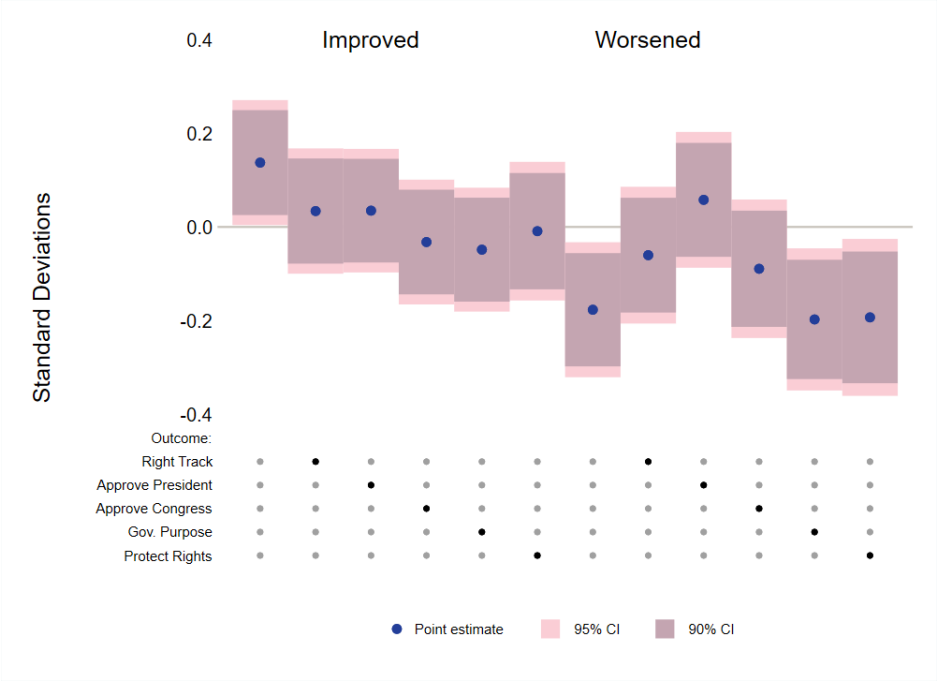
(b) Efficiency Index



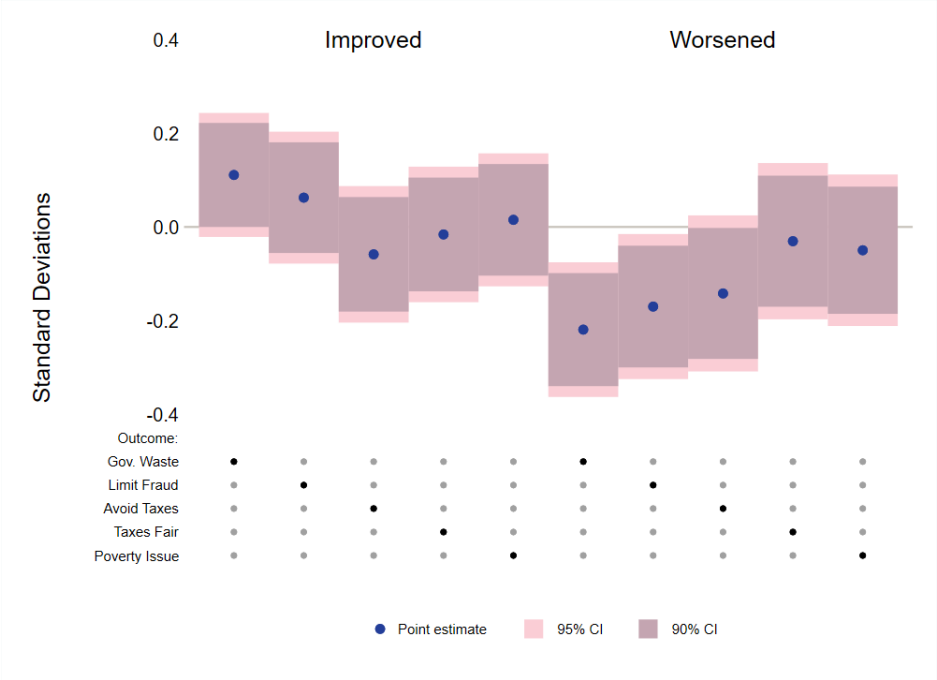
(c) Compromise Index

Notes: This figure presents heterogeneity of the treatment-on-the-treated effects of perception changes on the three primary indices, Panel (a) for the Support Index, Panel (b) for the Efficiency Index, and Panel (c) for the Compromise Index. Both 95 percent and 90 percent confidence intervals are displayed. Results are displayed for various heterogeneous samples.

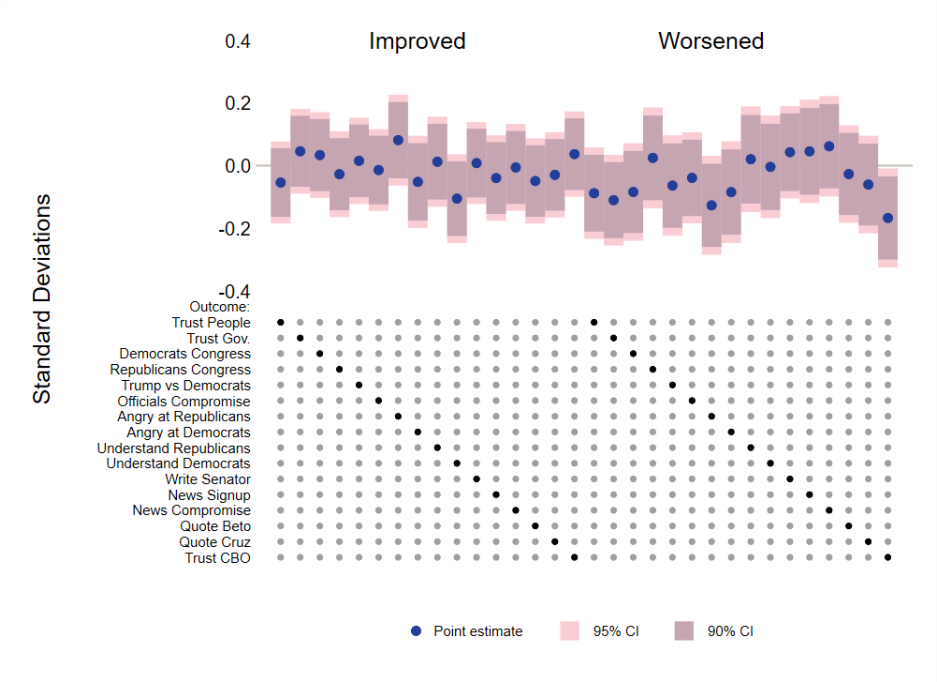
Figure A.6: Individual Outcomes for Perceptions and Beliefs



(a) Support Index



(b) Efficiency Index



(c) Compromise Index

Notes: This figure presents the treatment-on-the-treated effects of perception changes on the individual questions comprising the three primary indices, Panel (a) for the Support Index, Panel (b) for the Efficiency Index, and Panel (c) for the Compromise Index. Both 95 percent and 90 percent confidence intervals are displayed.

B Online Appendix Experiment Instructions

You are invited to participate in a research study conducted by a research team from Texas A&M University. Please read the following information carefully.

In this study, we are trying to learn more about political preferences and associated behaviors. You were selected as a possible participant in this study because you are an MTURK worker. You must be 18 years of age or older to participate. It will take no more than 10 minutes to complete the survey.

If you decide to participate, you will be directed to a survey. This survey will ask you questions about demographics, political preferences, and beliefs about the government. Your participation in this study is voluntary. You can decide not to participate in this research and it will not be held against you. There are no questions in this survey that should cause discomfort. However, you can choose to exit the survey at any point.

You may view the survey host's confidentiality policy at:

https://www.qualtrics.com/security-statement/

All information will be kept on a password protected computer and is only accessible by the research team. The results of the research study may be published but no one will be able to identify you.

You will be paid a base payment of $1.00 for completing this survey. After completing the survey, you will receive a code that you need to enter into MTURK's platform.

Please feel free to ask questions regarding this study. You may contact the research team later if you have additional questions or concerns at political.preferencesgmail.com to talk with the research team.

You may also contact the Human Research Protection Program at Texas A&M University by phone at 1-979-458-4067, toll free at 1-855-795-8636, or by email at irbtamu.edu for additional help with any questions about the research, voicing concerns or complaints about the research, obtaining answers to questions about your rights as a research participant,

concerns in the event the research staff could not be reached, the desire to talk to someone other than the research staff.

If you want a copy of this consent for your records, you can print it from the screen.

C Online Appendix Variable Definitions by Category

Variable Name	Question Text
	Category 1: Government Representation and Support
GovRepWel	When it comes to spending only on Welfare Programs, the current government does a (Bad/Good) job representing my welfare spending preferences.
GovRepMil	When it comes to spending only on Military and Homeland Security, the current government does a (Bad/Good) job representing my military spending preferences.
GovRep	Overall, how well do the current president, congressmen, and senators represent your preferences as a whole?
RightTrack	All in all, do you think things in the U.S. are generally headed in the right direction, or do you feel things are off on the wrong track?
ApproveTrump	In general, do you approve or disapprove of the job Donald Trump is doing as president?
ApproveCongress	In general, do you approve or disapprove of the job that Congress is doing?
GovPurpose	Think more broadly about the purpose of government in general. Where would you rate yourself on a scale of 0 to 100, where 0 means you think the government should do only those things necessary to provide the most basic government functions, and 100 means you think the government should take active steps in every area it can to try and improve the lives of its citizens?
ProtectRights	Please indicate whether you agree or disagree with the following statement: "If I have to resort to violence to protect my rights, I will."
	Category 2: Government Efficiency, Fraud, and Waste
GovWaste	Do you think that people in the government waste a lot of the money we pay in taxes, waste some of it, or don't waste very much of it?
Poverty	Do you think poverty is a serious problem in America?
LimitFraud	Do you agree or disagree with the following statement? "Currently, the federal government is very effective in limiting fraud, waste, and abuse in the programs it administers."

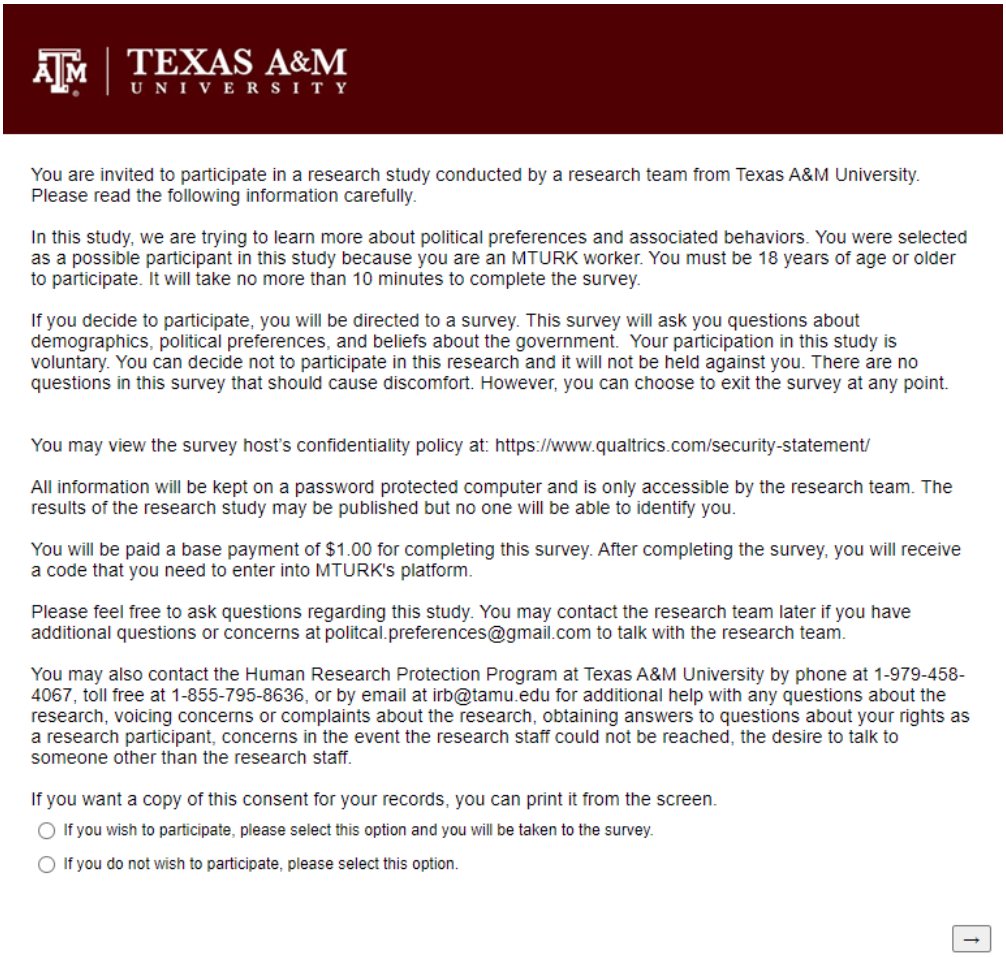
TaxesFair	How fair do you think our present federal tax system is? Overall would you say that our tax system is... a) Very fair, b) Not fair at all.
AvoidTaxes	Do you agree or disagree with the following statement? "It's really American to avoid paying taxes, legally." -Lindsey Graham
	Category 3: Compromise and Trust
Trust	Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?
GovDoRight	How much of the time do you think you can trust the government in Washington to do what is right?
DemsInCongress	Think about the relationship between Democrats in Congress and President Trump. Do you think Democrats in Congress are too inflexible in dealing with the President, are too quick to give in to the President, or are they striking the right balance in dealing with the President?
RepsInCongress	Think about the relationship between Republicans in Congress and President Trump. Do you think Republicans in Congress are too inflexible in dealing with the President, are too quick to give in to the President, or are they striking the right balance in dealing with the President?
TrumpVsDems	Think about how Donald Trump and Democratic leaders should address the most important issues facing the country. Imagine a scale from zero to 100 where 100 means Democratic leaders get everything they want and Trump gets nothing he wants, and zero means Trump gets everything and Democratic leaders get nothing. Where on this scale from zero to 100 do you think they should end up?"
Officials	Which statement comes closer to your view, even if neither is exactly right? I like elected officials who a) Make compromises with people they disagree with, b) Stick to their positions
QuoteBeto	Would you like to read a quote about investing in border security from Beto O'Rourke?
AgreeBeto	(if QuoteBeto==1) Do you agree with this position? "I have to convince other Democrats and Republicans that it's wise to invest in the U.S.-Mexico border, not just for security, but also for mobility and trade, and that's why we should open up the border."

QuoteCruz	Would you like to read a quote about investing in health and welfare from Ted Cruz?
AgreeCruz	(if QuoteCruz==1) Do you agree with this position? "I don't think it is government's job to find health care for people. I think it's the individual's job to find health care."
WriteToSenator	Writing to the Senators of your state gives you an opportunity to influence government spending. Few citizens email their elected officials. Therefore, Senators and their staff take such emails from their constituents very seriously. If you would like to write to your Senator, go to the official US Senate list and click on your Senator's contact webpage. We are not able to record what you write on the external (Senator's) website, so your letter and private information are kept fully confidential. For our survey, we would just like to know from you: 1) I will send an email to my Senator asking for no change in the current level of spending on social programs. 2) I will send an email to my Senator asking for a decrease in the current level of spending on social programs. 3) I will send an email to my Senator asking for an increase in the current level of spending on social programs. 4) I do not want to email my Senator. 5) Please remind me at another time.
NewsPolarization	Thinking back over the last 4 weeks, how many times (Never, One Time, Two Times, Three Times, Four Times, Five or More Times) did you see a news event that... 1) ...made you angry at the Republican Party?, 2) ...made you angry at the Democratic Party?, 3) ...made you better understand the point of view of the Republican Party?, 4) ...made you better understand the point of view of the Democratic Party?
NewsSkew	On the scale below, please indicate where you would prefer to get the majority of your news sources from. (Liberal Leaning, Neutral, Conservative Leaning)
Newsletter	Would you be interested in signing up for a newsletter from... (if yes, we will begin the sign up process) 1) Vox (skewed liberal), 2) The Atlantic (skewed liberal), 3 Daily KOS (skewed strongly liberal), 4) The Fiscal Times (skewed conservative), 5) National Review (skewed conservative), 6) The Federalist (skewed strongly conservative).

TrustStat	According to the Congressional Budget Office, for an additional $100, the government distributes $44 towards Welfare Programs and $56 towards Military Spending. Do you believe this statistic?

D Online Appendix Experimental Survey

Figure D.1: Survey Screen #1



TEXAS A&M UNIVERSITY

You are invited to participate in a research study conducted by a research team from Texas A&M University. Please read the following information carefully.

In this study, we are trying to learn more about political preferences and associated behaviors. You were selected as a possible participant in this study because you are an MTURK worker. You must be 18 years of age or older to participate. It will take no more than 10 minutes to complete the survey.

If you decide to participate, you will be directed to a survey. This survey will ask you questions about demographics, political preferences, and beliefs about the government. Your participation in this study is voluntary. You can decide not to participate in this research and it will not be held against you. There are no questions in this survey that should cause discomfort. However, you can choose to exit the survey at any point.

You may view the survey host's confidentiality policy at: https://www.qualtrics.com/security-statement/

All information will be kept on a password protected computer and is only accessible by the research team. The results of the research study may be published but no one will be able to identify you.

You will be paid a base payment of $1.00 for completing this survey. After completing the survey, you will receive a code that you need to enter into MTURK's platform.

Please feel free to ask questions regarding this study. You may contact the research team later if you have additional questions or concerns at politcal.preferences@gmail.com to talk with the research team.

You may also contact the Human Research Protection Program at Texas A&M University by phone at 1-979-458-4067, toll free at 1-855-795-8636, or by email at irb@tamu.edu for additional help with any questions about the research, voicing concerns or complaints about the research, obtaining answers to questions about your rights as a research participant, concerns in the event the research staff could not be reached, the desire to talk to someone other than the research staff.

If you want a copy of this consent for your records, you can print it from the screen.

- ◯ If you wish to participate, please select this option and you will be taken to the survey.
- ◯ If you do not wish to participate, please select this option.

→

If a participant chooses not to participate, then the survey ends. If they do, they are revealed the rest of the following survey.

Figure D.2: Survey Screen #2

TEXAS A&M UNIVERSITY

Thank you for your interest in participating in this research study. First, please tell us a little bit about yourself.

What is your age? (in years)

What is your gender?

- Male
- Female
- Other

Please indicate the highest level of education completed.

- Less than High School
- High School or equivalent
- Vocational/Technical School (2 year)
- Bachelor's Degree (4 year)
- Master's Degree (MS)
- Doctoral Degree (PhD)
- Professional Degree (MD,JD, etc.)

What was your total household income before taxes during the past 12 months?

- Less than $25,000
- $25,000 to $34,999
- $35,000 to $49,999
- $50,000 to $74,999
- $75,000 to $99,999
- $100,000 to $149,999
- $150,000 or more

What is your current marital status?

- Divorced
- Living with another
- Married
- Separated
- Single
- Widowed

From the following options, do you consider yourself to be:

- Black, or African American
- White
- Asian
- American Indian
- Native Hawaiian or other Pacific Islander
- I prefer not to answer

Do you identify yourself as Hispanic or Latino?

- Yes
- No

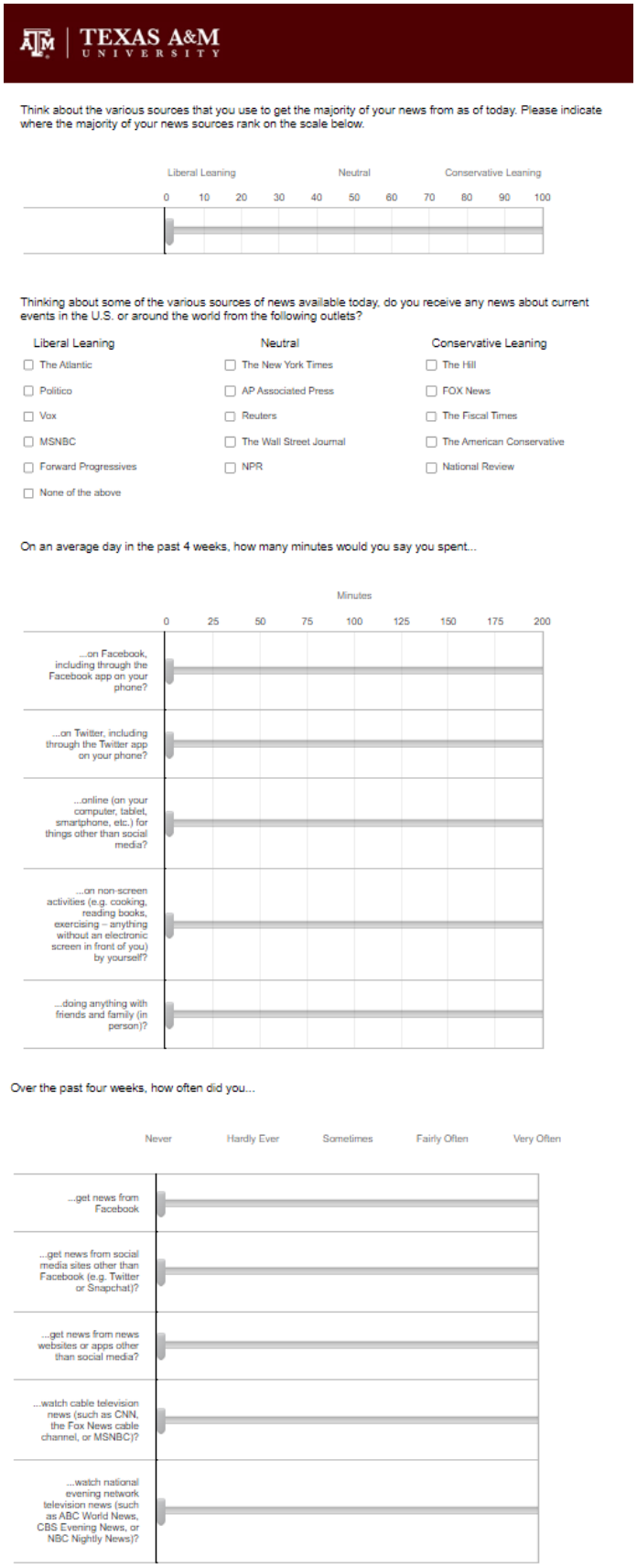
How many children do you have?

Which of the following best describes the area you currently live in?

- Urban
- Suburban
- Rural

→

Figure D.3: Survey Screen #3



TEXAS A&M UNIVERSITY

Think about the various sources that you use to get the majority of your news from as of today. Please indicate where the majority of your news sources rank on the scale below.

Liberal Leaning — Neutral — Conservative Leaning

0 10 20 30 40 50 60 70 80 90 100

Thinking about some of the various sources of news available today, do you receive any news about current events in the U.S. or around the world from the following outlets?

Liberal Leaning	Neutral	Conservative Leaning
The Atlantic	The New York Times	The Hill
Politico	AP Associated Press	FOX News
Vox	Reuters	The Fiscal Times
MSNBC	The Wall Street Journal	The American Conservative
Forward Progressives	NPR	National Review
None of the above		

On an average day in the past 4 weeks, how many minutes would you say you spent...

Minutes

0 25 50 75 100 125 150 175 200

...on Facebook, including through the Facebook app on your phone?

...on Twitter, including through the Twitter app on your phone?

...online (on your computer, tablet, smartphone, etc.) for things other than social media?

...on non-screen activities (e.g. cooking, reading books, exercising – anything without an electronic screen in front of you) by yourself?

...doing anything with friends and family (in person)?

Over the past four weeks, how often did you...

Never — Hardly Ever — Sometimes — Fairly Often — Very Often

...get news from Facebook

...get news from social media sites other than Facebook (e.g. Twitter or Snapchat)?

...get news from news websites or apps other than social media?

...watch cable television news (such as CNN, the Fox News cable channel, or MSNBC)?

...watch national evening network television news (such as ABC World News, CBS Evening News, or NBC Nightly News)?

Figure D.4: Survey Screen #4

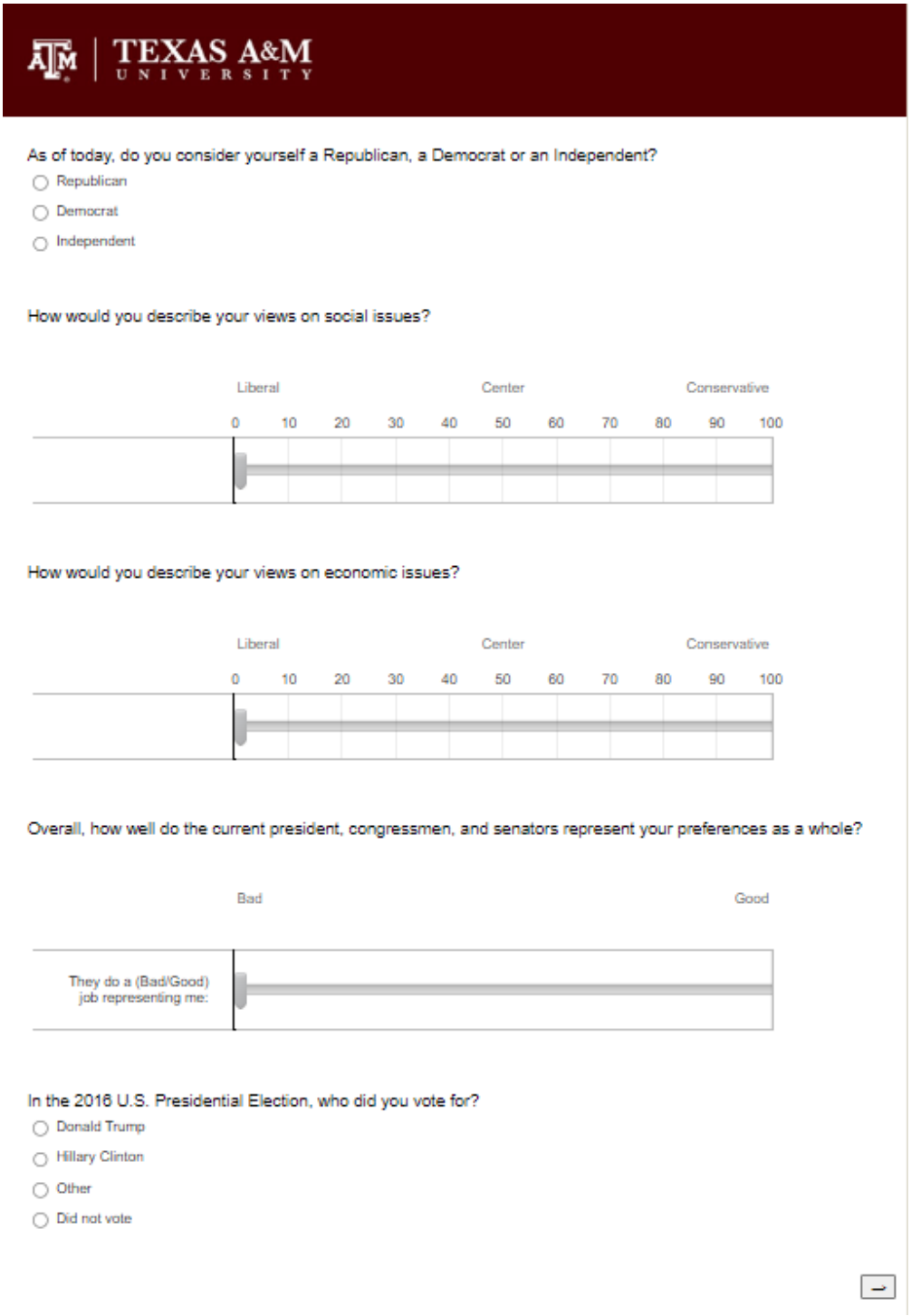


Figure D.5: Survey Screen #5

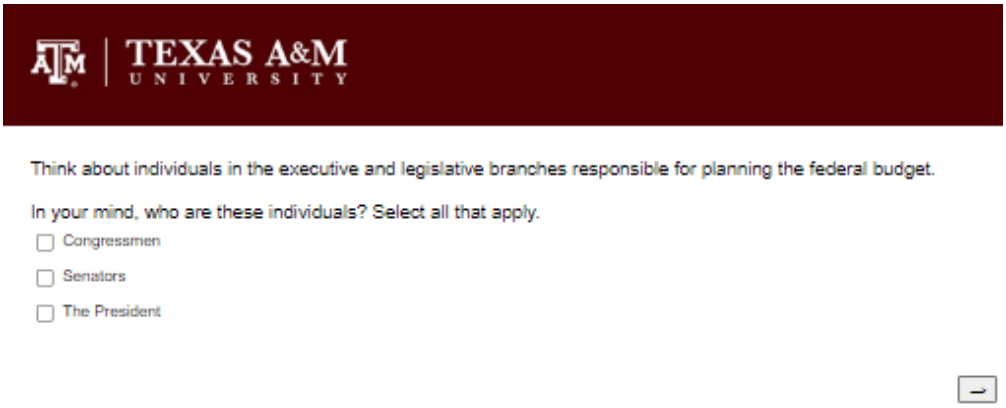
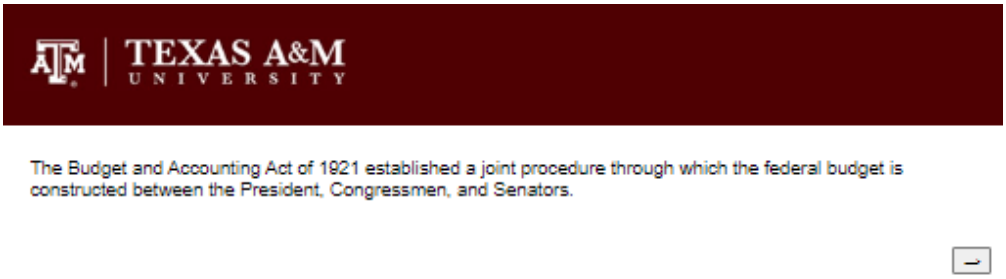


Figure D.6: Survey Screen #6



Note: The following two screens, #7 and #8, were randomized to participants along with the order of question options.

Figure D.7: Survey Screen #7

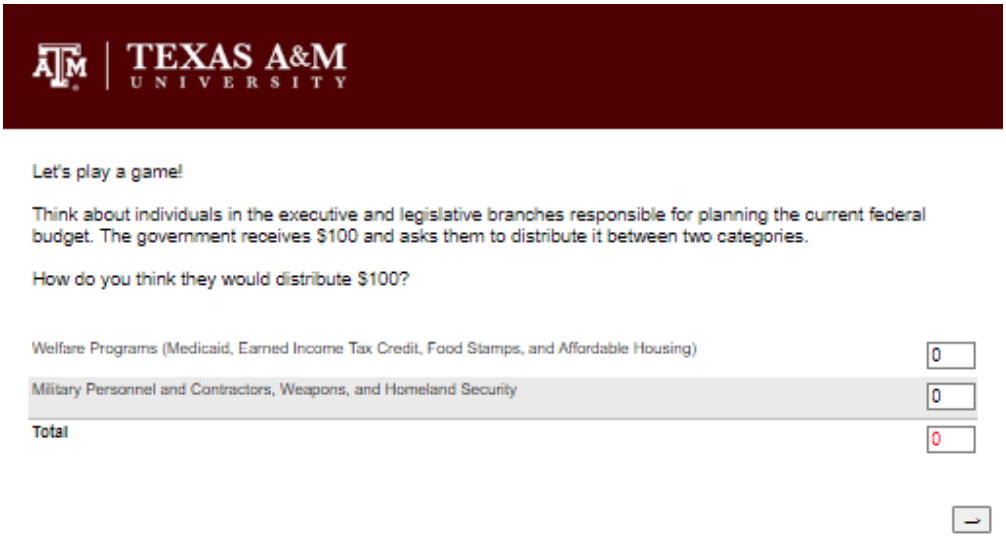
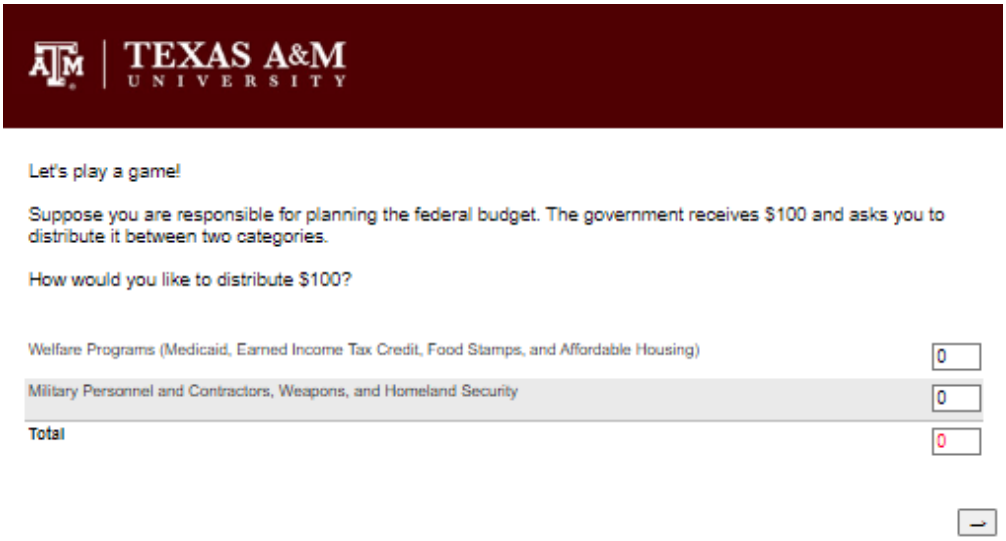


Figure D.8: Survey Screen #8



Note: For the following two screens, #9 and #10, participants randomly received information specific to one of the two government expenditure categories, but not both.

Figure D.9: Survey Screen #9

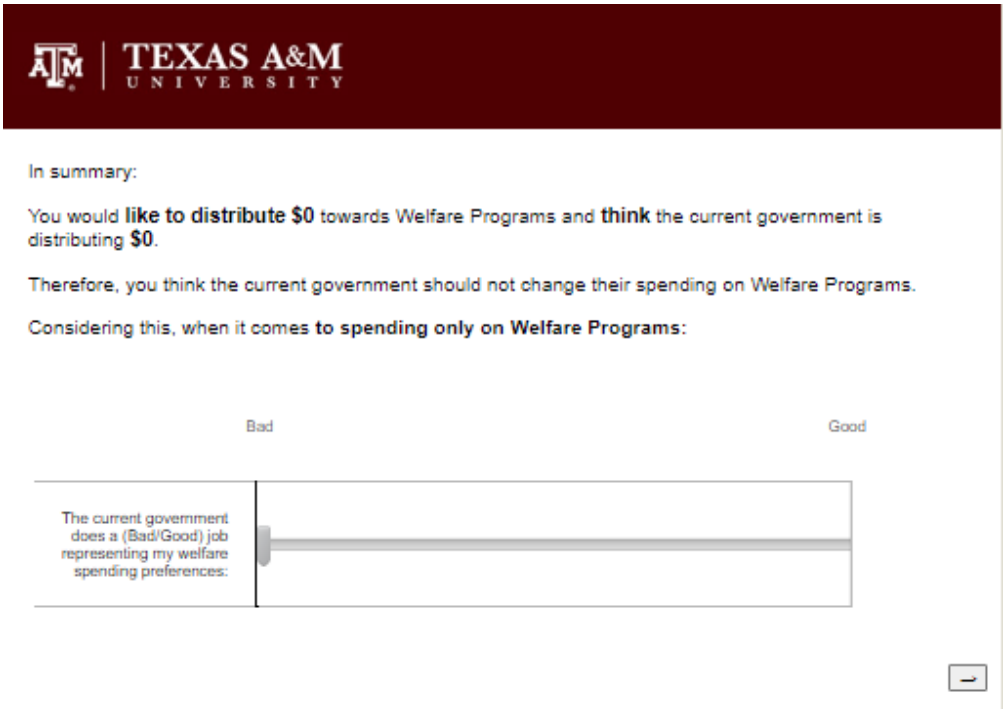


Figure D.10: Survey Screen #10

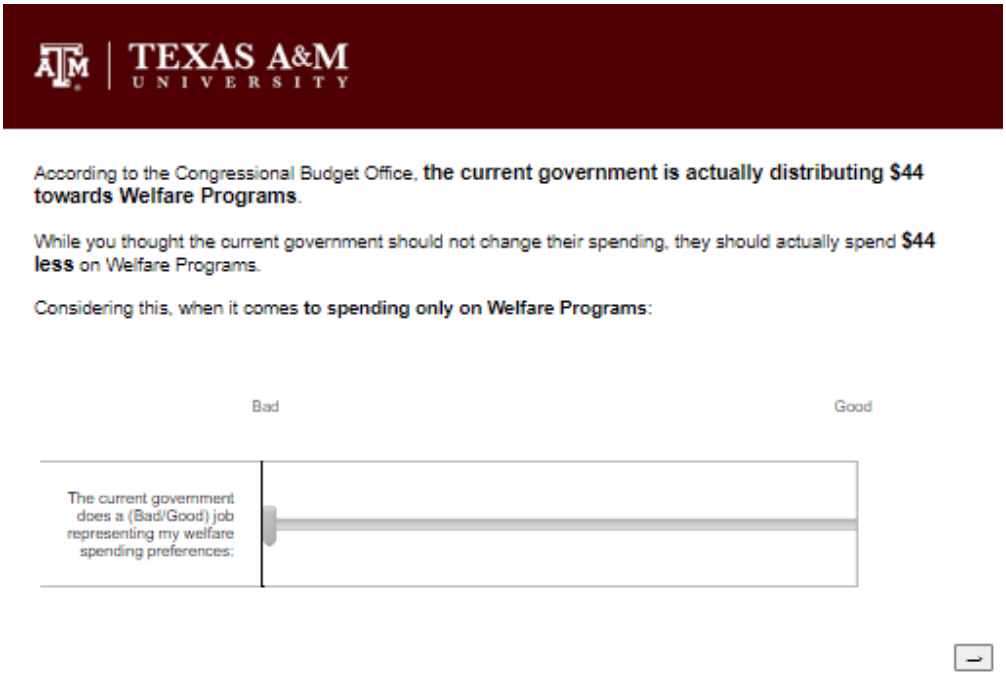


Figure D.11: Survey Screen #11

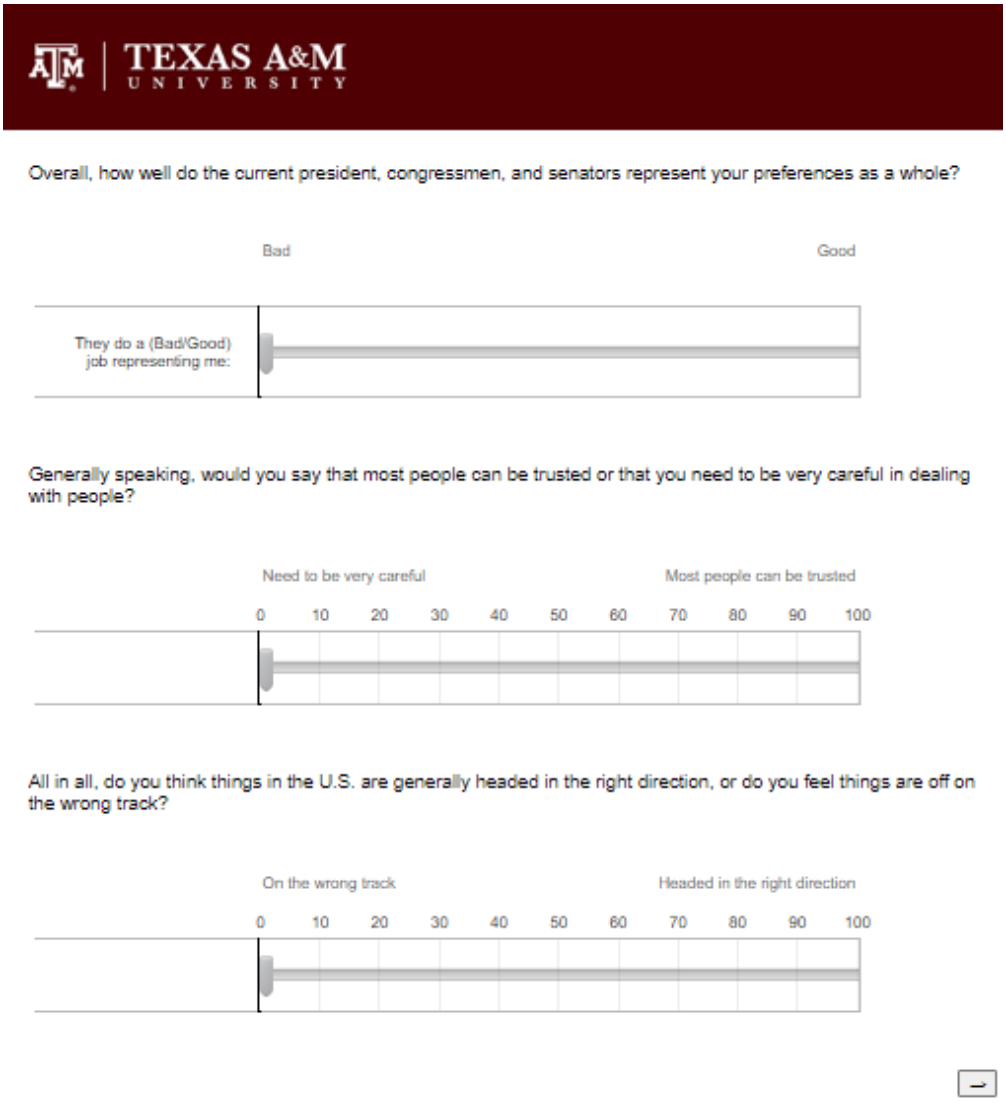


Figure D.12: Survey Screen #12

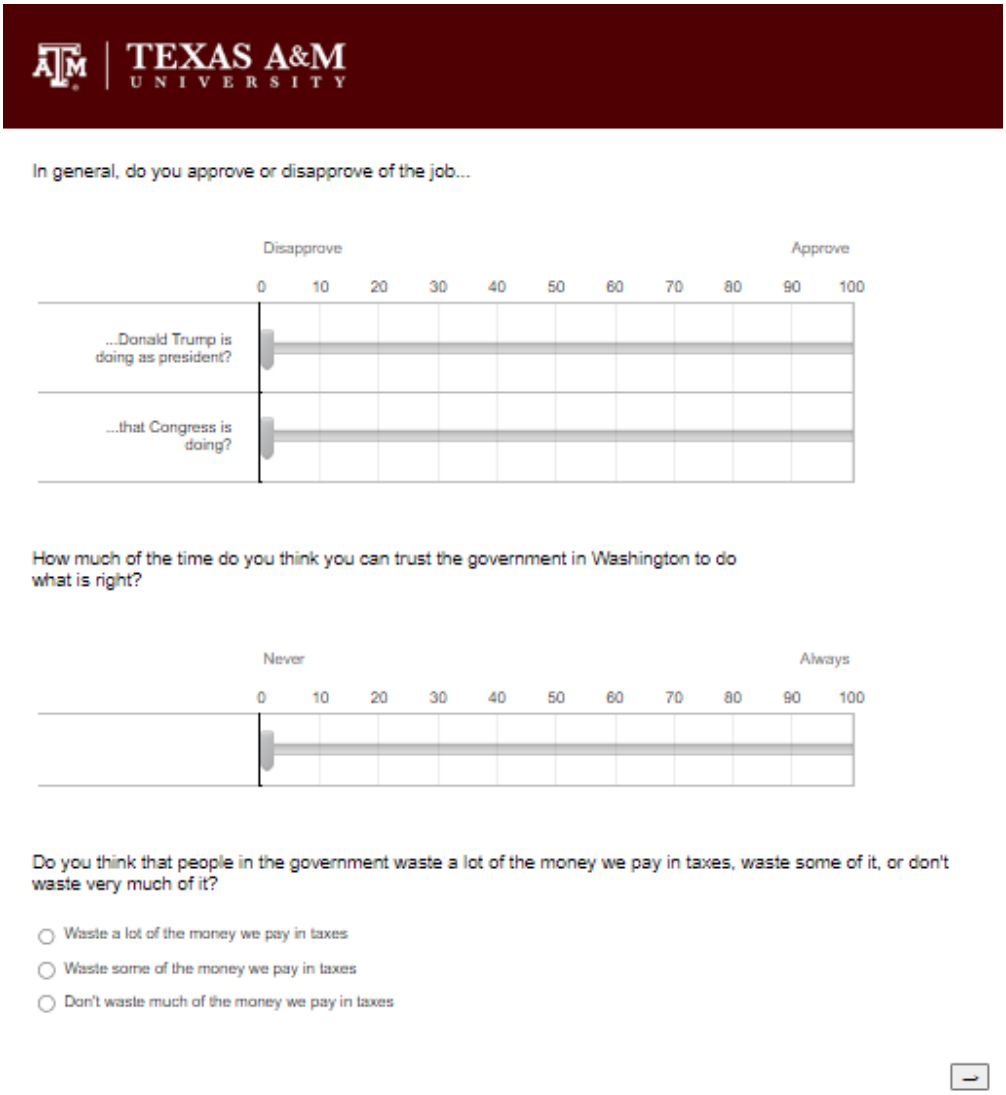
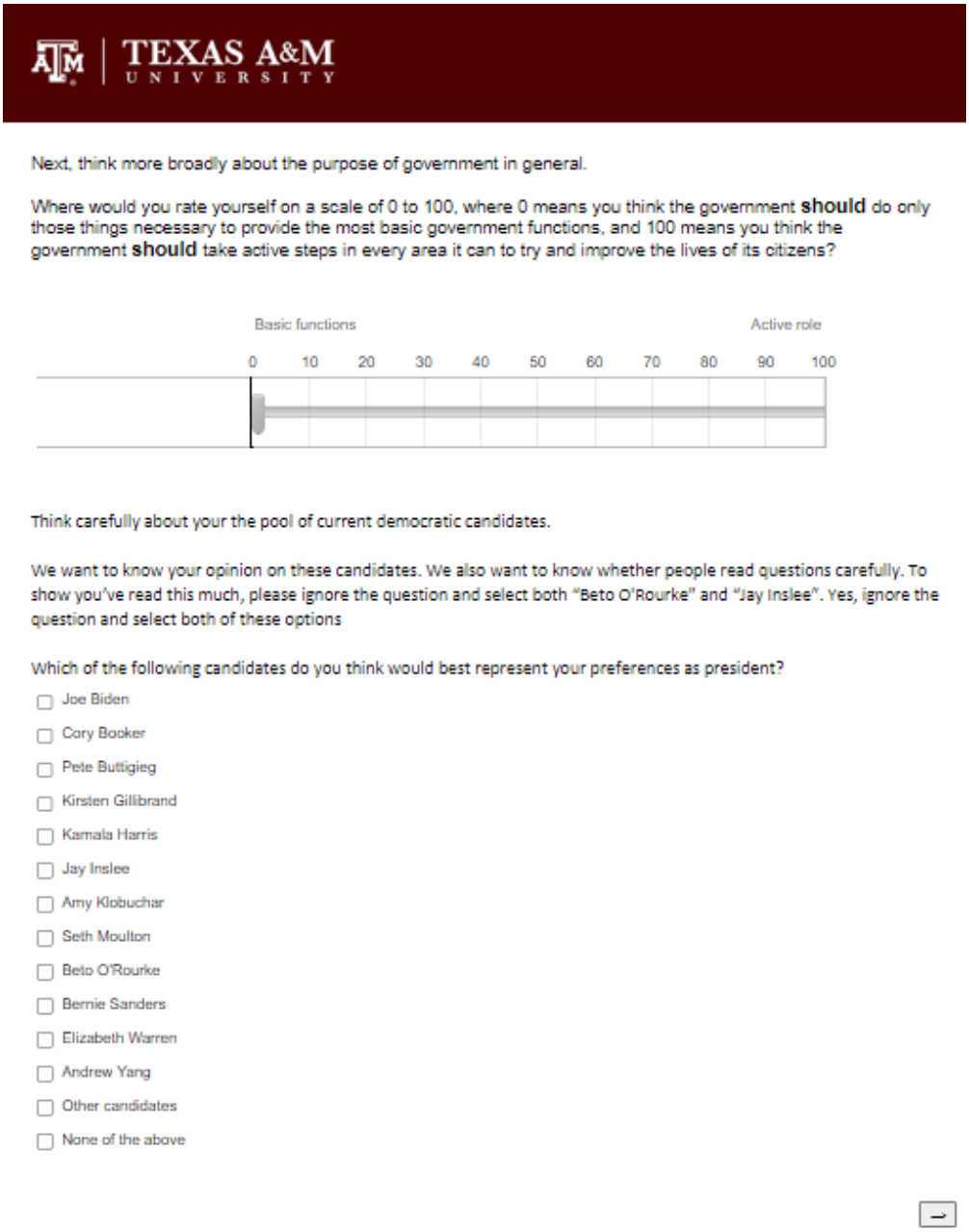


Figure D.13: Survey Screen #13



Note: The question above contains an "Attention Check." If a participant fails this question, the survey promptly ends and the participant is removed from completing any further.

Figure D.14: Survey Screen #14

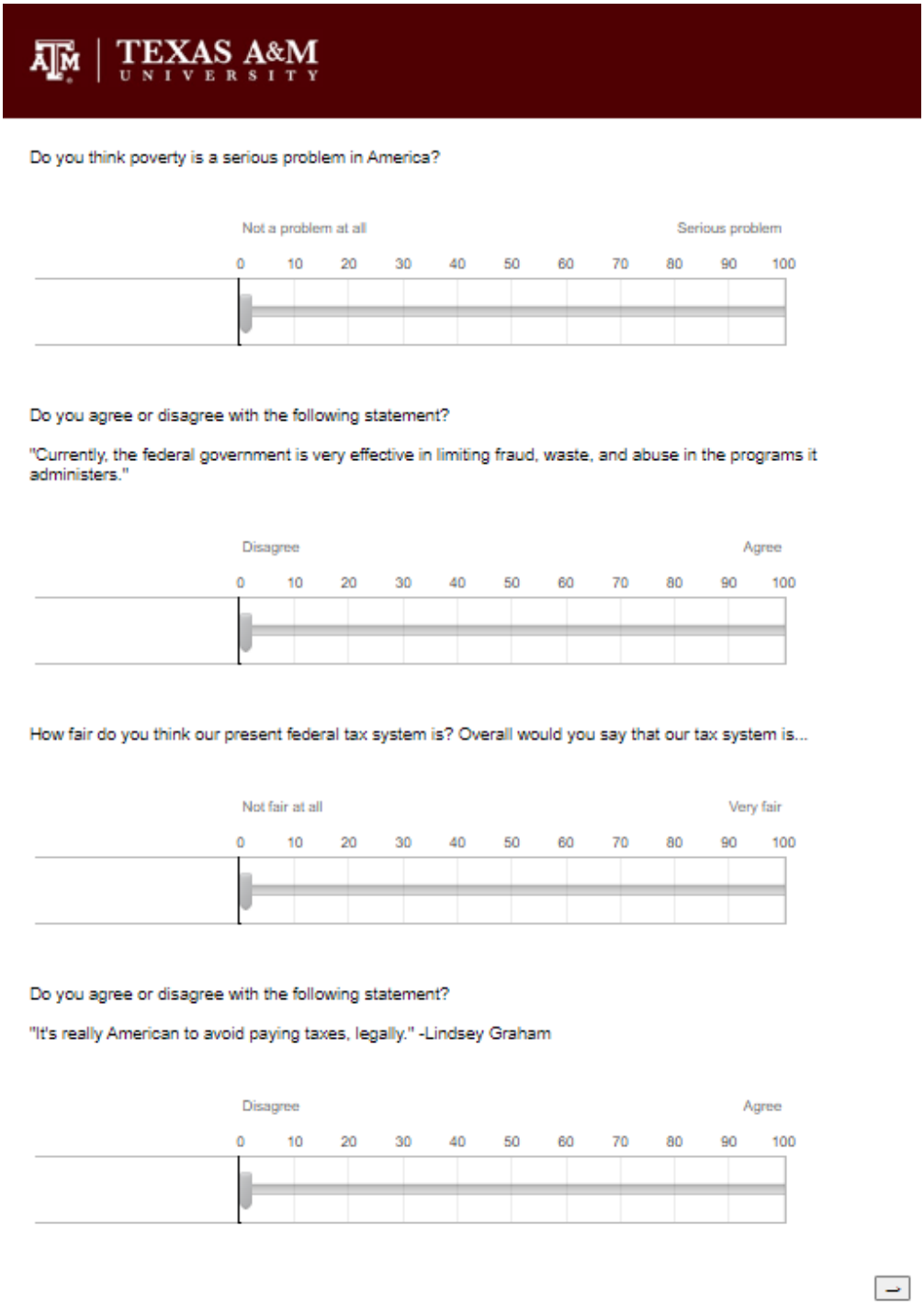


Figure D.15: Survey Screen #15

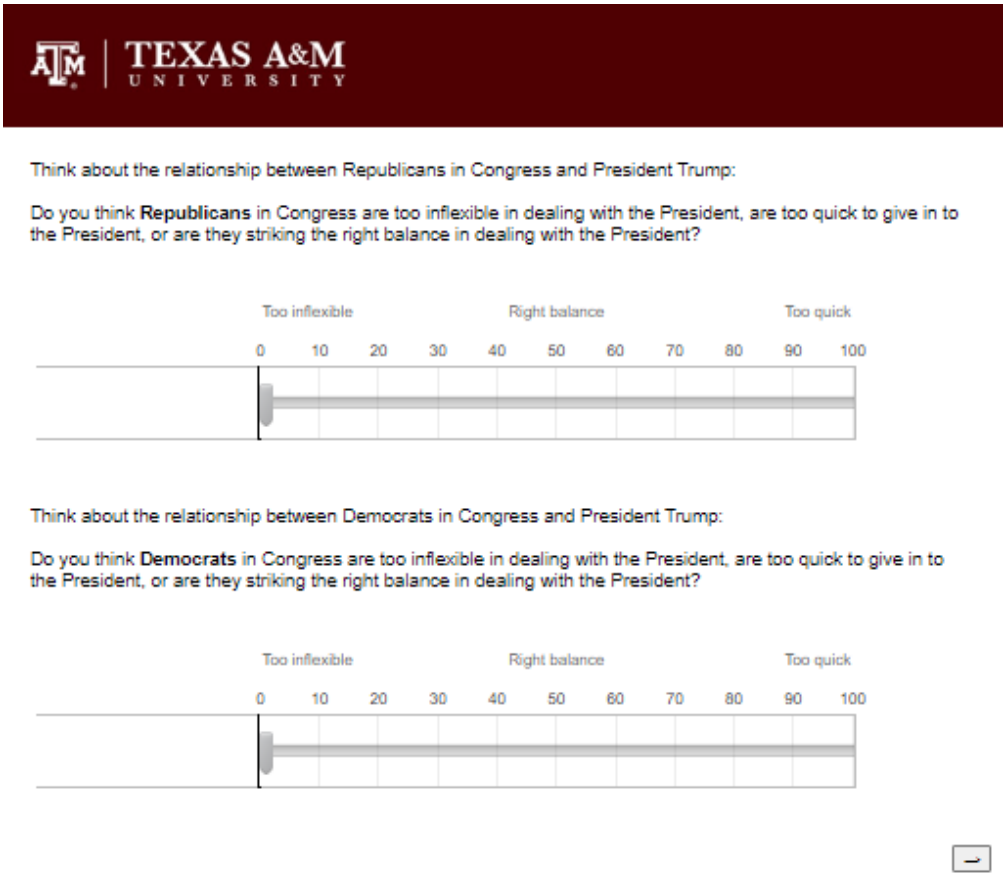


Figure D.16: Survey Screen #16

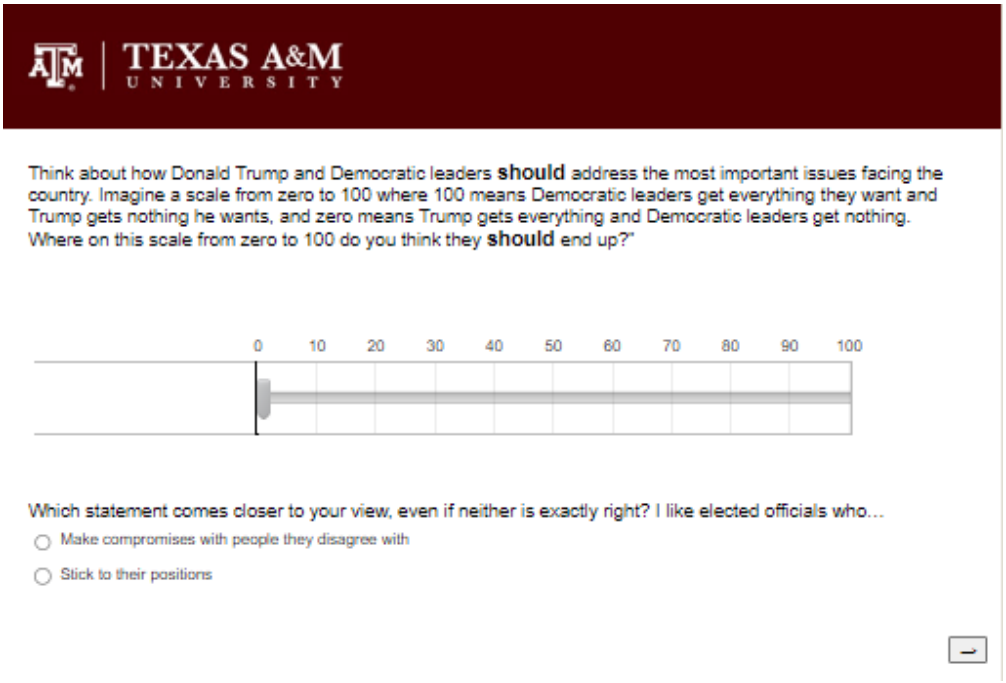


Figure D.17: Survey Screen #17

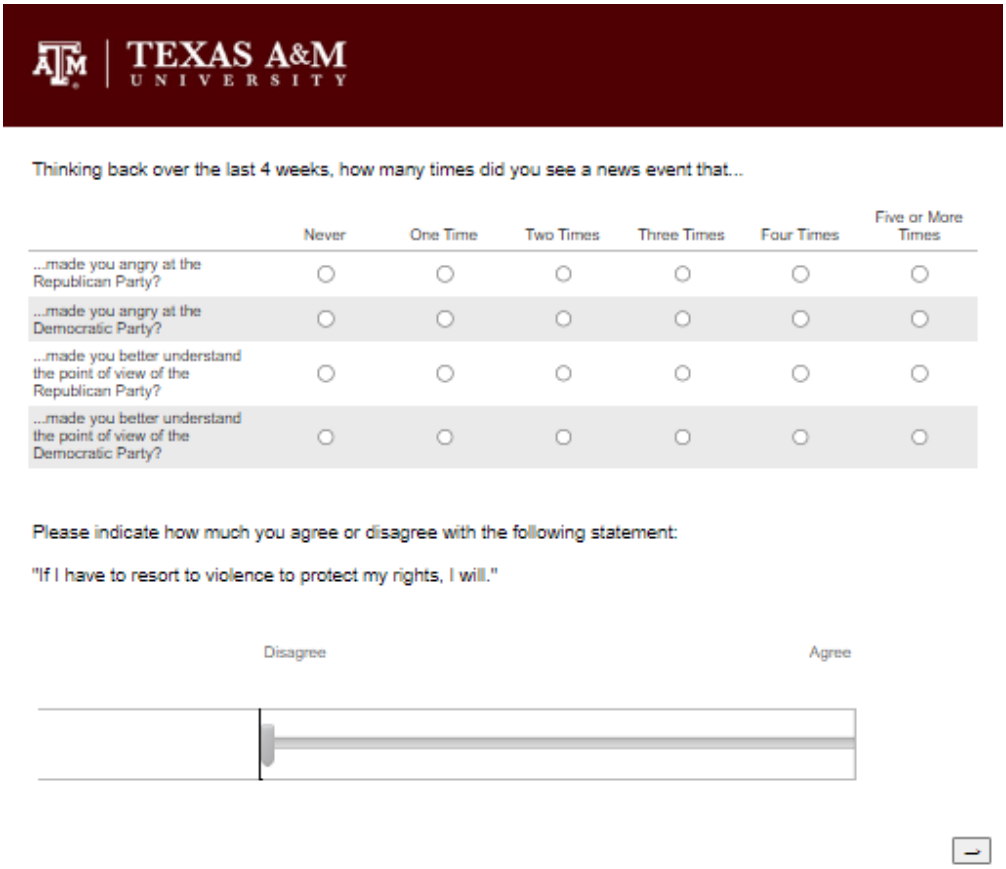
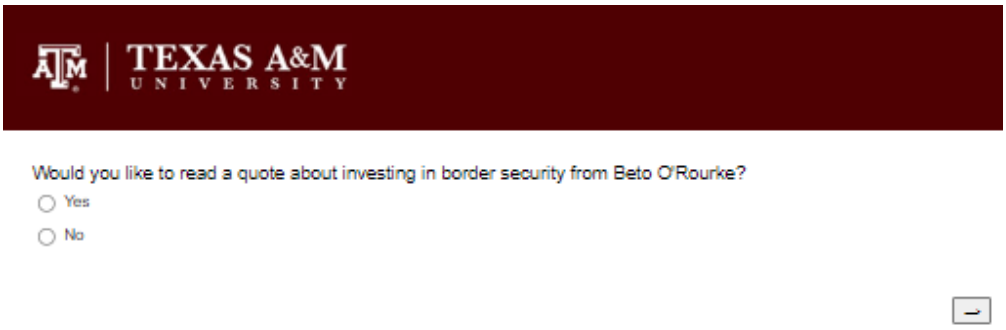


Figure D.18: Survey Screen #18



Note: The following screen, #19, is only displayed if a participants selects "Yes" to the previous question, #18.

Figure D.19: Survey Screen #19

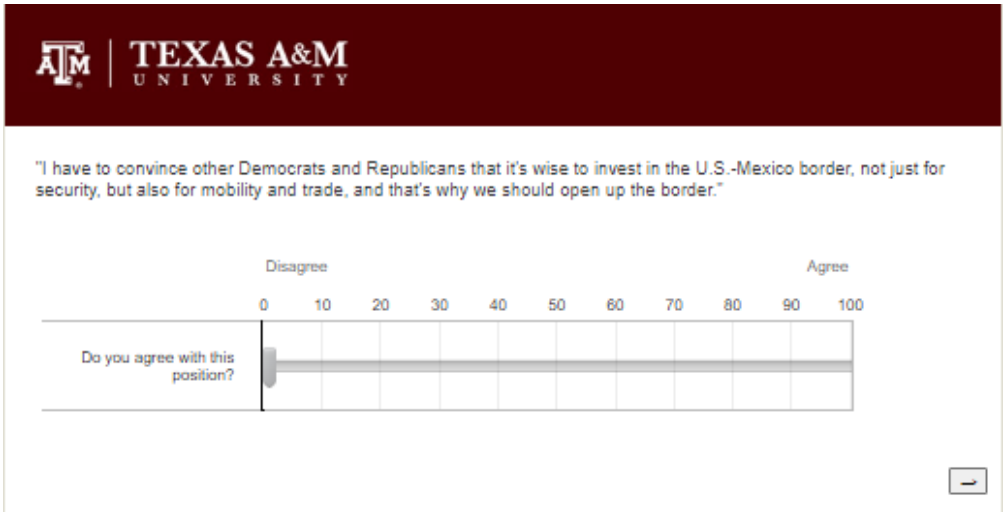
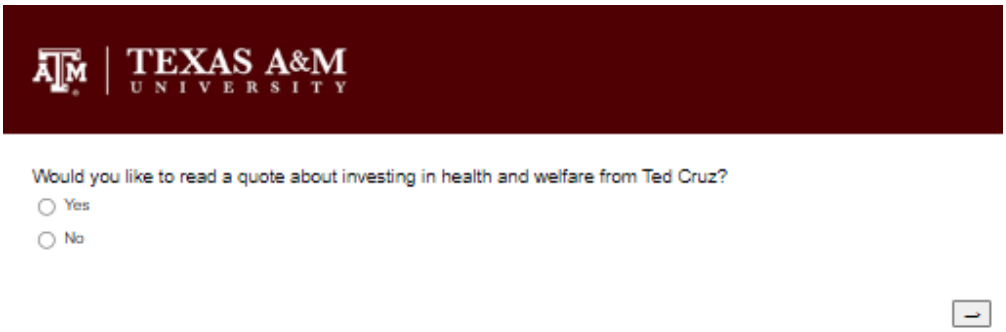


Figure D.20: Survey Screen #20



Note: The following screen, #21, is only displayed if a participants selects "Yes" to the previous question, #20.

Figure D.21: Survey Screen #21

Figure D.22: Survey Screen #22

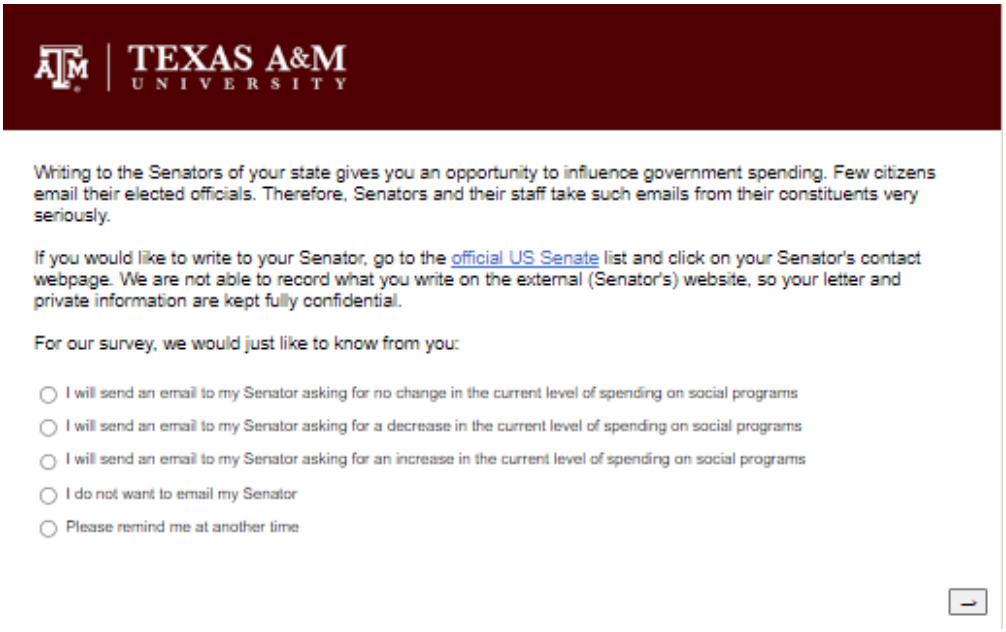


Figure D.23: Survey Screen #23

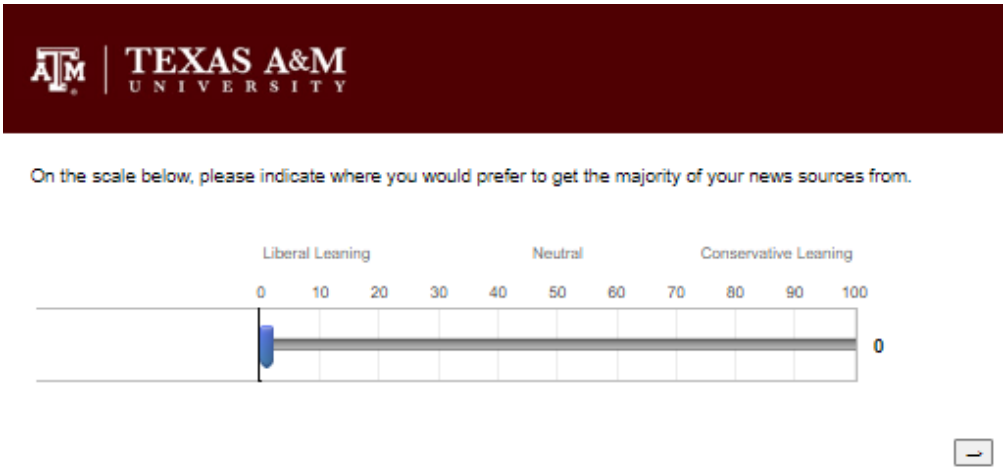


Figure D.24: Survey Screen #24

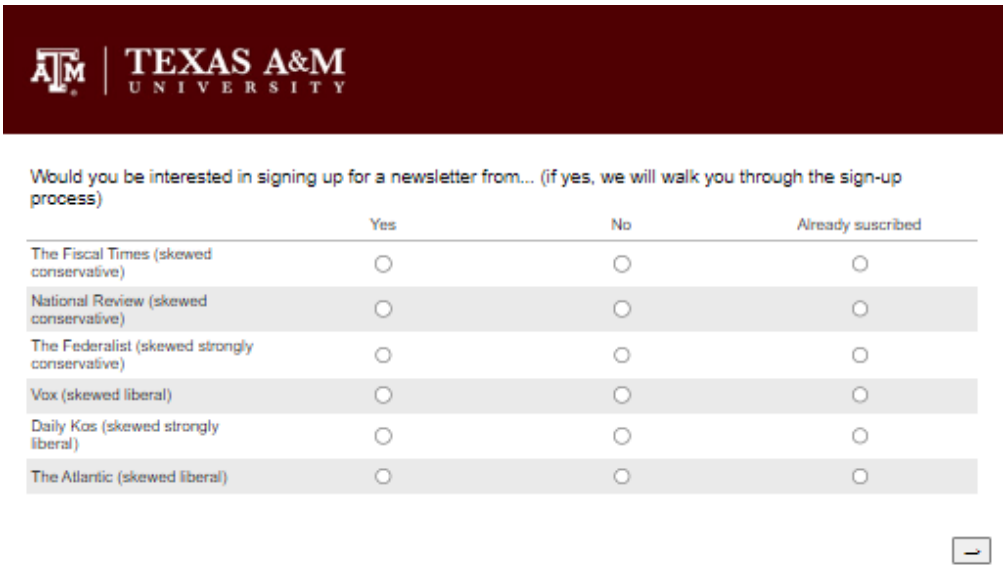


Figure D.25: Survey Screen #25

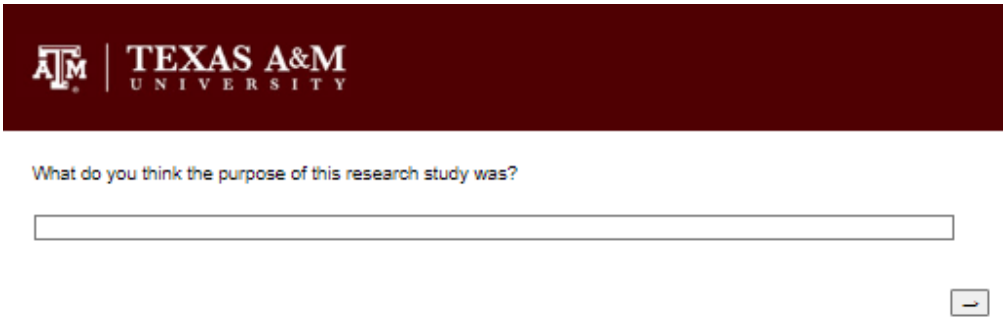


Figure D.26: Survey Screen #26

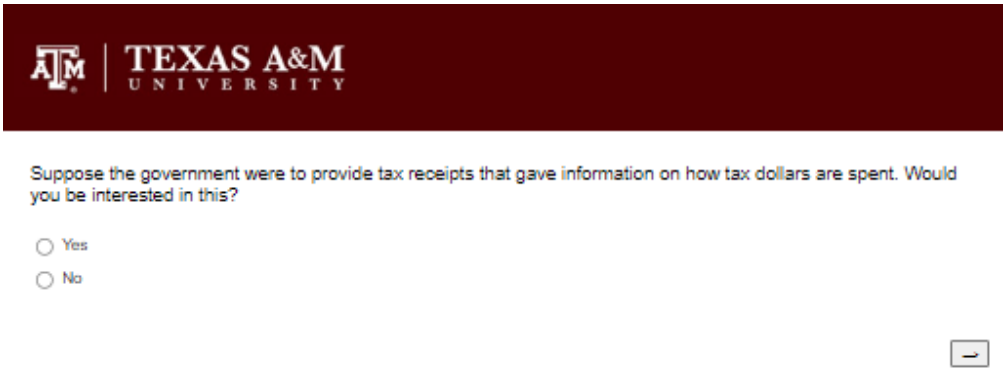
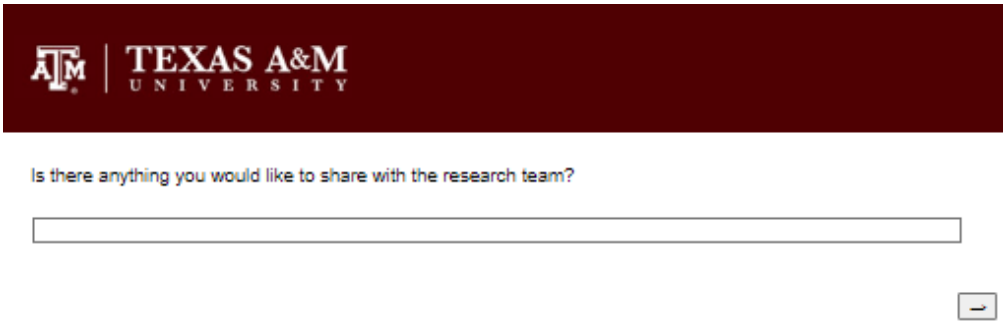


Figure D.27: Survey Screen #27

Figure D.28: Survey Screen #28



Note: The following slide contains a randomized code that MTURK workers use to verify completion of their assignment.

Figure D.29: Survey Screen #29