Accurate Information Can Substantially and Durably Increase Republicans' Beliefs in Election Integrity

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Abstract

Low confidence in the integrity of elections is a growing concern in the US, and questioning election integrity has become a core part of Republican identity in recent years. These beliefs appear to be the result of an uninformed or misinformed electorate. However, despite growing evidence that factual information can shift political beliefs even on contentious issues, election integrity beliefs have so far proven resistant to information-based approaches, arguably because they are tightly linked to partisan identity and reinforced by a polarized information environment. To examine whether election integrity beliefs are indeed resistant to corrective information, we develop and test a novel informational treatment that employs an intensive fact-based training. Unlike prior approaches, which typically deliver brief informational corrections, our treatment provides a high volume of accurate and politically balanced evidence on election integrity and facilitates sustained engagement with the materials. Immediately prior to the 2024 general election, we randomly assigned N = 871 Republicans to either the experimental group or a control group engaging with general political information. The treatment substantially increased participants' overall beliefs about the integrity of US elections, retrospective beliefs about the integrity of the 2020 election, and prospective beliefs about the expected integrity of the upcoming 2024 election ($.6 < d\text{s} < .8$). Effects were similarly large in key subgroups, including demographically "prototypical" Republicans ($.5 < d\text{s} < .95$) and highly engaged individuals ($.7 < d\text{s} < .86$). Furthermore, a follow-up shows that the effects persist two weeks later, following the 2024 election. These findings demonstrate that even beliefs closely tied to partisan identity are responsive to credible factual information.

Significance

Low confidence in elections has become a serious threat to American democracy, especially on the political right, where questioning election integrity has become a core part of Republican identity. Recent evidence suggests that factual information can shift political beliefs in line with evidence, yet election integrity beliefs have so far proven immune to fact-based treatments. We directly test this claim using an informational treatment providing a high volume of accurate, balanced, and unbiased factual information on election integrity. Contrary to prior studies, which failed to align Republicans' elections-related beliefs with the evidence, our treatment substantially and durably increased Republicans' general confidence in US elections and their beliefs that the 2020 and 2024

elections were free from widespread fraud. These results suggest that getting people to learn the facts can meaningfully reduce partisan bias, even in the context of highly charged beliefs that are central to a political group's identity.

Introduction

Low confidence in election integrity has emerged as a serious and pervasive problem in the US, especially among Republican voters. A September 2024 Gallup poll showed that only 57% of Americans were either very or somewhat confident that the votes for president would be accurately cast and counted in that year's election. This number masks a striking partisan divide: while 84% of Democratic respondents to that Gallup poll showed confidence in electoral integrity before the 2024 election, among Republicans, the number was only 28% (Saad, 2024).

The problem of low confidence in the integrity of US elections is not unique to the 2024 presidential race. Longitudinal data shows that Republicans' trust in the US electoral process has been low since 2008 (Saad, 2024), and there is evidence that trust is decreasing over time (Norris, 2019; Sances & Stewart, 2015). Perhaps most notable is reaction to the 2020 presidential election. A large nationwide survey conducted after that election found that 38% of Americans lacked confidence in its fairness. That survey revealed, once again, a massive partisan gap: 64% of Republicans reported a lack of confidence in the integrity of the 2020 election, compared to only 11% of Democrats (Kulke, 2021). This partisan gap has been largely attributed to repeated claims of widespread election fraud made by Donald Trump and his allies both before and after the 2020 election, and further research has demonstrated that elite rhetoric on this topic has had a negative causal effect on people's trust in elections (Ballhaus et al., 2021; Clayton et al., 2021). In short, questioning election integrity has become not only widespread but also a central and enduring component of Republican partisan identity.

Republicans' belief that US elections are "rigged" – i.e., that massive fraud has changed the outcomes of specific elections – represents a case where people's beliefs diverge sharply from the documented evidence. In the context of the 2020 general election, for example, multiple comprehensive investigations found no evidence of systematic fraud (e.g., Eggers et al., 2021). Similar investigations of previous US elections have consistently found them to be secure and legitimate (Cottrell et al., 2018; Minnite, 2010). Given the disconnect between many Republicans' beliefs and the existing evidence, a natural approach to restoring trust would be to provide individuals with accurate factual information about the integrity of US elections.

Despite the intuitive appeal of fact-based approaches, much of the classic literature in psychology and political science has been skeptical of the ability of facts to meaningfully change political attitudes, citing factors such as motivated reasoning for why information is ineffective (Bolsen & Palm, 2019; Kahan et al., 2011; Taber & Lodge, 2006). However, recent work suggests that individuals do typically incorporate arguments and information and update their political views in the direction of evidence

(Coppock, 2023). From changing policy attitudes (Stagnaro & Amsalem, 2025), to belief in conspiracy theories (Costello et al., 2024), to candidate preferences (Lin et al., 2025), this growing body of literature argues that facts can change ideological beliefs and increase participant accuracy even on contentious political topics.

Despite these recent findings about the role of information in promoting accurate beliefs, fact-based treatments have so far not been successful in the domain of election integrity beliefs. Specifically, various recent studies have attempted to restore Americans' trust in elections by presenting people with corrective information. Yet these studies have largely failed to shift beliefs about election fraud, particularly among those most skeptical of election integrity. For instance, Bailard, Porter, and Gross (2022) found that exposure to fact-checks of Donald Trump's false claims about the 2020 election failed to increase electoral confidence among Republicans. Similarly, Carey et al. (2025) found that while specific false claims about the 2022 Arizona governor's race could be debunked, such debunking did not change voters' broader beliefs about election fraud, as well as their general confidence in the 2020 and 2022 elections. Furthermore, in a large-scale field experiment designed to address concerns about voting by mail, Biggers et al. (2023) found that mailing information about election protections and ballot tracking systems to California voters did not produce any measurable increase in voter turnout, with the authors suggesting that the information voters received may have been insufficient to overcome their electoral distrust.

These empirical findings align with the more classic motivated reasoning theoretical perspective described above, arguing that individuals are unlikely to update their beliefs in the direction of counter-attitudinal evidence, especially in contexts where the belief being challenged has become a strong marker of one's group affiliation – as some have argued the rejection of the 2020 result has become on the political right. It may be that in such hyper salient contexts, politically motivated reasoning renders counter-attitudinal evidence ineffective. Perhaps under such circumstances, people ignore or reject counter-attitudinal information and prefer to protect and maintain their preexisting beliefs by strongly adhering to their partisan identities (Doell et al., 2021), personal experiences (Kubin et al., 2021), or cultural worldviews (Kahan et al., 2011). At the same time, an alternative interpretation of these null findings is that previous informational approaches have simply not been sufficiently strong or well suited to address the distinctive features of election integrity beliefs.

Within this context of theoretical and empirical uncertainty, as well as the overall importance of the topic for American democracy, we set out to attempt a strong test of information's ability to permeate Republicans' electoral beliefs. Our approach differs from that used in prior studies on election integrity beliefs in both intensity and structure. Rather than relying on brief exposure, we use a lengthy, incentivized factual learning treatment in which individuals engage with a high volume of balanced evidence. This design is intended to provide a strong test of whether election integrity

beliefs are genuinely resistant to corrective information, or whether prior null results reflect interventions that were not sufficiently intensive or engaging.

Our data come from an online experiment conducted with a sample of $N = 871$ US conservative Republicans in the four days immediately preceding the 2024 presidential election. In the experiment, we first measured participants' pre-treatment confidence in US elections. Next, we randomly assigned them to engage with the treatment or control training. The treatment training materials included roughly 24 modules covering topics from "chain of custody," to the Mueller Report, to non-citizens voting in the 2020 election. Each module was presented in an engaging format, with a page of interactive text, infographics and images, the ability to take notes, rate content, and an AI tutor to help explain the content of each module. For the control training, all of the above features were also present, with the focus on general political information about the three branches of government. Both trainings incentivized participants to attend to and learn the facts they were presented (that is, both conditions experienced an incentive to learn). Our treatment was politically balanced in the sense that it presented to participants major (inaccurate) claims about election fraud made by both Republicans and Democrats, and debunked each claim using publicly verifiable, non-partisan factual evidence. After participants finished engaging with their randomly assigned information condition, we measured their post-treatment confidence in US elections. Finally, to examine the durability of any treatment effect, we conducted a follow-up survey two weeks later (and, critically, after the 2024 election occurred), once again measuring participants' electoral confidence.

An important aspect of our design is that the treatment and control groups experienced identical procedures, incentives, and learning structures, with the only difference between groups being in the content of the informational modules: the treatment group learned about elections and election fraud claims, while the control group learned about the three branches of government and how the government functions. The control topic was selected for its association with the outcome variables while having no explicit corrective information on elections. Thus both conditions encouraged the perception that the government and elections "function well," and so, to the extent that participant demand effects were cued, it should be similar across conditions. We also note that empirical evidence for demand effects in survey experiments is limited (Mummolo & Peterson, 2019; Woodley et al., 2025). Finally, we incentivized participants in both groups to learn the facts presented to them, while making it clear that there was no incentive to change their beliefs; that is, factual learning was incentivized while belief change was not. Together, these design features maximize the chance that differences across conditions in post-treatment electoral confidence reflect the impact of corrective informational content rather than other forces.

Our study represents a particularly demanding test of whether factual information can shift election beliefs. First, election integrity beliefs have become a core part of Republican identity over the last four years, which could make them harder

to change than less politically charged beliefs. Second, we conducted this study during a period of intense election campaigning, when people's information environment was saturated with competing claims about election fraud (Wendling, 2024). The fierce competition between perspectives (Amsalem & Zoizner, 2022), alongside the increased potential for "pre-treatment effects" stemming from prior exposure to election (mis)information (Druckman & Leeper, 2012), are all likely to reduce the ability of our informational treatment to change people's election-related beliefs.

Results

As our primary outcomes of interest, we use two composites: overall belief in the integrity of US elections (a composite of four items; α = .865) and specific belief in the integrity of the 2020 election (a composite of seven items, α = .963; for more details on the outcomes, see Methods and SI Sections 1 and 2; for analyses showing that all our conclusions are consistent when disaggregating the composites, see SI Section 3). In all analyses presented below, we report intent-to-treat models, which combine data from participants who completed the full study and those who opted to drop out of the informational treatment but still provided their post-treatment outcomes via a form of re-capture (see SI Section 4 for more information). Importantly, all our conclusions hold when examining compliers only (i.e., those who completed the full study; see SI Section 5). Both composites are recoded to range from 0 to 100, such that higher scores indicate greater confidence in the integrity of elections.

Importantly, since we measured participants' confidence in election integrity not only after but also prior to the treatment, we are able to identify, in advance, those who are most in need of corrective information. Hence, in the analyses that follow, we treat individuals whose pre-treatment electoral confidence was below the scale midpoint as Republicans who are skeptical of election integrity. Since this group constitutes the primary target of any effort to correct election integrity misperceptions, below, we present results separately for them and for the full sample whenever possible. This approach allows us to assess both the effectiveness of the treatment among those most in need of belief change and its broader impact across the entire sample.

Treatment Effects on Election Integrity Beliefs

We first predict post-treatment general election integrity belief using linear regression, with a treatment dummy as the predictor and a control for pre-treatment general election integrity belief. Doing so finds a large and statistically significant treatment effect, both among the N = 463 participants who were initially distrusting (i.e., whose belief was below the scale midpoint), b = 14.7, SE = 1.52, d = .919, p <.001, and in the full sample, b = 9.58, SE = 1.04, d = .642, p <.001; see Figure 1A. Turning to beliefs about the integrity of the 2020 election, we observe similarly large and significant effects, both among the N = 462 initially skeptical participants, b = 15.19, SE = 1.7, d = .857, p < .001, and in the full sample, b = 10.86, SE = 1.06, d = .712, p <.001; see Figure 1B (for underlying distributions of each effect, see SI 6).

These results are robust to various approaches to addressing attrition (see SI Section 7).

We find little evidence of heterogeneity across participant characteristics: the only consistent moderator was political knowledge, with higher-knowledge participants showing significantly larger treatment effects for both outcomes (*p*s < .002 in individual models including only this moderator; *p*s =< .009 in omnibus models with all potential moderators; see SI Section 8). For all moderators other than political knowledge, we find little evidence of heterogeneous treatment effects.

We also continue to find large and significant effects when subsetting on the *N* = 93 individuals matching the common demographic profile of Republicans (male, white, over the age of 35, holding a bachelor's degree or less, voted for Trump in 2016 and 2020): General integrity, *b* = 12.01, *SE* = 2.66, *d* = .943, *p* <.001; 2020 integrity, *b* = 6.76, *SE* = 2.53, *d* = .558, *p* <.001; and when subsetting on the *N* = 64 individuals who are highly politically engaged and knowledgeable: General integrity, *b* = 13.01, *SE* = 4.08, *d* = .799, *p* =.002; 2020 integrity, *b* = 14.07, *SE* = 4.12, *d* = .86, *p* =.001. For further details, as well as and figures subsetting on these subgroups, see SI Section 8. In sum, rather than being ineffectual or backfiring, our informational treatment has a large positive effect which, among Republicans who initially had low confidence in election integrity, amounts to an increase of close to a full pre-treatment standard deviation.

Figure 1. Both panels depict pre- (x-axis) and post-treatment (y-axis) election integrity beliefs, with higher scores indicating greater confidence in elections. The solid lines represent a linear fit to the data with 95% CIs, while dotted lines impose no linearity and represent a locally weighted regression. Green represents the treatment group, orange the control group. Panel A presents pre- and post-treatment general election integrity beliefs, while Panel B presents pre- and post-treatment beliefs in the integrity of the 2020 general election.

Learning as the Possible Mechanism of Belief Change

Next, we explore the mechanism of our treatment. In particular, we provide correlational evidence consistent with election integrity beliefs changing as a result of gaining factual knowledge from the informational treatment. Specifically, we predict post-treatment values of each electoral integrity belief using randomly assigned condition, the number of post-training knowledge questions the participant answered correctly about their randomly assigned topic, and the interaction of these two predictors, controlling for pre-treatment levels of the outcome. We find a significant interaction when predicting both general integrity beliefs and belief in the integrity of the 2020 election (both *p*s < .001), such that test scores positively predict election integrity beliefs in the treatment ($\boldsymbol{\beta}$ = .243 and $\boldsymbol{\beta}$ = .241, respectively, both *p*s < .001) but not the control ($\boldsymbol{\beta}$ = -.018 and $\boldsymbol{\beta}$ = -.046, respectively, both *p*s > .3). Although the evidence presented in this section is not causal because the extent of individual learning was not randomly assigned, this pattern is consistent with the argument that learning the treatment materials drives changes in electoral integrity beliefs.

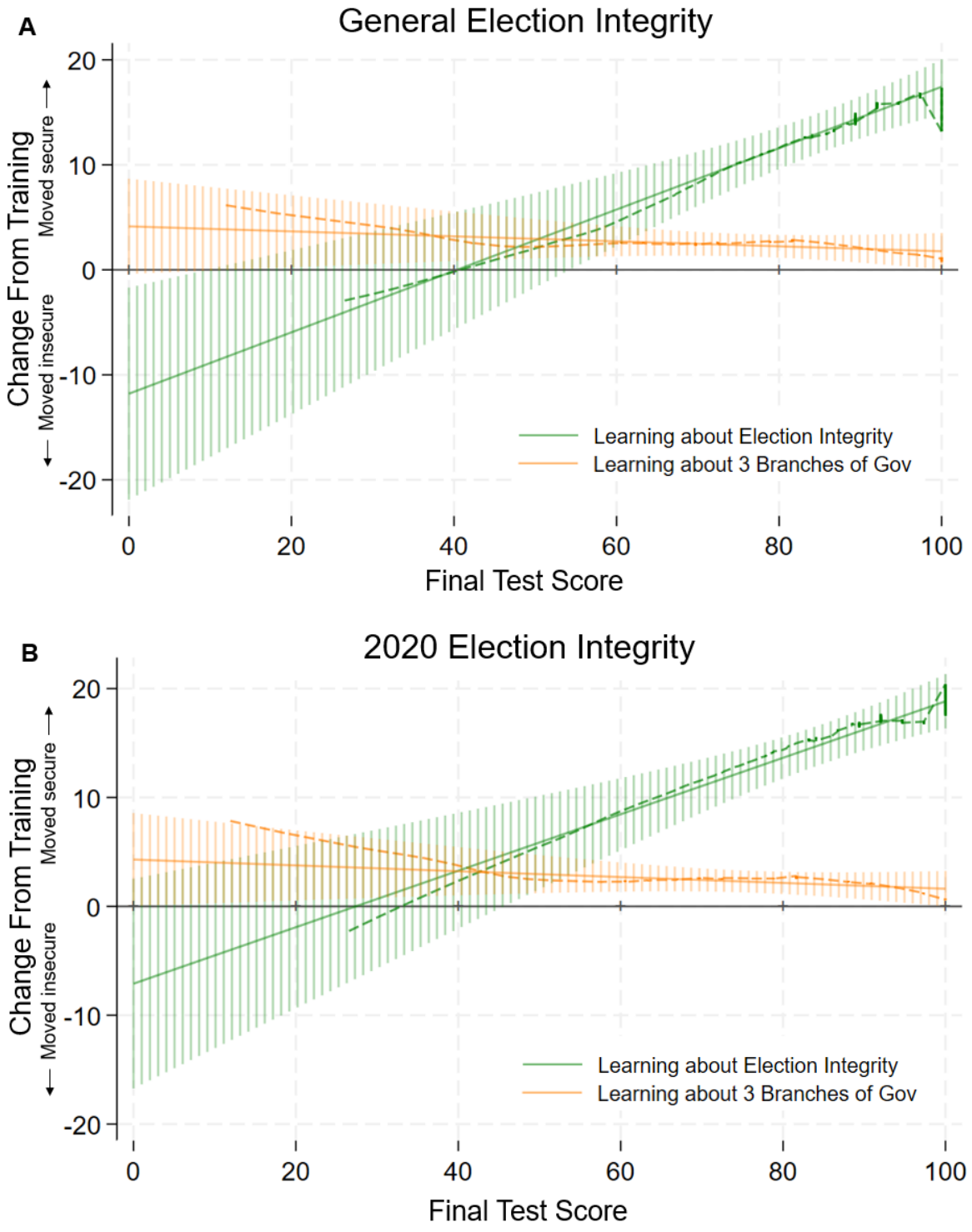


Figure 2. Both panels depict change in outcome (post-treatment minus pre-treatment) on the y-axis, such that scores above zero indicate an increase in election integrity beliefs, and scores below zero indicate a decrease in election integrity beliefs. On the x-axis, final test scores on the knowledge quiz (from the end of the learning phase) are plotted, with higher scores indicating more correct answers (indicating greater learning). The solid lines represent a linear fit to the data with 95% CIs, while dotted lines impose no linearity and represent a locally weighted regression. Green represents the treatment group, orange the control group. Panel A presents effects on general election integrity beliefs, while Panel B presents effects on beliefs in the integrity of the 2020 general election.

Treatment Effects on Expectations about the 2024 Election

In addition to the two primary outcomes discussed above, we also estimated the effects of our informational treatment on participants' perceptions of the expected integrity of the upcoming (at the time) 2024 election. These perceptions were only measured post-treatment and are, therefore, presented separately. We used two items asking participants to predict the integrity of the 2024 election, which were combined into a composite (α = .855). These items, which were asked after the main outcomes, provide further insight into the impact of our treatment on election integrity beliefs. The 2024 election was never directly discussed in the training material, which allows us to assess whether the treatment's impact on election integrity beliefs generalizes beyond the specific elections discussed in the materials. The two items related to the 2024 election are also unique in that they are prospective in nature, whereas all content in the treatment (and in all previous outcomes) discussed contemporary and retrospective content. Hence, these items provide insight into whether the content participants have learned informs not only their perceptions of what happened in previous elections or how well the electoral system generally works, but also their prediction of future outcomes.

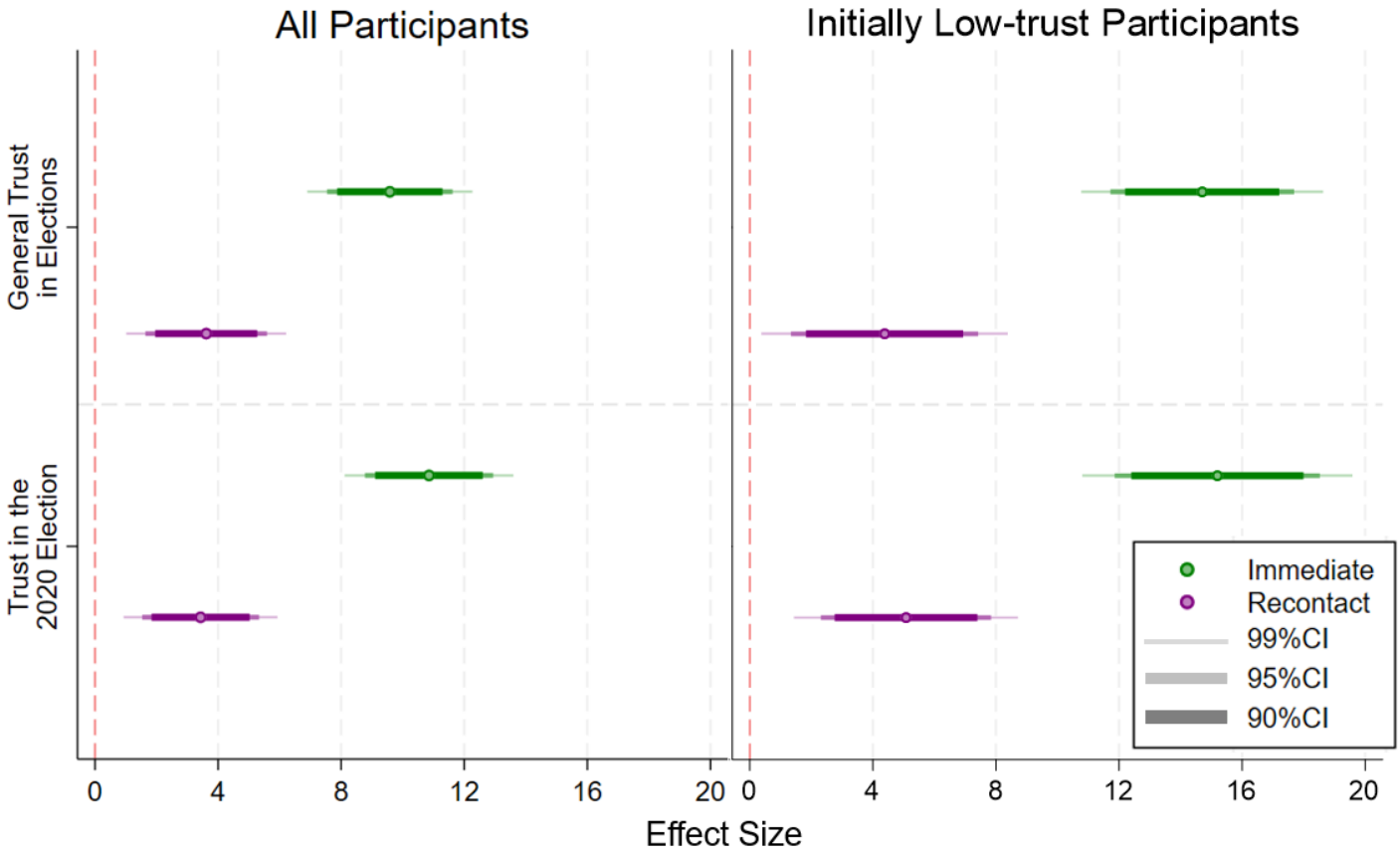
To estimate the treatment effects on these prospective beliefs, we run an OLS regression predicting the 2024 election integrity composite, with randomly assigned condition as the predictor. As we have no pre-treatment measurement of this outcome, we control for the other pre-treatment integrity items used above to get some indication of individuals' pre-treatment concerns about electoral integrity. Here, we again observe substantial treatment effects (b = 8.47, SE = 1.19, p <.001, d = .513; for results by individual item, see SI Section 3). This analysis suggests that our informational treatment not only shapes participants' perceptions of past elections or elections in an abstract sense but also their expectations of future elections – even highly contentious ones such as the 2024 general election.

Durability of Effects

Two weeks after the initial collection – and, critically, after Donald Trump's victory in the 2024 election – we re-contacted all participants and asked them to again complete the outcome measures. Beyond a simple test of durability, this follow-up allows us to examine how real-world political events influence electoral integrity beliefs. Donald Trump's victory in the 2024 election potentially shifted Republicans' election integrity beliefs, creating an environment where the control condition might show increased faith in elections – a pattern that would work against us finding durable treatment effects. Depending on the outcome, between 692 and 695 participants provided answers to this follow-up survey. This yields a retention rate of 88.9%-89.3% of those who completed the initial study. For any individual who did not return for the second collection, we imputed their trust scores as being equal to their wave 1 pre-treatment scores (i.e., we assume that any treatment effect completely decayed

among participants who did not return for the follow-up).[1] Importantly, the conclusions reported in this section hold when, instead of the imputation approach just described, we analyze the data only from participants who completed the follow-up (see SI Section 5).

Using general election integrity as the outcome and randomly assigned condition as the predictor, while controlling for pre-treatment general integrity scores, we first look at the subsample who started below the scale midpoint of confidence and observe a significant effect roughly a third to half the size of the original (b = 4.47, SE = 1.58, d = .272, p = .005), with similar results for the full sample (b = 3.615, SE = 1.01, d = .29, p < .001). When examining effects on beliefs about the integrity of the 2020 election, we see a similar effect, both among those starting lower on this outcome (b = 5.07, SE = 1.46, d = .338, p = .001), and in the full sample (b = 3.43, SE = .97, d = .242, p < .001).[2]



[1] Pre-treatment scores on all outcomes did not differ between those who returned for the follow-up and those who did not (all ps > .353). Further, subsetting on the experimental group showed the same for all outcomes (all ps > .260). Thus, there is no evidence that the follow-up results are biased by selective attrition.

[2] We do not present follow-up results for beliefs about the 2024 presidential election because the nature of the question changed between waves. In wave 1, which was conducted before Election Day, the question was prospective (asking about expectations for the upcoming election). In wave 2, conducted after the election, the question asked about the election that had just taken place. Since the nature of the question changed fundamentally, testing for effect duration would not be meaningful.

Figure 3. The coefficient plot shows treatment effects in wave 1 (immediate effects; in green) and wave 2 (follow-up results; in purple). The left panel shows treatment effects for the full sample, whereas the right panel shows the treatment effect for those who started below the scale midpoint in trust. The treatment effects here are raw coefficients from the full 0-100 aggregate scale for each outcome (general election integrity on top and 2020 election integrity on bottom). These estimates include the imputation of pre-treatment scores for individuals who did not return at either timepoint. CIs represent three levels: 99% (thin lines), 95% (medium lines), 90% (thick lines).

Discussion

Here, we have asked whether Republicans' election integrity beliefs, which in recent years have become a core part of this group's political identity, are responsive to corrective factual information. To test this question, we exposed participants to a high volume of information on election integrity. The corrective information aimed to be accurate and politically balanced: it debunked major claims about election fraud made by both Republicans and Democrats, and used non-partisan, publicly verifiable evidence to do so. We observe large increases in Republicans' general confidence in election integrity, retrospective confidence in the integrity of the 2020 election, and prospective confidence in the integrity of the 2024 election. Across outcomes, the treatment effects are substantial. Participants in the treatment condition increased their confidence in election integrity by 14% to 17%, on average, compared to their pre-treatment levels; and among those who were initially skeptical (i.e., below the scale midpoint), confidence increased by 35% to 43%, on average. Comparing the treatment and control conditions revealed large treatment effects ($.6 < d < .8$).

When recontacting participants about two weeks later – following the 2024 election – these treatment effects were still observable: those who had engaged with information about US elections in the days before the 2024 election continued to express greater confidence in election integrity compared to their pre-treatment confidence levels, and the increase in confidence remained larger in the experimental group compared to the control group. As discussed above, since our treatment and control groups experienced the same procedure, instructions, and incentives to learn, we can attribute the difference in electoral confidence between groups to the impact of informational content. Notably, we observe a slight positive shift in the control group's election integrity beliefs between time points. This suggests that engagement with the learning task may modestly influence attitudes even without election-specific content, and may reflect some degree of experimental demand. However, since individuals in both conditions experienced the same procedures, incentives, and learning structure, any demand to express greater confidence in elections should have affected both groups similarly. Since our estimates rely on comparisons between the treatment and control conditions, this design accounts for potential demand effects, suggesting that the observed treatment effect reflects the impact of election-specific corrective information.

From a theoretical perspective, the findings reported here advance our understanding of political belief updating. By demonstrating that exposure to factual information about election integrity can substantially and durably shift Republicans'

attitudes in the direction of evidence, our results advance recent work showing that factual content can shape people's beliefs on contentious, identity salient issues (Lin et al., 2025; Hackenburg et al., 2025), challenging classic assumptions about how individuals process and incorporate counter-attitudinal political content. The direction, magnitude, and durability of these effects suggest that individuals are receptive to information-based belief updating, even in the context of highly contentious topics and core beliefs where partisan identities are strongly activated (e.g., confidence in the outcome of the 2020 election). Our results support an emerging theoretical framework that views individuals not necessarily as "blind partisans" who automatically dismiss counter-attitudinal information, but as capable of meaningful belief revision. Importantly, this does not suggest that people are never biased or that partisan-motivated reasoning is irrelevant. However, it suggests that, given credible information and appropriate incentives, people's beliefs can be meaningfully directed toward the best available evidence.

Equally important to advancing theory, our findings broaden understanding of the dynamics of electoral confidence in the United States. Democracy depends crucially on citizens' willingness to accept credible electoral results, both when they are winning and losing (Levitsky & Ziblatt, 2018). At a time when many Americans report that they do not trust the integrity of the electoral process and question the legitimacy of specific election results, our work provides insight into the factors driving these beliefs. First, public discourse following the 2020 election attributed the refusal of many Republicans to accept Biden's win as stemming from motivated reasoning and biased evaluation of the facts. However, our work suggests that these voters were not necessarily acting in an irrational manner; it is equally likely they were simply weighing information from trusted information sources (e.g., Fox News or Donald Trump) as more legitimate that more mainstream sources making the opposite claim. Second, our results point to a need for mainstream sources to invest further into identifying how they can regain the trust of these voters. As shown in previous work (Brady & Kent, 2022), the decline in trust in elections coincides with a broader decline in trust in other institutions, such as the news media. Critically, since our work shows there is receptivity among Republicans to a counter narrative, mainstream news organizations should do more to regain the trust of this group of citizens if they wish to fulfill their role in supporting democracy among this group, too.

Importantly, recent developments indicate that challenges to electoral confidence are not limited to one party. In the wake of the 2024 election, while Republican trust in electoral integrity has increased, Democratic trust has *decreased* (AP-NORC Center for Public Affairs Research, 2025). This suggests that troubling trends may emerge on both sides of the partisan aisle. Although the present study focused exclusively on Republicans, our findings illuminate the broader dynamics through which citizens evaluate claims about elections and how willing they are to update their election integrity beliefs in response to corrective information.

While our treatment does not claim to offer an immediate scalable solution to the problem of low electoral confidence, our results suggest that accurate and balanced information can move such beliefs in the direction of evidence. Critically, the fact that the treatment effects are largest among participants with initially low electoral confidence, while having little effect on those who already trust elections, suggests that an information-based approach can effectively address electoral distrust by targeting the individuals most in need of corrective information while causing no backlash among those who already hold accurate beliefs.

Future work should examine whether evidence-based approaches are equally influential among Democrats and Independents, particularly in contexts where their preferred candidates face electoral defeats. Furthermore, the intensive nature of our treatment, which required sustained participant engagement and the use of monetary incentives, raises questions about scalability and real-world implementation. In this context, we acknowledge the possibility that our study may have attracted participants who are more receptive to new information than the average Republican voter. Future research should explore ways to deliver evidence-based interventions at scale while minimizing resource requirements, for example, on social media or through interpersonal communication, and look for ways to encourage individuals who are typically less engaged to participate.

In sum, we provide evidence that Republicans' confidence in election integrity can be substantially and durably increased through exposure to accurate information. That participants in our study updated their beliefs in the direction of evidence challenges the view that partisan-motivated reasoning renders individuals unresponsive to counter-attitudinal political information. Studies of electoral trust – and political attitude formation more broadly – should consider the potential of factual information to move even deeply held political beliefs in the direction the evidence supports.

Methods

Sample

To evaluate the effects of factual information on people's election integrity beliefs, we recruited participants from *CloudResearch Connect*'s panel, which uses quota matching to approximate aspects of the US population. Note that our sample (N = 1,134) is of participants who identified as conservative and Republican, and thus is not fully representative of the US population. The study was conducted between 1–4 of November 2024, in the final days before Election Day in the US. N = 263 individuals were excluded from the study after revealing they were actually not conservative or Republican, were not paying attention, were trying to take the study for the second time, or indicated they did not wish to take part in a lengthy study. All exclusions were done before random assignment to condition. Among those N = 871 remaining, 35 attrited at some point in the study, 58 chose to exit early but provided their outcomes

for an intent-to-treat analysis, and 778 individuals completed the full study (see SI Section 7 for full information on attrition).

Procedure

At the beginning of the study, all participants completed a consent form, answered several questions informing them of the length and effort required in this study, and were informed of the compensation they could expect upon completion (the average compensation was $8.85). Participants were explicitly informed that a significant portion of their compensation would be based on how well they had learned the material presented to them. Next, participants answered several questions that measured their socio-demographic background and attitudes and were informed about different aspects of the task, including what features they could use to better learn about their topic.

At this stage, participants were randomized to one of two conditions (as elaborated below), informed of the topic they were assigned to learn about (elections or government), and answered questions measuring their pre-treatment electoral integrity beliefs. Since the control condition learned about the three branches of government, we measured pre-treatment election attitudes alongside other political items in a way that combined several topics. We did this so the items made sense for those learning about elections (in the treatment condition) and those learning about government (in the control condition). After completing the pre-treatment measures, participants proceeded to their training session.

Participants were randomly assigned to one of two conditions. Those in the experimental group learned about election integrity in the US, and those in the control group learned about the three branches of government. We intentionally used a political control condition (i.e., general civic information) rather than a non-political placebo. Since both conditions involve learning about democratic institutions and both use the same incentives and structure, if the learning procedure elicits demand effects, they should be similar across conditions. In both conditions, participants received an informational treatment based on the paradigm used in Stagnaro & Amsalem (2025), where individuals are exposed to a series of modules that break down the topic into multiple easy-to-learn subsections. Participants were first introduced to the broad topic and the major issues associated with it. Then, they learned in depth about key questions and concerns related to the issue. In the election integrity condition, several specific claims made by the political left and right surrounding electoral integrity in the 2016 and 2020 general elections were addressed in detail. Participants engaged across multiple modules with a high volume of factual information that is accurate and politically balanced, and were incentivized to pay attention to and learn that information. The result is a high-volume, high-engagement treatment that offers a particularly strong test of evidence-based belief updating.

The election integrity modules were designed to be balanced and unbiased. We achieved this by presenting and debunking prominent claims made by both

Republicans and Democrats using detailed, non-partisan, and publicly verifiable evidence. False claims made by Republicans (e.g., that fake votes cost Donald Trump the 2020 election) and by Democrats (e.g., that the Trump campaign coordinated with Russian officials to alter vote tallies in the 2016 election) were each addressed directly. This approach ensured that the content did not advocate for a partisan position but instead provided a comprehensive review of factual evidence relating to the integrity of US elections.

During the training, participants had several features available to help them better learn their assigned content. These features included a highlighting feature, a note-taking feature, and an AI assistant designed to answer participants' follow-up questions if they had any (see Figure 4 for an example of a treatment module). Moreover, at the end of each module, participants were asked several multiple-choice questions about the material covered in that module. If participants answered correctly on the first try, they would earn an additional small bonus. If they did not get the quiz question correct on the first try, they were prompted again and unable to proceed until they had provided the correct answer. Example content of the learning modules and example quiz items can be found in SI Sections 9 and 10, respectively.

Figure 4. Example of a module participants in the treatment condition engaged with. Modules have pictographs, text describing the content that can be highlighted and categorized, hyperlink citations, spaces for taking notes, and an AI assistant that can help them better understand the material.

After finishing the training, participants took a final test that assessed their overall learning of the content covered in their condition. For the full wording of the 11 items that participants in the treatment condition (on election integrity) were tested on, see SI Section 12. After completing the final test, participants were asked again to answer the main election integrity items and answered two additional prospective items that focused on the upcoming election (for the full wording of all election integrity items, see SI Section 1).

Critically, participants only received bonuses for correctly answering the factual learning quizzes and final test. These monetary incentives were tied solely to factual accuracy, not to participants' beliefs, as the electoral confidence questions were presented as a separate component of the study and were explicitly presented as not incentivized. Critically, the treatment and control groups experienced the same procedure, instructions, and incentives. Since the only difference between conditions was the informational content (election integrity vs. the three branches of government), we can attribute any post-treatment difference in electoral confidence to informational content rather than task-related demands.

Finally, before concluding, participants were asked to share their experience with the study. Specifically, they were asked about their perceptions of the information they learned, which learning tools they used and what they thought of them, their overall experience, and any additional thoughts they had about the study. Many participants were highly positive about the study and the content presented (see SI Section 13).

Measures

General Election Integrity. To assess participants' overall perceptions of election integrity in the US, we created a composite measure combining four items via percent-of-maximum-possible scores (α = .867). Three items measured people's perceived frequency of illegal voting practices: "How often do you think these illegal practices occur in US general elections?" (a) People who are not US citizens voting, (b) Casting a ballot more than once, and (c) Voters pretending to be someone else (1 = *It almost never occurs*, 4 = *It is very common*). In the fourth item, participants rated their perception of overall election security: "When thinking about elections in the US overall, how secure and reliable would you say they are?" (0 = *Not at all secure*, 100 = *Very secure*).

2020 Election Integrity. Beliefs about the legitimacy of the 2020 presidential election were measured using seven items (α = .963). Two items used 7-point Likert scales (1 = *Strongly agree*, 7 = *Strongly disagree*): "If it wasn't for Democrats' interference in ballot counts and voting machines, Joe Biden would not have won in 2020" and "Because of mass misinformation and confusion, driven by Democratic interference, Joe Biden illegitimately won the 2020 election."

Two other items employed 7-point scales with different anchors: “When thinking about the 2020 election, how accurately did the result reflect the actual ballots that were cast?” (1 = *The outcome was completely accurate*, 7 = *The outcome was completely inaccurate*) and “When thinking about the 2020 election, to what extent was the result influenced by outside interference and manipulation?” (1 = *The process was completely secure*, 7 = *The process was completely insecure*).

Two additional items used 5-point scales: “The 2020 presidential election was the result of voter fraud” and “The 2020 presidential election was held in a free and fair manner” (1 = *Definitely Not*, 5 = *Definitely Yes*).

A final item had participants rate their perception of the likelihood that fraud changed the 2020 election outcome: “How likely do you think it is that fraud (e.g. voter fraud, rigging, tally manipulation) changed the outcome of the 2020 US Presidential election?” (0 = *No – Definitely false*, 100 = *Yes – Definitely true*).

2024 Election Integrity. Prospective beliefs about the expected integrity of the upcoming 2024 election were assessed using two items (α = .855): “How likely do you think it is that fraud (e.g. voter fraud, rigging, tally manipulation) will change the outcome of the 2024 US Presidential election?” (1 = *Definitely false*, 7 = *Definitely true*); and “To what extent do you agree with the following statement? Votes will be counted fairly in the upcoming 2024 Presidential elections” (1 = *Definitely Not*, 5 = *Definitely Yes*).

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Supplemental Information for "Accurate Information Can Substantially and Durably Increase Republicans' Beliefs in Election Integrity"

SI Section 1: Full Election Integrity Items

1. When thinking about elections in the U.S. overall, how secure and reliable would you say they are?
0 (Not at all secure) - 50 (Moderately secure) - 100 (Very secure)

2. How likely do you think it is that fraud (e.g. voter fraud, rigging, tally manipulation) changed the outcome of the 2020 U.S. Presidential election?
0) No-Definitely false - 100) Yes-Definitely true
(REVERSED)

3. How often do you think these illegal practices occur in U.S. general elections?:
(a) People who are not U.S. citizens voting?
(b) Casting a ballot more than once?
(c) Voters pretending to be someone else?
1) It almost never occurs, 2) It occurs infrequently, 3) It occurs occasionally, 4) It is very common
(REVERSED)

4. How much do you agree with the following statement:
If it wasn't for Democrats' interference in ballot counts and voting machines, Joe Biden would <u>not</u> have won in 2020.
1) Strongly agree
2) Somewhat agree
3) Slightly agree
4) Unsure/ don't know
5) Slightly disagree
6) Somewhat disagree
7) Strongly disagree (REVERSED)

5. How much do you agree with the following statement:
Because of mass misinformation and confusion, driven by Democratic interference, Joe Biden <u>illegitimately</u> won the 2020 election.
1) Strongly agree
2) Somewhat agree
3) Slightly agree
4) Unsure/ don't know
5) Slightly disagree
6) Somewhat disagree
7) Strongly disagree (REVERSED)

6. When thinking about the 2020 election, how accurately did the result reflect the actual ballots that were cast?
The outcome was completely accurate
The outcome was mostly accurate
The outcome was somewhat accurate
It's unclear if the outcome was accurate
The outcome was somewhat inaccurate
The outcome was mostly inaccurate
The outcome was completely inaccurate

7. When thinking about the 2020 election, to what extent was the result influenced by outside interference and manipulation?
The process was completely secure
The process was mostly secure
The process was somewhat secure
It's unclear if the process was secure
The process was somewhat insecure
The process was mostly insecure
The process was completely insecure

8. To what extent do you agree with the following statements? The 2020 presidential election was the result of voter fraud.
Definitely Not Probably Not Not sure Probably Yes Definitely Yes (REVERSED)

9. To what extent do you agree with the following statements? The 2020 presidential election was held in a free and fair manner.
Definitely Not Probably Not Not sure Probably Yes Definitely Yes

10. How likely do you think it is that fraud (e.g. voter fraud, rigging, tally manipulation) will change the outcome of the 2024 US Presidential election?
Definitely false Probably false Possibly false Uncertain Possibly true Probably true Definitely true (REVERSED)

11. To what extent do you agree with the following statement? Votes will be counted fairly in the upcoming 2024 Presidential elections
Definitely Not Probably Not Not sure Probably Yes Definitely Yes

SI Section 2: Correlation Matrix of Election Integrity Items

SI Table 2. Correlation between all pre-treatment items. Black text represents items in the 2020 integrity aggregate, while blue items represent items in the overall integrity aggregate.

	1	2	3	4	5	6	7	8	9	10	11
When thinking about elections in the U.S. overall, how secure and reliable would say they are? 0-100	1										
How likely do you think it is that fraud (e.g. voter fraud, rigging, tally manipulation) changed the outcome of the 2020 U.S. Presidential election? 0-100 (REVERSED)	0.6264	1									
How often do you think: People voting who are not U.S. citizens? 1-4 (REVERSED)	0.4943	0.5974	1								
How often do you think: Casting a ballot more than once? 1-4 (REVERSED)	0.5054	0.5681	0.7176	1							
How often do you think: Voters pretending to be someone else? 1-4 (REVERSED)	0.5125	0.5891	0.6795	0.7779	1						
How much do you agree with the following statement: If it wasn't for Democrats' interference in ballot counts and voting machines, Joe Biden would not have won in 2020. 1-7 (REVERSED)	0.611	0.8601	0.5956	0.582	0.5966	1					
How much do you agree with the following statement: Because of mass misinformation and confusion, driven by Democratic interference, Joe Biden illegitimately won the 2020 election. 1-7 (REVERSED)	0.5437	0.7549	0.5137	0.4988	0.4986	0.8394	1				
When thinking about the 2020 election, how accurately did the result reflect the actual ballots that were cast? 1-7	0.6397	0.8063	0.5682	0.5474	0.565	0.8277	0.7375	1			
When thinking about the 2020 election, to what extent was the result influenced by outside interference and manipulation? 1-7 (REVERSED)	0.6457	0.7649	0.5813	0.5666	0.576	0.8037	0.7423	0.847	1		
To what extent do you agree with the following statements? The 2020 presidential election was the result of voter fraud. 1-5 (REVERSED)	0.6124	0.9093	0.5571	0.5209	0.5713	0.8464	0.7485	0.7958	0.751	1	
To what extent do you agree with the following statements? The 2020 presidential election was held in a free and fair manner. 1-5	0.6445	0.8111	0.5468	0.5044	0.5476	0.7685	0.6965	0.7568	0.7348	0.8172	1

SI Section 3: Treatment Effects by Individual Item

Item 1 – Overall security of elections

Looking specifically at the single item *"When thinking about elections in the U.S. overall, how secure and reliable would you say they are?" (0 - Not at all secure – 100 - Very secure)*, we conduct a linear regression, using the single item collected post-treatment as the outcome, the dichotomous condition variable as the predictor, and controlling for the same single item pre-treatment. As with the aggregate results in the main text, we see a substantial and significant effect, b = .086, SE = .01, d = .606, p < .001.

Item 2 – Different forms of fraud changed 2020

Looking specifically at the single item "*How likely do you think it is that fraud (e.g. voter fraud, rigging, tally manipulation) changed the outcome of the 2020 US Presidential election?" (0 - No - Definitely false – 100 - Yes - Definitely true)* (reversed), we conduct a linear regression, using the single item collected post-treatment as the outcome, the dichotomous condition variable as the predictor, and controlling for the same single item pre-treatment. As with the aggregate results in the main text, we see a substantial and significant effect, b = .13, SE = .014, d = .705, p < .001.

Item 3a – Three kinds of illegal voting (a)

Looking specifically at the single item "*How often do you think these illegal practices occur in U.S. general elections? People who are not U.S. citizens voting" (1 - It almost never occurs – 4 - It is very common)* (reversed), we conduct a linear regression, using the single item collected post-treatment as the outcome, the dichotomous condition variable as the predictor, and controlling for the same single item pre-treatment. As with the aggregate results in the main text, we see a substantial and significant effect, b = .114, SE = .015, d = .533, p < .001.

Item 3b – Three kinds of illegal voting (b)

Looking specifically at the single item "*How often do you think these illegal practices occur in U.S. general elections? Casting a ballot more than once" (1 - It almost never occurs – 4 - It is very common)* (reversed), we conduct a linear regression, using the single item collected post-treatment as the outcome, the dichotomous condition variable as the predictor, and controlling for the same single item pre-treatment. As with the aggregate results in the main text, we see a substantial and significant effect, b = .1, SE = .015, d = .486, p < .001.

Item 3c – Three kinds of illegal voting (c)

Looking specifically at the single item "*How often do you think these illegal practices occur in U.S. general elections? Voters pretending to be someone else" (1 - It almost never occurs – 4 - It is very common)* (reversed), we conduct a linear

regression, using the single item collected post-treatment as the outcome, the dichotomous condition variable as the predictor, and controlling for the same single item pre-treatment. As with the aggregate results in the main text, we see a substantial and significant effect, b = .108, SE = .015, d = .505, p < .001.

Item 4 – Democrats interfered with 2020 election

Looking specifically at the single item "*How much do you agree with the following statement: If it wasn't for Democrats' interference in ballot counts and voting machines, Joe Biden would not have won in 2020" (1 - Strongly agree – 7 - Strongly disagree)*, we conduct a linear regression, using the single item collected post-treatment as the outcome, the dichotomous condition variable as the predictor, and controlling for the same single item pre-treatment. As with the aggregate results in the main text, we see a substantial and significant effect, b = .092, SE = .014, d = .47, p < .001.

Item 5 – Mass misinformation by Democrats in 2020

Looking specifically at the single item "*How much do you agree with the following statement: Because of mass misinformation and confusion, driven by Democratic interference, Joe Biden illegitimately won the 2020 election" (1 - Strongly agree – 7 - Strongly disagree)*, we conduct a linear regression, using the single item collected post-treatment as the outcome, the dichotomous condition variable as the predictor, and controlling for the same single item pre-treatment. As with the aggregate results in the main text, we see a substantial and significant effect, b = .1, SE = .017, d = .417, p < .001.

Item 6 – Accuracy of 2020 ballot count

Looking specifically at the single item "*When thinking about the 2020 election, how accurately did the result reflect the actual ballots that were cast?" (1 - The outcome was completely accurate – 7 - The outcome was completely inaccurate)* (reversed), we conduct a linear regression, using the single item collected post-treatment as the outcome, the dichotomous condition variable as the predictor, and controlling for the same single item pre-treatment. As with the aggregate results in the main text, we see a substantial and significant effect, b = .124, SE = .02, d = .59, p < .001.

Item 7 – 2020 results influenced by interference

Looking specifically at the single item "*When thinking about the 2020 election, to what extent was the result influenced by outside interference and manipulation?" (1 - The process was completely secure – 7 - The process was completely insecure)* (reversed), we conduct a linear regression, using the single item collected post-treatment as the outcome, the dichotomous condition variable as the predictor, and controlling for the same single item pre-treatment. As with the aggregate results in the

main text, we see a substantial and significant effect, b = .129, SE = .014, d = .658, p < .001.

Item 8 – 2020 results affected by voter fraud

Looking specifically at the single item "*To what extent do you agree with the following statements? The 2020 presidential election was the result of voter fraud" (1 - Definitely Not – 5 - Definitely Yes)* (reversed), we conduct a linear regression, using the single item collected post-treatment as the outcome, the dichotomous condition variable as the predictor, and controlling for the same single item pre-treatment. As with the aggregate results in the main text, we see a substantial and significant effect, b = .143, SE = .016, d = .652, p < .001.

Item 9 – 2020 election was free and fair

Looking specifically at the single item "*To what extent do you agree with the following statements? The 2020 presidential election was held in a free and fair manner" (1 - Definitely Not – 5 - Definitely Yes)*, we conduct a linear regression, using the single item collected post-treatment as the outcome, the dichotomous condition variable as the predictor, and controlling for the same single item pre-treatment. As with the aggregate results in the main text, we see a substantial and significant effect, b = .135, SE = .017, d = .588, p < .001.

Item 10 – Will fraud change the 2024 election outcome

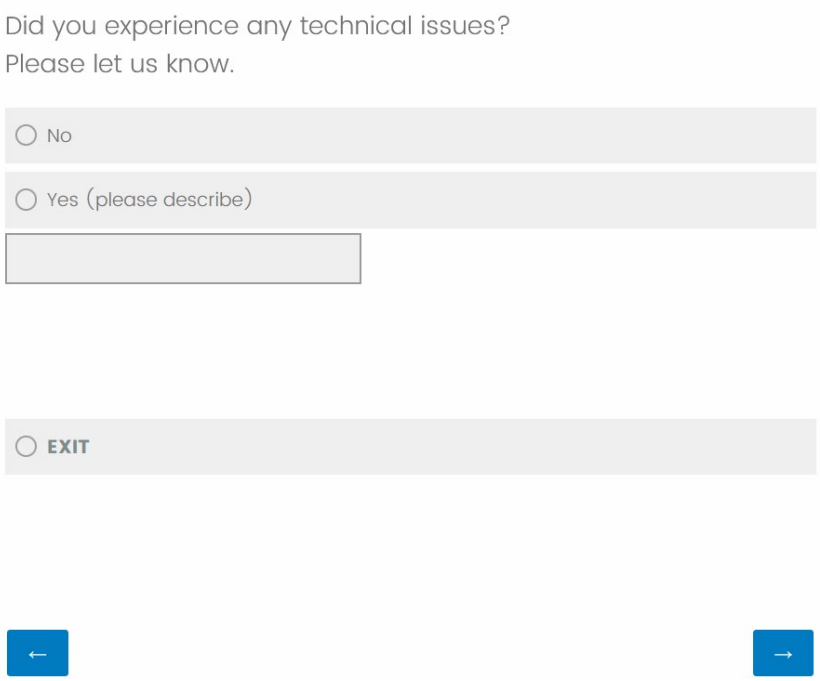
Looking specifically at the single item "*How likely do you think it is that fraud (e.g. voter fraud, rigging, tally manipulation) will change the outcome of the 2024 US Presidential election?" (1 - Definitely false – 7 - Definitely true)* (reversed), we conduct a linear regression, using the single item collected post-treatment as the outcome and the dichotomous condition variable as the predictor; here, since the 2024 items were only collected post-treatment, we do not control for them. Note that in the main text, we control for the pre-treatment aggregates from the other measures; here, however, we use the simplest model with no controls. As with the aggregate results in the main text, we see a substantial and significant effect, b = .056, SE = .02, d = .204, p = .005.

Item 11 – Will votes be counted fairly in 2024 election

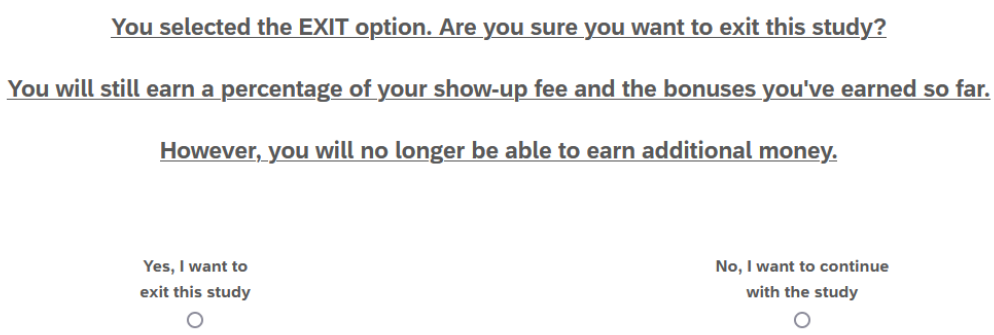
Looking specifically at the single item "*To what extent do you agree with the following statement? Votes will be counted fairly in the upcoming 2024 Presidential elections" (1 - Definitely not – 5 - Definitely yes),* we conduct a linear regression, using the single item collected post-treatment as the outcome and the dichotomous condition variable as the predictor; here, too, since the 2024 items were only collected post-treatment, we do not control for them. Note that in the main text, we control for the pre-treatment aggregates from the other measures; here, however, we use the simplest model with no controls. As with the aggregate results in the main paper, we see a substantial and significant effect, b = .077, SE = .019, d = .294, p < .001.

SI Section 4: Opt-out Mechanism for Intent-to-Treat Model

As a way to help preserve internal validity and protect against high rates of attrition, we implemented a design feature used in previous work (Stagnaro & Amsalem, 2025). This involved providing participants with the opportunity to exit the study at any point in the training if they no longer wished to continue. In such an event, the participant would find the "exit" option at the end of a given module.



They would confirm they actually wanted to exit, then advance out.



At this point, the participants would have left the study and would no longer be able to continue. Participants would then answer the main outcomes and the study would conclude. The answers provided after this point are included in all intent-to-treat

(ITT) models. In all ITT models reported in the main text, we insert these opt-out values for the standard outcome values participants who finished provided.

SI Section 5: Results among Compliers Only

Here, we look at the complier-only models, which do not take into account those who left the study post-randomization. First, we predict post-treatment general election integrity belief using linear regression, with a treatment dummy as the predictor and a control for pre-treatment general election integrity belief. Doing so finds a large and statistically significant treatment effect, both among the $N = 415$ participants who were initially distrusting (i.e., whose belief was below the scale midpoint), $b = 15.79$, $SE = 1.58$, $d = .982$, $p < .001$, and in the full sample ($N = 778$), $b = 10.3$, $SE = 1.08$, $d = .687$, $p < .001$.

Second, turning to beliefs about the integrity of the 2020 election, we observe similarly large and significant effects, both among the $N = 408$ initially skeptical participants, $b = 17.41$, $SE = 1.7$, $d = 1.023$, $p < .001$, and in the full sample ($N = 778$), $b = 12.29$, $SE = 1.06$, $d = .832$, $p < .001$.

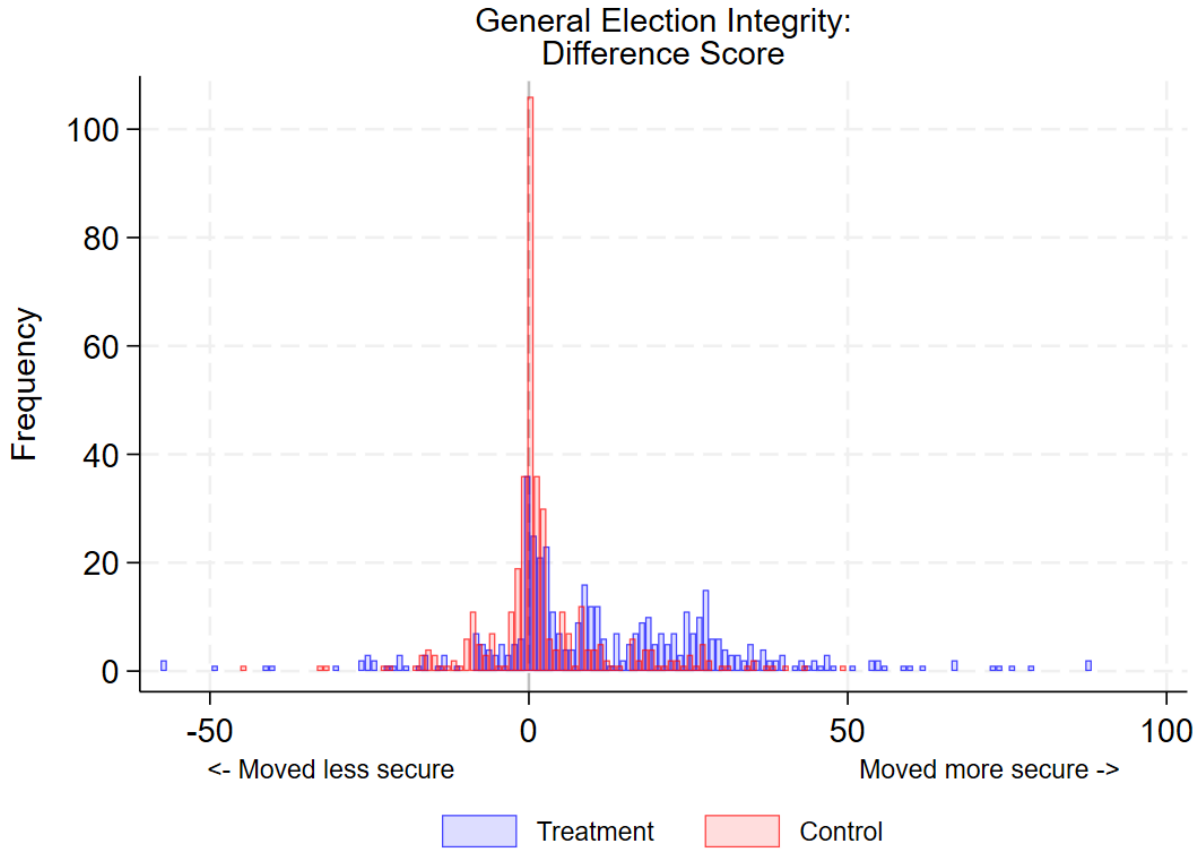
Third, examining treatment effects on prospective beliefs regarding the upcoming 2024 election, we predict the 2024 election integrity composite with a treatment dummy as the predictor. As in the main text, since we have no pre-treatment measure for this outcome, we control for the other pre-treatment composites to give us some signal of individuals' pre-treatment concerns on electoral integrity. Here, we again observe substantial treatment effects, $b = .092$, $SE = .012$, $d = .563$, $p < .001$.

Finally, when re-estimating the follow-up results with no imputation but focusing instead only on the individuals who returned, we find a sizable effect persists for general integrity, $b = 10.30$, $SE = 1.07$, $p < .001$, $d = .687$ for the full sample, and an even larger effect for those who started below the midpoint, $b = 16.3$, $SE = 1.6$, $p < .001$, $d = 1.02$. Looking at 2020 trust, we again see that a large effect persists, $b = 12.29$, $SE = 1.06$, $p < .001$, $d = .832$ for the full sample, and again an even larger effect for those who started below the midpoint, $b = 17.12$, $SE = 1.76$, $p < .001$, $d = .996$. Thus, we see clear persistence of all of our effects when subsetting only on compliers.

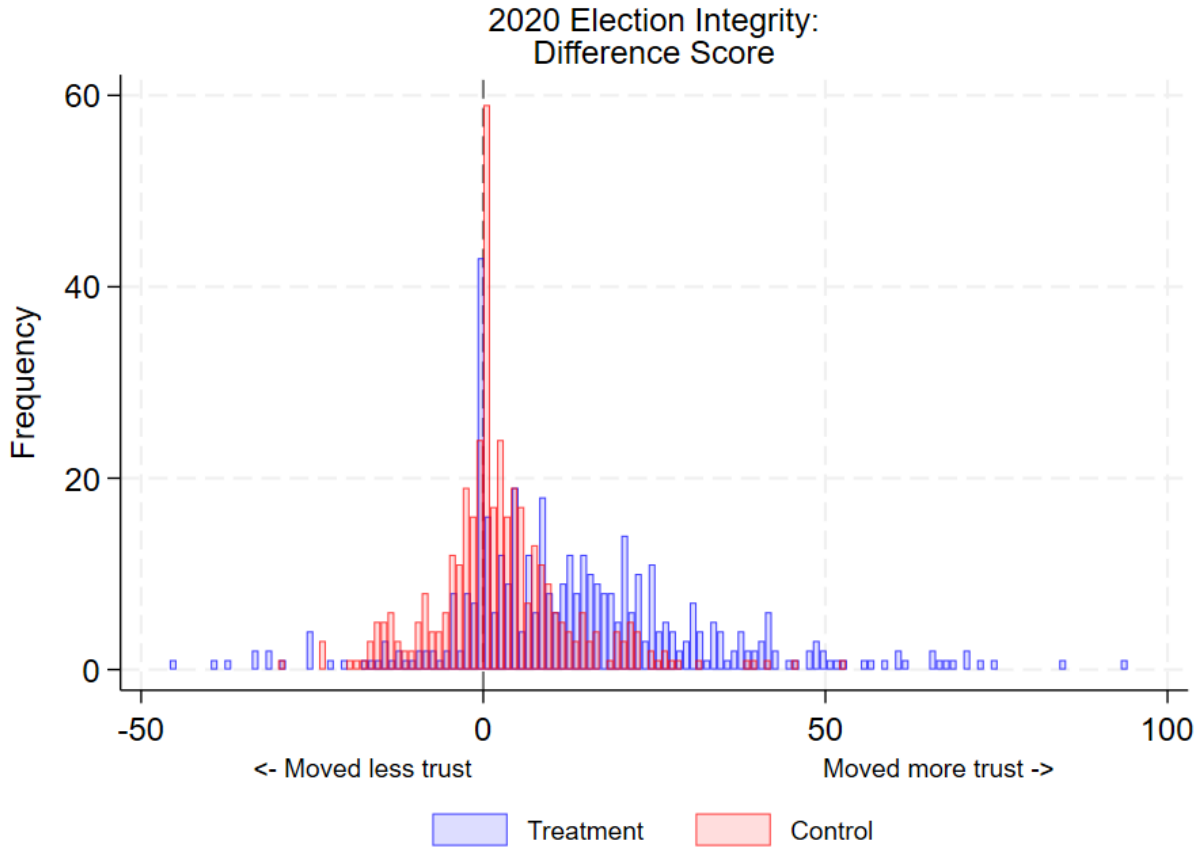
SI Section 6: Depictions of the Underlying Distributions of the Effects

In the main manuscript, our primary findings (i.e., the effect of the treatment on election integrity beliefs) is depicted using linear fit, lowes lines and 95% CIs. Here, we present the main findings using underlying distributions to provide a better sense of the effect. We first compare the difference score (post scores minus pre scores)

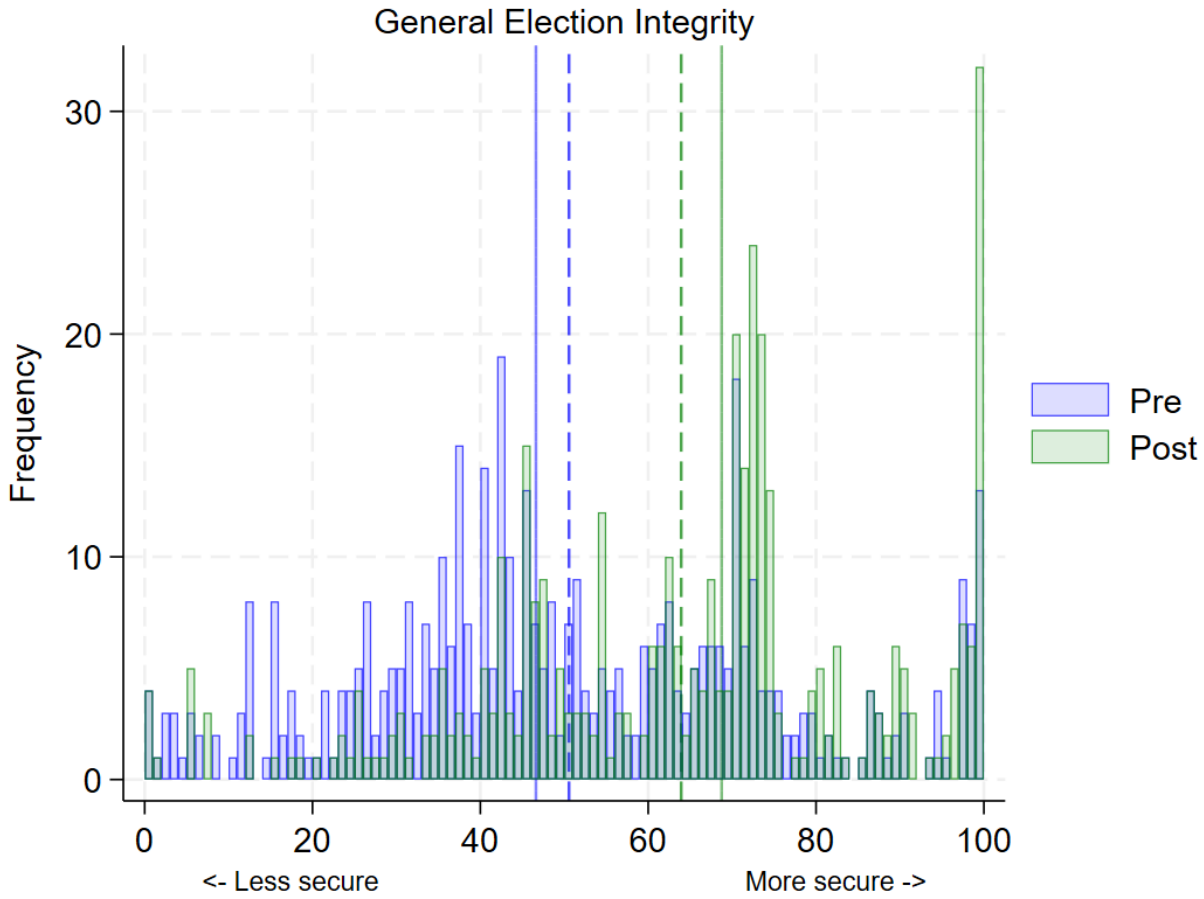
between conditions (SI Figures 6-1 & 6-2) and then focus on the pre scores compared to the post scores in the treatment arm only (SI Figures 6-3 & 6-4).



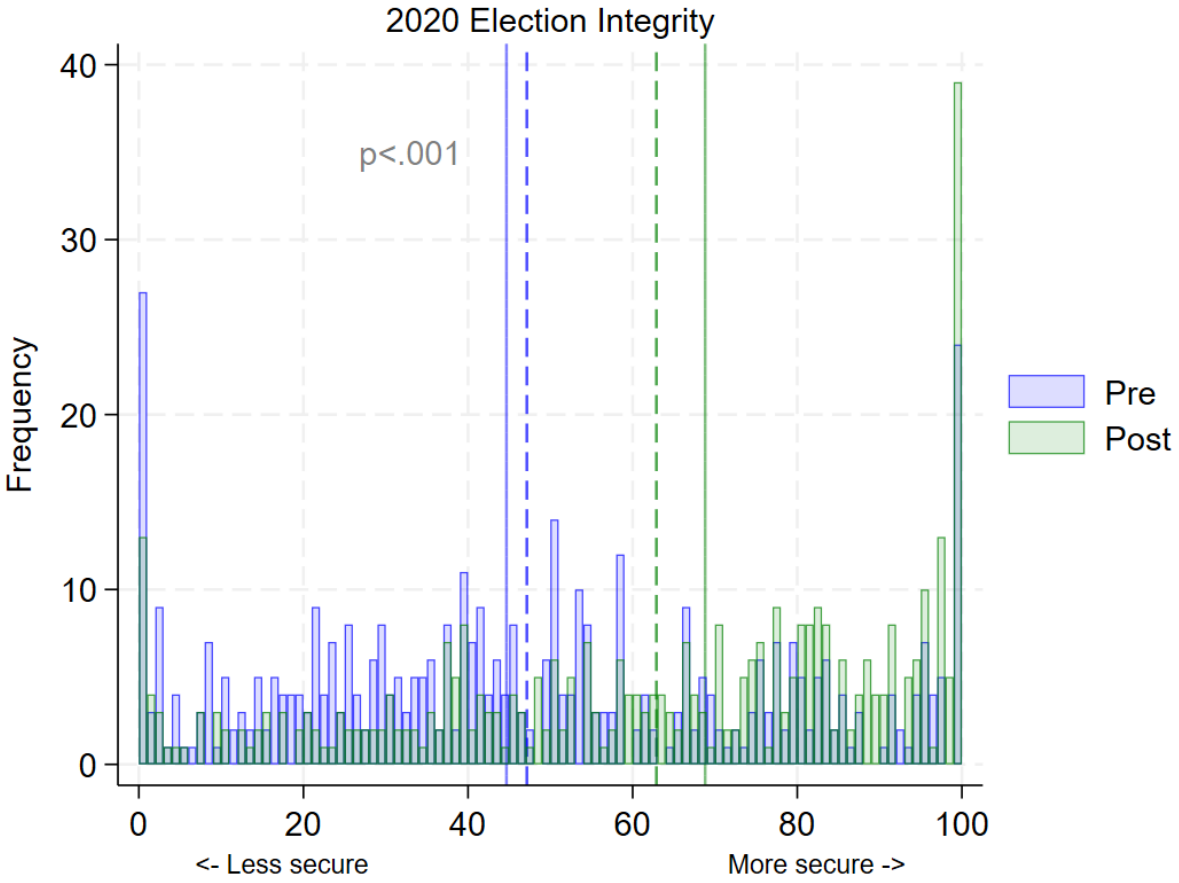
SI Figure 6-1. Histogram representing difference scores (post minus pre) of the general electoral belief aggregate for those in the treatment group (blue) and those in the control group (red). Scores further to the left indicate changes in the less secure direction. Scores to the right indicate changes in the more secure direction. The dotted line indicates the zero mark representing no change.



SI Figure 6-2. Histogram representing difference scores (post minus pre) of the 2020 electoral belief aggregate for those in the treatment group (blue) and those in the control group (red). Scores further to the left indicate changes in the less secure direction. Scores to the right indicate changes in the more secure direction. The dotted line indicates the zero mark representing no change.



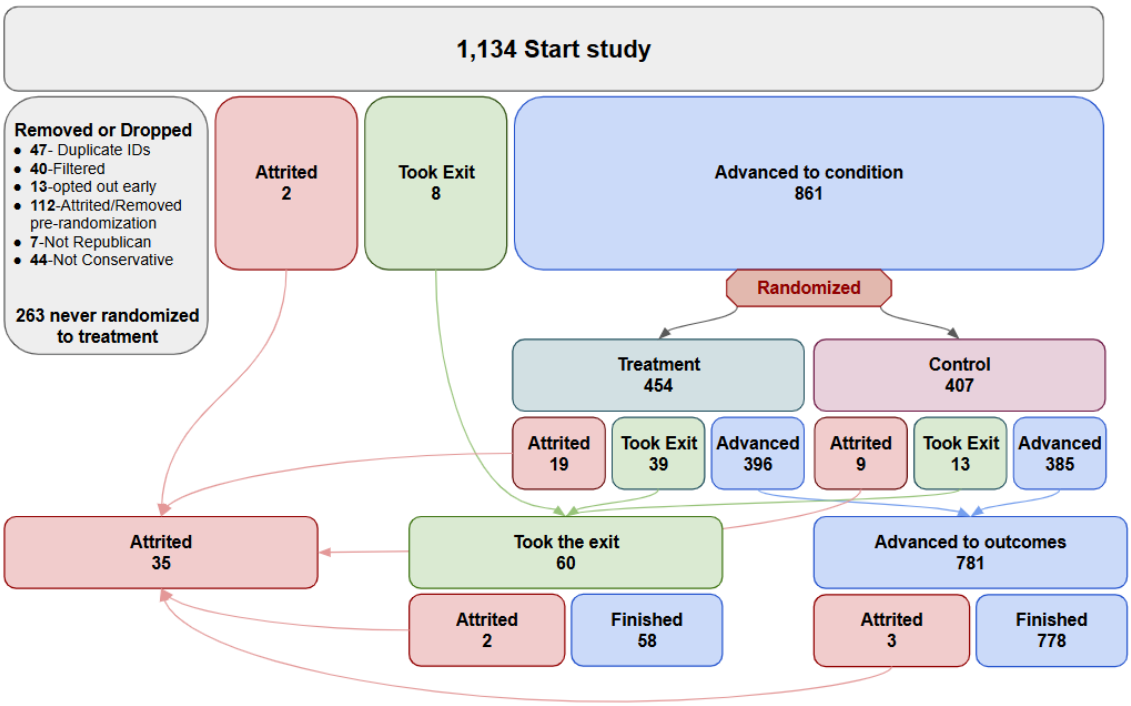
SI Figure 6-3. Histogram representing the pre-distribution (blue) and post-distribution (green) of general electoral belief, specifically within the treatment group. Scores further to the left indicate being less secure in elections overall. Scores to the right indicate being more secure in elections overall. The dotted lines indicate means for both distributions, with solid lines indicating the median.



SI Figure 6-4. Histogram representing the pre-distribution (blue) and post-distribution (green) of 2020 electoral belief, specifically within the treatment group. Scores further to the left indicate being less secure in elections overall. Scores to the right indicate being more secure in elections overall. The dotted lines indicate means for both distributions, with solid lines indicating the median.

SI Section 7: Attrition

SI Section 7a: Attrition by Stage



SI Figure 7a-1. This figure shows how retention, opting out via the exit, and full attrition occurred at each step of the study, as well as the numbers removed due to different screeners pre-treatment.

SI Section 7b: Robustness Models Addressing Attrition

We first test if the experimental paradigm produced differential attrition. We see that of the n = 35 individuals that fully attrited from the study, 22 dropped out of the treatment condition, while 13 dropped out of the control condition. This was a significant difference (t = 7.58, p < .001). Below, we use Manski bounds to test the "worst case scenario" range and see if our results still hold.

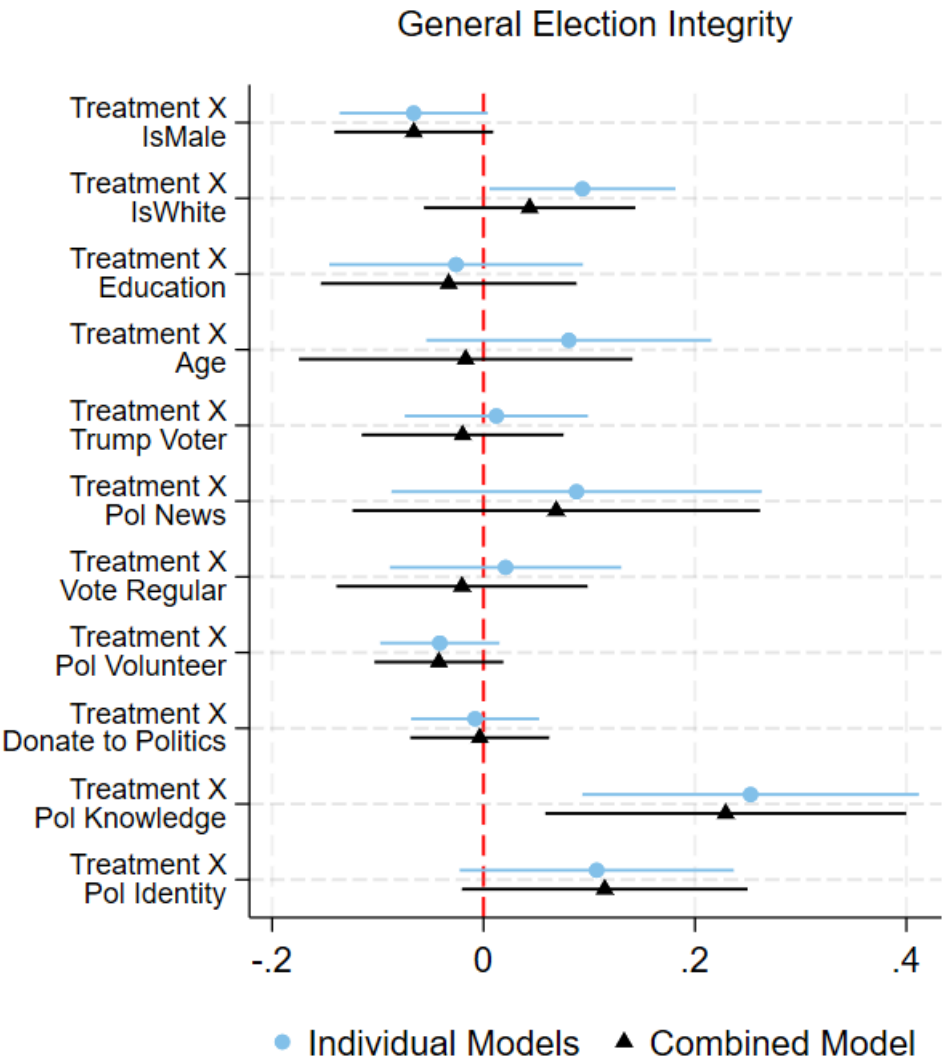
The Manski "worst case scenario" approach gives all missing observations in the treatment group the lowest score, and all missing observations in the control the highest score. With this highly punitive bounding approach, we still see clear effects for general election integrity among initially skeptical participants (b = 14.7, SE = 1.52, d = .919, p < .001), as well as in the full sample (b = 5.59, SE = 1.24, d = .308, p < .001). We see comparable preservation of treatment effects for the 2020 election integrity outcome among initially skeptical participants (b = 10.35, SE = 1.97, d = .493, p < .001), as well as in the full sample (b = 6.61, SE = 1.29, d = .351, p < .001). Lastly, looking at the prospective 2024 outcome, we see that the bounding technique

meaningfully diminishes the effect and renders it non-significant (*b* = .023, *SE* = .014, *d* = .11, *p* = .106).

In sum, even when using the highly punitive Manski bounding technique, we are still able to identify clear treatment effects for two of the three main outcomes. Importantly, the two main results that are still observable, are also still of substantial magnitude.

SI Section 8: Further Robustness Checks

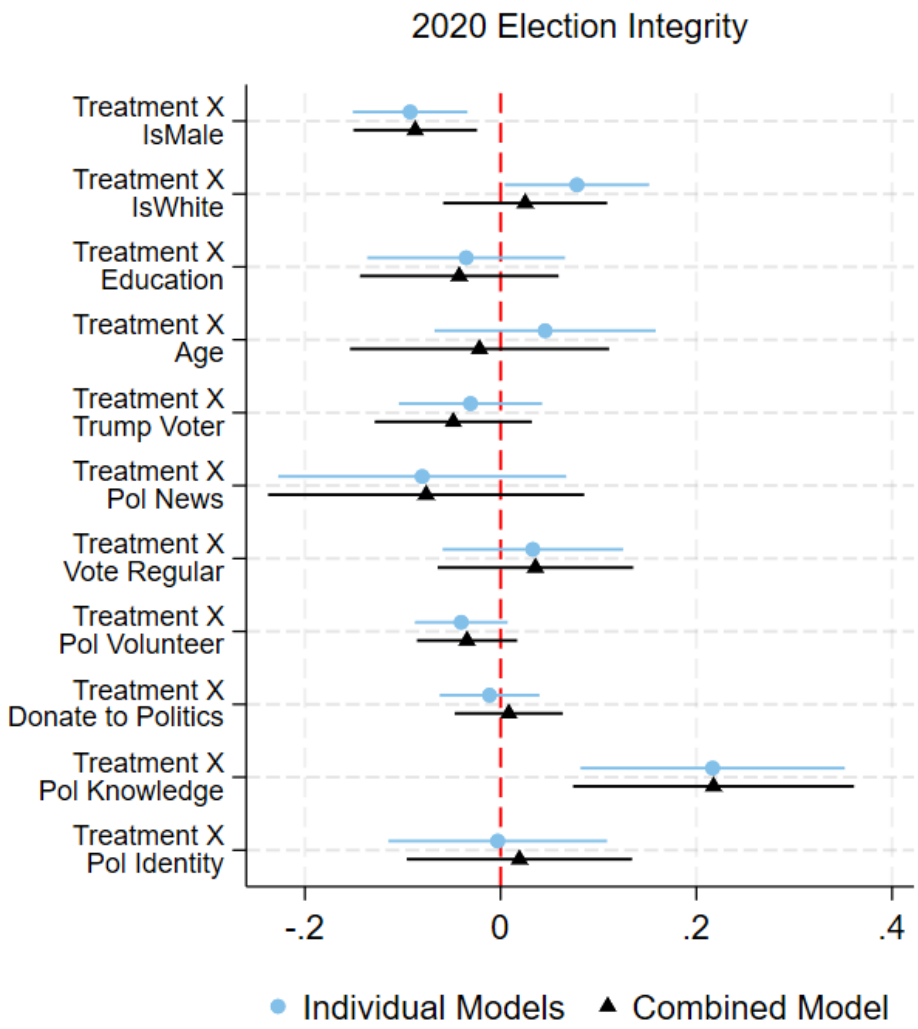
SI Section 8a: Moderation Models



SI Figure 8-1. Standardized interaction coefficients from two models. Light blue coefficients depict individual models predicting the general election integrity outcome using the treatment dummy, the moderator of interest, and their interaction. Black coefficients are all from a single model that predicts the general election integrity outcome using the treatment dummy, all moderators, and all their interaction with the treatment dummy.

Gen Elect Trust I2T	Coefficient	Std. err.	t	P>t	[95% conf	interval]
exp_con	0.158	0.15	1.06	0.288	-0.13	0.45
Gen Elect Trust w1	0.899	0.03	28.87	0.001	0.84	0.96
is Male	0.022	0.03	0.71	0.479	-0.04	0.08
is White	0.017	0.03	0.52	0.602	-0.05	0.08
BA or Less	0.010	0.03	0.31	0.76	-0.05	0.07
Age	-0.028	0.04	-0.77	0.439	-0.10	0.04
Trump Voter	-0.003	0.03	-0.09	0.925	-0.07	0.06
News amount	-0.028	0.03	-0.85	0.393	-0.09	0.04
Vote Regularly	0.011	0.03	0.35	0.725	-0.05	0.07
Volenteer Pol	0.026	0.03	0.84	0.402	-0.03	0.09
Donate Pol	-0.008	0.03	-0.26	0.792	-0.07	0.05
Pol Knowledge	0.011	0.04	0.32	0.75	-0.06	0.08
Pol ID composit	-0.058	0.03	-1.82	0.07	-0.12	0.00
exp_con X is Male	-0.066	0.04	-1.72	0.085	-0.14	0.01
exp_con X is White	0.044	0.05	0.86	0.392	-0.06	0.14
exp_con X BA or Less	-0.033	0.06	-0.54	0.593	-0.15	0.09
exp_con X Age	-0.017	0.08	-0.21	0.834	-0.17	0.14
exp_con X Trump Voting	-0.020	0.05	-0.41	0.684	-0.12	0.08
exp_con X News amount	0.069	0.10	0.7	0.484	-0.12	0.26
exp_con X Vote Regularly	-0.020	0.06	-0.34	0.736	-0.14	0.10
exp_con X Volenteer Pol	-0.042	0.03	-1.36	0.174	-0.10	0.02
exp_con X Donate Pol	-0.004	0.03	-0.11	0.915	-0.07	0.06
exp_con X Pol Knowledge	0.229	0.09	2.63	0.009	0.06	0.40
exp_con X Pol ID composit	0.115	0.07	1.66	0.096	-0.02	0.25
exp_con X Gen Elect Trust w1	-0.302	0.05	-5.53	0.001	-0.41	-0.20
Intercept	0.000	0.02	0.01	0.992	-0.04	0.04
Number of obs	827	R-squared	0.674	Adj R-squared		0.6638
F(25, 801)	66.24	Prob > F	0	Root MSE		0.5784

SI Table 8a1. Shows the full model predicting the general election integrity outcome using the treatment dummy, all moderators, and all their interaction with the treatment dummy.



SI Figure 8-2. Standardized interaction coefficients from two models. Light blue coefficients depict individual models predicting the 2020 election integrity outcome using the treatment dummy, the moderator of interest, and their interaction. Black coefficients are all from a single model that predicts the general election integrity outcome using the treatment dummy, all moderators, and all their interaction with the treatment dummy.

All 2020 Trust I2T	Coefficient	Std. err.	t	P>t	[95% conf.	interval]
exp_con	0.267	0.12	2.19	0.029	0.03	0.51
All 2020 Trust w1	0.944	0.03	35.02	0.001	0.89	1.00
is Male	0.020	0.03	0.74	0.459	-0.03	0.07
is White	0.006	0.03	0.21	0.837	-0.05	0.06
BA or Less	-0.004	0.03	-0.16	0.873	-0.06	0.05
Age	-0.034	0.03	-1.14	0.256	-0.09	0.02
Trump Voter	0.005	0.03	0.19	0.85	-0.05	0.06
News amount	-0.007	0.03	-0.26	0.797	-0.06	0.05
Vote Regularly	0.022	0.03	0.79	0.427	-0.03	0.08
Volenteer Pol	-0.004	0.03	-0.15	0.881	-0.05	0.05
Donate Pol	-0.003	0.03	-0.1	0.923	-0.06	0.05
Pol Knowledge	-0.020	0.03	-0.68	0.497	-0.08	0.04
Pol ID composit	0.007	0.03	0.25	0.801	-0.05	0.06
exp_con X is Male	-0.087	0.03	-2.71	0.007	-0.15	-0.02
exp_con X is White	0.025	0.04	0.59	0.557	-0.06	0.11
exp_con X BA or Less	-0.042	0.05	-0.82	0.414	-0.14	0.06
exp_con X Age	-0.022	0.07	-0.32	0.749	-0.15	0.11
exp_con X Trump Voting	-0.048	0.04	-1.18	0.237	-0.13	0.03
exp_con X News amount	-0.076	0.08	-0.92	0.355	-0.24	0.09
exp_con X Vote Regularly	0.036	0.05	0.7	0.484	-0.06	0.14
exp_con X Volenteer Pol	-0.034	0.03	-1.31	0.189	-0.09	0.02
exp_con X Donate Pol	0.008	0.03	0.3	0.766	-0.05	0.06
exp_con X Pol Knowledge	0.218	0.07	2.98	0.003	0.07	0.36
exp_con X Pol ID composit	0.019	0.06	0.33	0.743	-0.10	0.13
exp_con X All 2020 Trust w1	-0.186	0.04	-4.66	0.001	-0.26	-0.11
Intercept	-0.001	0.02	-0.07	0.943	-0.03	0.03
Number of obs	827	R-squared	0.7721	Adj R-squared		0.765
F(25, 801)	108.58	Prob > F	0	Root MSE		0.48575

SI Table 8a2. Shows the full model predicting the general election integrity outcome using the treatment dummy, all moderators and all their interaction with the treatment dummy.

SI Section 8b: Results among "Prototypical" Republicans

Another concern one could have is with the sample itself. This study used conservative Republicans sampled from *Cloud Connect*'s panel, which uses quota matching to approximate aspects of the U.S. population and has been shown to be more representative than many other participant platforms (Stagnaro et al., 2024). Still, one may be concerned that our treatment was moving less prototypical conservative Republicans. To address this, we subset the sample on observable features to create a sample of more demographically "typical" conservative Republicans (i.e., male, white, over the age of 35, holding a bachelor's degree or less, and reporting voting for Trump in 2016 and 2020). Constraining our analysis to this notably reduced

subsample (*n* = 93) still revealed highly similar treatment effects for all three outcomes (General integrity: *d* = .929, *B* = .422, *p* < .001, 95% *CI* [.23, .61]; 2020 integrity: *d* = .563, *B* = .272, *p* = .008, 95% *CI* [.07, .47]; 2024 integrity: *d* = .317, *B* = .18, *p* = .002, 95% *CI* [.07, .29]). These results demonstrate that our treatment is as effective for the prototypical Republican as it is for our overall conservative Republican sample.

SI Section 8c: Results among Most Engaged Individuals

A final potential concern with the results reported above is that we may not have sampled particularly politically engaged participants, the kind most associated with strongly held political beliefs. To address this, we utilize several variables: the first is an aggregate measure capturing self-reported political participation (voting regularly, donating to political campaigns, and volunteering with political organizations); the second is a proxy for political knowledge, measured pre-treatment (correctly identifying the three branches of government and multiple factors involved in U.S. elections); and the last is a single item of self-reported frequency of political news consumption. Using these items, we run the OLS models above for each outcome, while controlling for these political engagement items, and find that the overall effect sizes and significance levels remain robust (General integrity: *d* = .633, *B* = .3, *p* < .001, 95% *CI* [.24, .37]; 2020 integrity: *d* = .727, *B* = .341, *p* < .001, 95% *CI* [.28, .41]; 2024 integrity: *d* = .568, *B* = .182, *p* < .001, 95% *CI* [.14, .23]). Second, we subset our sample to the individuals who scored above the middle scale value on each of the three variables, then run the main OLS models separately for those below the mid point (n = 770) and those above the mid point (n = 64) on political engagement. We find that, even though the politically engaged group shows larger effect sizes (*ds* between: .82–.99, all *ps* < .001) than the politically unengaged group (*ds* between: .52–.71, all *ps* < .001), the treatment clearly shifts attitudes for both.

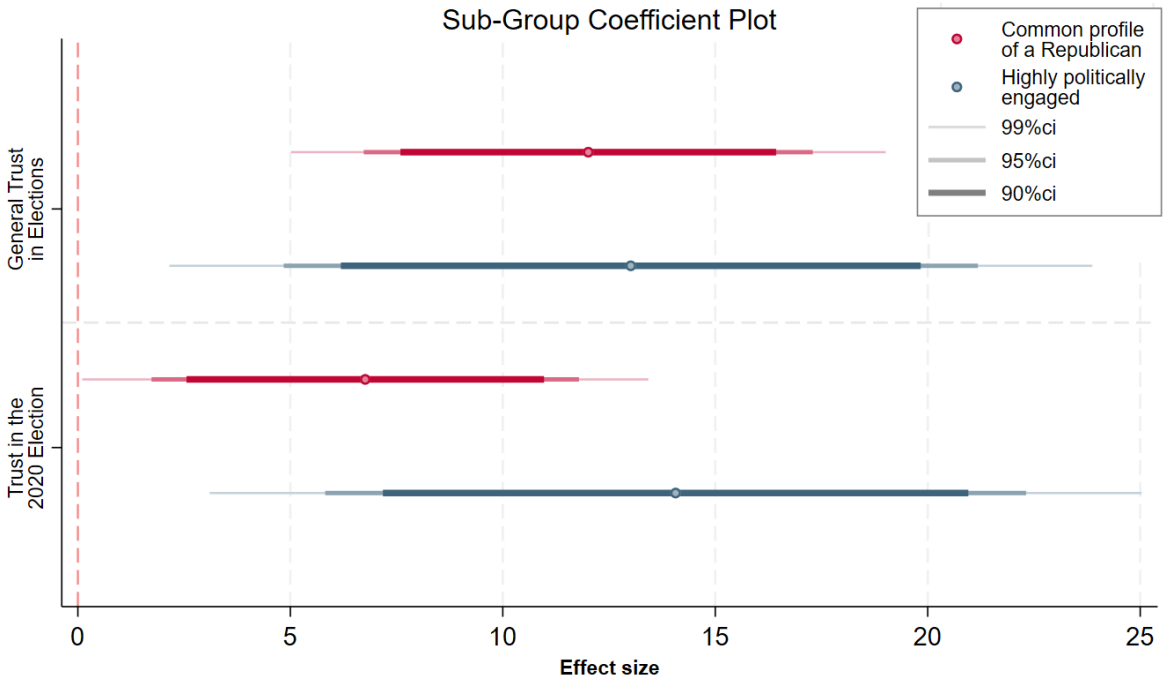
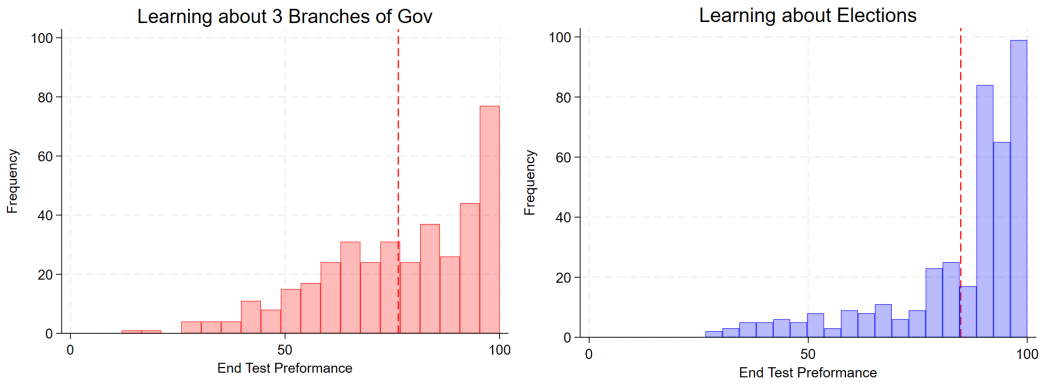


Figure 8-3. The coefficient plot shows treatment effects in wave 1 (immediate effects) subsetting on two different groups of interest. The red coefficients show treatment effects among those of a common Republican profile. gray coefficients are subsetting on highly politically engaged individuals. The top two coefficients are for general trust in elections, while the bottom two are for trust in the 2020 election. The treatment effects here are raw coefficients from the 0-100 aggregate scale for each outcome. CIs represent three levels: 99% (thin lines), 95% (medium lines), 90% (thick lines).

SI Section 9: How Much Did People Learn?

At the end of each informational module, we assessed how well people learned the material presented to them in that module using several multiple-choice questions. We find that knowledge scores are high in both groups. On a 0-100 scale, where 100 represents getting all questions right, the average end score in the control condition is M = 76.38 (SD = 18.5), whereas the average end score in the treatment group is M = 84.82 (SD = 16.5) (see SI Figure 9). These high mean values suggest strong content comprehension across conditions. One potential reason for the higher test scores in the treatment condition may be that our study was conducted right before a general election, which may have motivated people in that condition to learn more about their topic.



SI Figure 9-1. Overall knowledge scores for treatment and control conditions plotted as histograms. Red dotted lines indicate sample mean; *x*-axes represent the percentage of questions individuals answered correctly on the test.

SI Section 10: Training Material Examples

Below are a series of examples taken from a module in the treatment condition on election integrity. This specific module was in the section on the integrity of the 2020 election. It shows an example of the way information was presented, the sort of images that accompanied them, and the tools that were presented to all participants to help them learn.

Learning stage

Current earnings: $0

Foreign interference and the Cyber Symposium

The last claim is of foreign interference. Few made this claim in 2020 but one individual, Mike Lindell of "My Pillow," made a notable show surrounding the notion of foreign interference in the 2020 election.

Lindell claimed foreign hackers from China broke into computer systems of election offices to switch votes from Trump to Biden across the United States. Further, he claimed to have data that proved this interference. To promote these claims, Lindell produced a series of "documentaries" advancing his theories.

Lindell organized a "Cyber Symposium" in August 2021 in Sioux Falls, South Dakota, to present his evidence. Lindell held a challenge called "Prove Mike Wrong." Specifically, he claimed to have 37 terabytes of data proving election hacking, saying he spent millions of dollars to verify this data with unnamed experts and offering a $5 million reward to anyone who could disprove his claims.

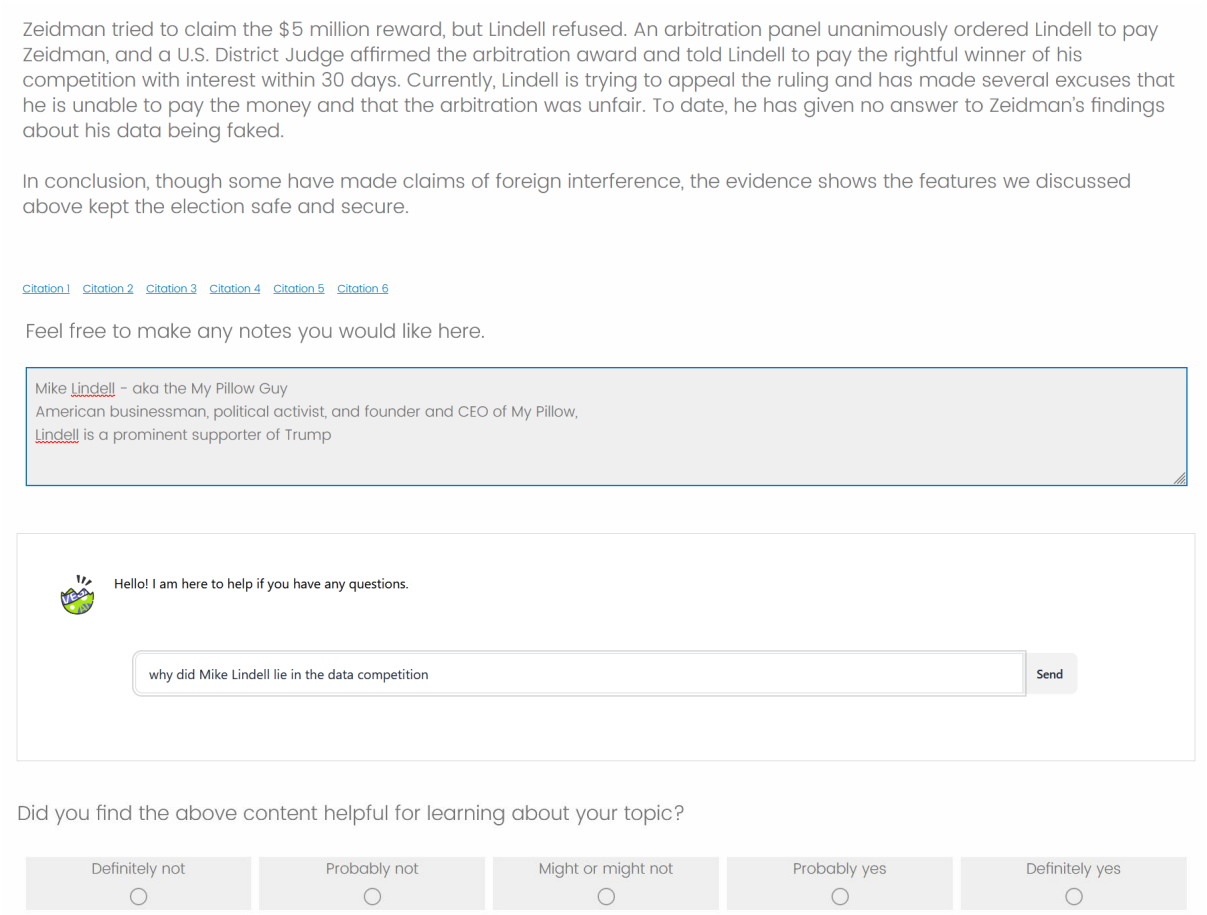
Election officials and poll workers from multiple states and counties stated Lindell's claims made no sense. They noted that their voting machines are not connected to the Internet (a standard cyber security procedure we have discussed earlier). They also noted that paper ballots confirmed the results - ballots that could not be changed remotely by any foreign actor (yet another safeguard we have discussed).

One participant at the "Cyber Symposium" was Robert Zeidman, a software engineer, registered Republican, and twice Trump voter. In an interview, Zeidman said he went into the event hoping Lindell was right. He added that his skills would be used to show the election was hacked.

However, Zeidman ended up successfully debunking Lindell's claims, showing the "data" Lindell claimed as evidence had nothing to do with the 2020 election. The data appeared to be a transformed Word file with a bunch of erratic keystrokes and randomly pasted content. Zeidman speculated someone with basic programming knowledge had combined basic Word data with easy-to-find political content on the web and transformed it in the hopes of making it supposedly unrecognizable.

Note Important Critical

More importantly, Zeidman discovered the files were altered, if not fully created, just before the symposium in August 2021. This made the claim that the files were from the 2020 election implausible.



SI Section 11: Quiz Examples

Throughout the training, the learning modules included a short single item quiz that asked a question that was covered in the preceding module. If participants got this quiz question correct on their first try they earned an additional 10 cents. If they did not get it correct on the first try, they would see an error message and need to try again. Participants would only be able to proceed once they answered correctly.

Below are several examples of quiz items from the treatment condition on election integrity. Asterisk indicates correct answers.

What is an example of a physical security measure used in voting equipment?

1. *Locks with limited key access*
2. *Security personnel*
3. *Surveillance cameras*
4. *All of the above**

How does the structure of the electoral system enhance the security of the presidential election in the U.S.? (select all that apply)

*A) It is a decentralized system making 51 elections**
*B) Swing state focus makes bipartisan oversight very likely in key areas**
*C) It gives one or two powerful individuals oversight over the whole system**
*D) State and local control means people closer to home have oversight**
*E) Diverse voting systems and procedures makes developing attacks much harder**
F) Local volunteers know each other and produce mutual accountability
G) The party in power can have final say if the election was fair or not

What is the main conclusion regarding the effect of Russian interference on the outcome of the 2016 U.S. presidential election?

1. *Russian interference significantly altered the election results, causing Trump to win and costing Clinton the election.*
2. *U.S. intelligence found that Russian interference directly changed vote counts in key states.*
3. *Studies suggest that while Russian interference occurred, it did not have a meaningful effect on votes cast or polling numbers.**
4. *There is no evidence to indicate there was any Russian interference.*

What is most likely true regarding the 2020 election controversies surrounding voting machines, particularly Dominion voting systems?

1. *Electronic voting machines are inherently unreliable, have regular issues and should be replaced with paper ballots.*
2. *Human error can lead to temporary issues, but multiple safeguards exist to ensure detection and corrections.**
3. *Dominion Voting Systems intentionally designed their machines to switch votes between candidates.*
4. *There have never been errors with voting machines and any claim that there has is just political rhetoric.*
5. *All of the above.*

SI Section 12: Full Final Knowledge Test Items

Each participant was informed that they would be taking a test at the end of their training on the topic they learned about. They were explicitly told they would be paid for correct answers as an incentive to learn the material. Below are the 11 items that participants in the treatment condition on election integrity were tested on. Asterisk indicates correct answers.

1) What is the purpose of primaries and caucuses in the United States?

1. *To elect the President directly from that vote.*
2. *To allocate delegates and choose party nominations.**

3. *To select State Senators in Congress.*
4. *To help elect the Senators and Representatives.*

2) Match each election security measure with its description. (1=A, 2=B, 3=C)

1. *Chain of Custody.*
2. *Tamper-Evident Seals.*
3. *Cybersecurity Measures.*

A. *Ensures all election materials are tracked and accounted for by multiple witnesses.*
B. *Provides visual evidence of unauthorized access attempts on voting equipment and materials.*
C. *Safeguards electronic voting systems against hacking and cyber threats.*

3) Which of the following statements is true about electronic voting machines used in U.S. elections?

1. *They are regularly connected to the internet for real-time updates.*
2. *They produce hard copies of electronic events, allowing for audits.**
3. *Their inner workings are never inspected or audited.*
4. *They rely solely on digital records without any physical backups.*

4) Which of the following is a method used to verify the accuracy of electronic voting results?

1. *Conducting audits that compare electronic vote records with paper backups.**
2. *Adding ballots that require you to copy your drivers license and SSN.*
3. *Voting by way of cellphone, where you can vote through an online app.*
4. *Asking people after they vote who they voted for and comparing the totals.*

5) Which of the following are true about the security features of the U.S. election system? (Select all that apply)

1. *They create multiple layers of protection against large-scale fraud.**
2. *They work in conjunction with cybersecurity measures.**
3. *They make it challenging for any single actor to manipulate the overall election outcome.**
4. *They are fully based on AI tools and technology.*

6) Why is large-scale election fraud particularly challenging to execute in swing states?

1. *Swing states have fewer voters, making fraud easier to detect.*
2. *The politically divided local governments ensure shared power and oversight.**
3. *Only one party is allowed to monitor the election process in swing states.*
4. *Swing states do not use the winner-take-all system for allocating electoral votes.*

7) Which of the following are true about public engagement in election security? (Select all that apply)

1. *Poll workers add a layer of transparency by feeling held accountable to the local community.**
2. *Bipartisan public observation allows citizens to witness election processes.**
3. *Having the general public participate in the electoral process builds trust between communities and election officials.**
4. *When people are familiar with the voting community and area they are more likely to identify possible threats.**
5. *Most people who work in elections are government officials flown in to run the local election and meet local people.*
6. *With the push to vote by mail, the general public now have few places to go to vote.*

8) True or False

- *Studies have shown that Russian social media efforts had a significant impact on voter perceptions of Clinton in the 2016 election. (T*/F)*
- *Russian interference in the 2016 election included the successful altering of actual votes cast in the election. (T/F*)*
- *There is clear evidence that due to foreign interference, the outcome of the 2016 election did not reflect the votes cast and ballots counted. (T/F*)*

9) Which of the following statements about Dominion Voting Systems during the 2020 election is true?

1. *Dominion Systems were proven to switch votes intentionally and systematically.*
2. *A small number of human errors with Dominion Systems were detected and corrected.**
3. *There have been widespread and systematic failures with Dominion Voting Systems.*
4. *There are zero reports of Dominion Voting Systems having any kind of error.*

10) Please match the reports to their conclusions on election fraud. (1=B, 2=C, 3=A)

1. *The Steele Dossier.*
2. *Cambridge Analytica.*
3. *Mueller Report.*

A. *Found no evidence of a criminal conspiracy between the Trump campaign and Russia, despite numerous contacts.*
B. *Suggested that Russia had compromising information on Trump, but many claims were unverified or discredited.*
C. *Claimed to influence the election through targeted ads, but evidence of significant impact was lacking.*

11) True or False

- *Rudy Giuliani's claims about election workers in Georgia were proven false and resulted in him admitting to lying in a defamation lawsuit. (T*/F)*
- *Mike Lindell provided credible evidence of foreign interference in the 2020 election at his Cyber Symposium. (T/F*)*
- *Cleta Mitchell's claim that 100,000 voters had been illegally registered in Pennsylvania due to a glitch with driver's license renewal. (T/F*)*
- *Hillary Clinton's claim that Russian collusion with Trump was responsible for falsifying votes and stealing the election. (T/F*)*

Trump's public call for Russia to hack Clinton's emails does not show clear proof of his active collaboration with Russians to steal the election. (T/F)*

SI Section 13: Participants' Reported Experience with Training

Along with measuring learning through test performance, we also asked participants, at the end of the study, to self-report their perceptions of the material. Participants reported, on a 1-7 scale, (a) how informed they thought the content was, (b) how biased they thought it was, and (c) how much they trusted it.

There was no difference in how informed the content in either condition was perceived to be, on average, such that election content (M = 6.07, SD = 1.4) and content about the three branches of government (M = 6.2, SD = 1.31) were both perceived as highly informed (p = .148).

For perceived bias, there was a significant difference between conditions, such that the control content (M = 1.9, SD = 1.26) was perceived, on average, to be less biased compared to the election content (M = 2.61, SD = 1.65; p < .001). However, as the distributions presented in SI Figure 12 show, the bias ratings were quite low among most participants in both conditions, and in both groups, the mean bias score is substantially and statistically significantly below the scale midpoint of 4 (p < .001 for both comparisons).

Lastly, we see a slight difference in trust ratings, such that control content (M = 6.14, SD = 1.4) was trusted slightly more, on average, than election content (M = 5.64, SD = 1.5; p < .001). However, again, looking at the distributions in SI Figure 12, we see that scores were high among most participants in both conditions. And here, too, election content was perceived, on average, as being significantly above the scale midpoint of 4 (p < .001 for both comparisons).

SI Figure 13-1. Distributions of Informed, Biased, and Trust perceptions of the information, with election content depicted in blue and three branches of government content in red. Dotted lines indicate sample mean for the group with corresponding color.

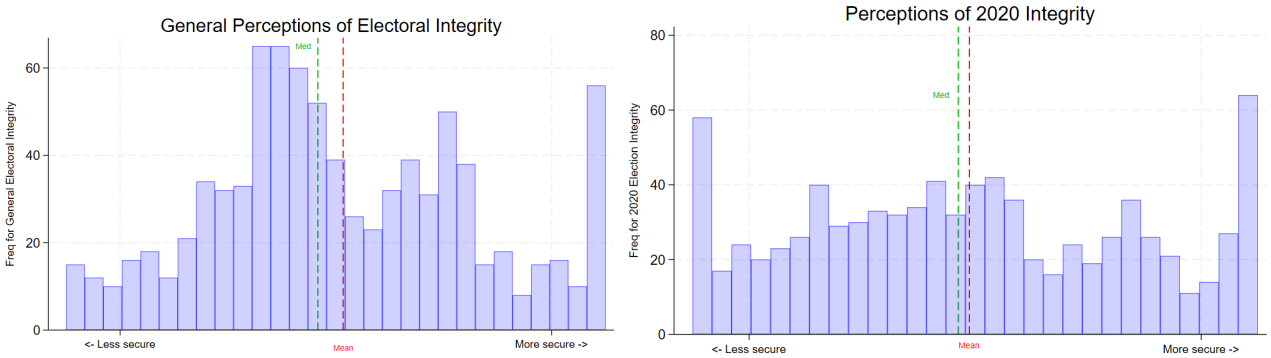
SI Section 14: Breakdown of Tools to Improve Learning

Beyond detailed information, the training provided a number of tools to help participants learn their assigned material. These included:

- Highlighting function that allowed for quick color-coded categorization of text.
- Notepad for quick module-specific notes.
- Hyperlinked citations for all material presented.
- Infographics and accompanying images to help comprehend the text.
- AI tutor to help address any additional questions the participant may have.

SI Section 15: Pre-Treatment Election Integrity Beliefs

Two of our primary outcomes were measured both before and after the treatment: participants' overall perceptions of US election integrity and their specific perceptions of integrity in the 2020 election. Here, we show the pre-treatment distributions of these two composites as a way to provide a sense of how insecure this sample was with elections prior to participating in the study. For both outcomes, the average levels of Republicans' beliefs in election integrity hover around the scale midpoint, and there is considerable variability in people's beliefs (General integrity: M = 51.36, SD = 24.6; 2020 election integrity: M = 48.85, SD = 29.4). Both distributions show a wide range of observed electoral confidence levels, with responses spanning the entire scale (see SI Figure 15-1).



SI Figure 15-1. The histogram to the left shows the distribution of General election integrity beliefs pre-treatment. The histogram to the right shows the distribution of 2020 election integrity beliefs pre-treatment. The red line indicates each group's mean, and the green line indicates the group median. Scores to the right in both plots indicate higher levels of reported integrity.