Expressive Responding and Trump's Big Lie

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May 25, 2023

Forthcoming in *Political Behavior*

Do surveys measure sincere belief in Donald Trump's "big lie" that fraud decided the 2020 election? We apply a comprehensive approach to detecting expressive responding: three honesty encouragements, a list experiment, two opportunities to express related sentiments, and two opportunities to bet on related predictions about the future. We find that nearly all respondents who endorse the big lie appear to genuinely believe it. These "believers" are evenly split between those who confidently accept the big lie and those who find it plausible but are not deeply convinced. Similarly, those who predicted that evidence of fraud would enable Trump to retain power in January 2021 or be reinstated in August 2021 were overwhelmingly sincere. Our findings indicate that Trump's big lie is unique in terms of the size and veracity of belief differences between Democrats and Republicans. We discuss implications for democratic stability.

Word count: 8,938

Keywords: partisanship, beliefs, expressive responding, democracy, experiments

Data availability: Replication materials are available at doi.org/10.7910/DVN/ZO1OAX.

Competing interests: The authors have no relevant financial or non-financial interests to disclose.

Funding: This research was supported by the John S. and James L. Knight Foundation through a grant to the Institute for Data, Democracy & Politics at The George Washington University.

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Former U.S. president Donald Trump's effort to delegitimize or overturn the results of the 2020 presidential election are widely viewed as a threat to American democracy. A core component of this threat is the apparent willingness of Trump's supporters to believe that his election loss was a consequence of fraud. Despite years of telegraphing his intent to dispute the result of any election he lost, surveys suggest that Trump has convinced a sizeable proportion of the American public that Biden's victory was fraudulent (Arceneaux and Truex 2022; Jacobson 2021). In turn, this appears to have constrained the public behavior of Republican elites, many of whom privately acknowledged Biden's victory while continuing to support Trump's claims in public.[1] The myth of a fraudulent election has become so central in contemporary American politics that it has become known as "the big lie."

Given the baseless and predictable nature of Trump's claims, as well as anecdotal evidence of elite dissembling, observers have questioned whether members of the public who endorse the big lie in surveys really believe it.[2] The leading alternative explanation is partisan expressive responding. According to this interpretation, many Trump supporters who endorse the big lie in surveys do not really believe that the election was decided by fraud. Instead, they endorse the big lie in order to convey some other partisan sentiment, such as their general support for Trump.

This paper examines the veracity of measured belief in Trump's big lie. We begin by borrowing three established methods from existing research on expressive responding, none of which yield evidence that respondents who endorse the big lie do not sincerely believe it. First, to address the possibility that respondents may not be sufficiently motivated to reveal their sincere beliefs, we test three encouragements to be honest. Second, to address the

[1] For example, see Jonathan Lemire and Lisa Mascaro, "GOP increasingly accepts Trump's defeat — but not in public," *Associated Press*, November 18, 2020. Randall Chase, "Fox hosts didn't believe 2020 election fraud claims," *Associated Press*, February 16, 2023.

[2] For example, see Emily Badger, "Most Republicans Say They Doubt the Election. How Many Really Mean It?," *The New York Times*, November 30, 2020. Elizabeth Connors, "Do Republicans really believe the election was stolen – or are they just saying that?," *The Washington Post*, December 22, 2020. Musa Al-Gharbi, "No, America is not on the brink of civil war: it's time to tell the truth about the big lie," *The Guardian*, January 27, 2022.

possibility that respondents who endorse the big lie are really trying to express some other sentiment, we test two interventions designed to mitigate "response substitution" (Gal and Rucker 2011; Yair and Huber 2020). Third, to address the possibility that respondents may endorse the big lie to maintain their self-image or comply with group norms, we anonymize responses using a list experiment (Miller 1984; Blair et al. 2020). Across these interventions, we find no evidence of expressive responding. None of our estimates are statistically significant. Among Republicans, the largest estimate is 2.3 percentage points (pp), with three of the six taking the wrong sign.

We next turn to a new approach to financial incentives, *betting on the future*.[3] Relative to honesty encouragement, payment for correct answers has a stronger track record of mitigating expressive responding (Bullock et al. 2015; Prior et al. 2015; Berinsky 2018; Peterson and Iyengar 2021). Yet for the study of partisan controversies and conspiratorial beliefs, it has an important downside: if researchers and respondents do not share a common basis for determining the truth, payments may encourage respondents to say what they believe the researcher thinks is true (Berinsky 2018; Malka and Adelman 2022). We circumvent this by taking advantage of a series of prominent predictions that imminent proof of the big lie would enble Trump to retain or be restored to power. In two such circumstances, we allowed respondents to bet on whether Trump would be president on the predicted date. Both studies suggest that large majorities of those who endorsed the predictions were being sincere. In November 2020, about 80% of Republicans who predicted that Trump would successfully overturn the election result appear to have been sincere. In July 2021, more than 90% of Republicans who predicted that evidence of fraud would lead to Trump's reinstatement were sincere.

Even as our experiments yield limited evidence of expressive responding, they leave open another important sense in which respondents may not "believe" their answers: do these individuals confidently accept the big lie, or is it simply their sincere best guess that

[3] We are aware of one previous study that includes a similar design (Allcott et al. 2020).

the big lie is more likely than not to be true (Kuklinski et al. 2000; Pasek et al. 2015; Graham 2020)? In a supplemental analysis, we find that those who endorse the big lie are split about 50-50 between confident acceptance and uncertain guesses by those who suspect that the big lie is probably true but have not fully accepted it. Those who express confidence are stable over time. This stands in contrast to the high degree of instability that has been observed on many other widely used measures of political misperceptions (Graham 2023*b*). As a point of comparison, we use ANES data to examine Trump's previously most notorious claim of election fraud, that millions of illegal votes were cast in the 2016 presidential election. We find substantially less temporal stability. Relative to other measured misperceptions, the big lie appears to be unique in terms of the veracity with which it is believed.

Our findings validate widespread concern that public belief in Trump's big lie is a threat to American democracy. Relative to earlier research on the magnitude of partisan belief differences and the public's degree of belief in misinformation, the findings suggest that the United States has entered uncharted territory. We elaborate in the concluding section.

Expressive Responding

Survey researchers would usually like to measure their subjects' genuine beliefs. Inconveniently, however, respondents sometimes misrepresent their beliefs: that is, they do not select the response that most accurately reflects their underlying beliefs. We define *partisan expressive responding* as the act of misrepresenting one's belief in a survey in order to convey a partisan sentiment. In this paper, we take a multi-method approach that addresses two different plausible motives for expressive responding: subjects may want to reap the psychological benefits of expressing a partisan sentiment (Bullock et al. 2015; Schaffner and Luks 2018; Malka and Adelman 2022) or avoid the costs, psychological and otherwise, of expressing beliefs that are inconsistent with one's self-image or self-presentation as a partisan (Blair et al. 2020).

Our first and simplest approach is *honesty encouragement.* This approach aims to increase the value that respondents place on revealing their true beliefs, either by heightening the expectation from the survey conductors of an honest survey response and/or by increasing the salience of the norm of truthfulness. We tested three honesty treatments: a pledge and two versions of a request. Requests to respond honestly or accurately have significantly reduced partisan differences in some studies (Prior et al. 2015; Rathje et al. 2023) but not in others (Berinsky 2018; Bullock et al. 2015).

Our second approach tests for *response substitution*, which occurs when respondents answer the question they want to answer rather than the question that was asked. Gal and Rucker (2011) use the example of a restaurant with good food and terrible service. In a one-question survey about the food, one might be tempted to provide a lower rating in order to express disapproval of the service, thereby "substituting" one's rating of the service for the rating of the food. Adding a question about the service would reverse the response substitution effect. Analogous effects have been documented in the study of politics (Yair and Huber 2020; Graham and Coppock 2021; Graham and Yair 2023). For example, partisans tend to say that members of the opposite party are less attractive (Nicholson et al. 2016; cf. Huber and Malhotra 2017). However, when given the chance to rate the potential partner's values, the apparent bias shrinks considerably (Yair and Huber 2020). In both of these examples, response substitution occurs because answering truthfully would prevent respondents from expressing another sentiment that they wish to convey. In our context, we would expect response substitution treatments to work if subjects are using questions about the big lie to express related sentiments. Fahey (2022) finds no evidence that Republicans who endorse the big lie are trying to express that "it would be better for America if Donald Trump were still the president."

Our third approach is a *list experiment*, also known as the item count technique. Rather than ask questions directly, list experiments ask subjects to count the number of statements with which they agree. For some randomly selected subjects, the list omits the belief of interest, in this case belief in the big lie. Comparing the average level of agreement with the two sets of statements allows one to estimate the prevalence of the belief of interest. By breaking the direct link between subjects and their response, list expeirments are thought to shield survey respondents from a number of costs of endorsing socially undesirable beliefs. In terms of the possible sources of sensitivity bias described by Blair, Coppock and Moor (2020, Table 1), we expect list experiments to work because one's position on the big lie is likely to be important to our respondents' self-image and self-presentation as partisans.[4] For example, list experiments have revealed that conservatives in Denmark exaggerate their opposition to progressive taxation (Heide-Jørgensen 2023).

Our fourth and final approach is *financial incentives* in the form of payment for correct answers. Though this is the most common strategy in research on expressive responding, it has an important downside: if respondents believe that they and the researcher do not share a common point of reference for establishing the truth, the incentive will motivate respondents to say what they believe the researcher believes to be true, not what the respondents themselves believe to be true (Berinsky 2018; Malka and Adelman 2022). This concern is especially relevant in the case of politicized controversies in polarized societies, which leave no common authority to appeal to. To circumvent this challenge, we allowed respondents to bet on two concrete predictions about the future that are closely related to belief in the big lie. The first study was conducted in late November 2020, at which time Trump and his allies claimed that soon-to-emerge evidence of fraud would allow them to overturn the election results through the courts. The second was conducted in July 2021, at which time Trump and his allies claimed that evidence of fraud would lead to his restoration to the presidency. We describe the two cases in more detail below.

As we selected our four approaches, we were conscious of three common limitations. First, they provide no information about how confidently respondents hold their beliefs (Kuklinski et al. 2000; Pasek et al. 2015). For example, someone who does not know much about the arguments on either side of the big lie could still make a sincere guess that fraud

[4]For more discussion of list experiments in the context of expressive responding, see Berinsky (2018) and Bullock and Lenz (2019).

probably determined the result. Though there is a sense in which such a respondent "believes" their answer, it is not something they believed independently of the survey. Most measures of political misperceptions appear to capture this sort of belief: respondents who endorse falsehoods generally find them plausible but have not accepted them outright (Graham 2023*b*). Consequently, after determining that our respondents are by and large sincere, we examine their degree of confidence in their beliefs and the temporal stability of their reported confidence.

Second, existing research does not provide much assurance that treatments are strong enough to eliminate all expressive responding. For example, though requests have worked to some extent in some contexts, we later found evidence that they do not fully eliminate expressive responding (Graham and Yair 2023). Similarly, our financial incentives were lotteries with a fairly small probabilities of victory. Though existing evidence suggests that small incentives and lotteries accomplish most of what is accomplished by larger or guaranteed payouts,[5] it is possible that larger payouts would have resulted in larger effects.

Third, there is uncertainty about which strategies should be expected to work. With regard to response substitution, there is no evidence regarding how precisely the "unasked question" needs to be targeted. Is any opportunity to express a partisan sentiment sufficient, or must the researcher choose exactly the sentiment the respondent wanted to express? We adapted to this possibility by fielding two versions of the response substitution treatment. However, if our sense of what our respondents are really trying to say is miscalibrated, our results could reflect a failure to choose the right treatment rather than an absence of expressive responding. List experiments are beset by uncertainty over scope conditions.

[5] Bullock et al. (2015) estimate that the effect of a 10-cent incentive was about three-quarters the size of a $1 incentive. The difference between these conditions is less than one standard error, suggesting that it would not have been statistically significant in a direct test (Table 4). Our reanalysis of Peterson and Iyengar (2022) finds no difference in effects on partisan difference between the high- and low-incentive conditions. DellaVigna and Pope (2018) find that MTurk subjects worked about 5 percent harder for a 4-cent incentive relative to a 1-cent incentive, that there was no difference between a 1-cent incentive and a 50 percent chance of a 2-cent incentive, and that there was only about a 10 percent difference between a 1 cent incentive and a 1% chance of $1 (Figure 3). Graham (2023*a*) finds that 90 percent of MTurk subjects looked up a correct answer for a lower chance of winning smaller amounts than we offered ("Estimating Sensitivity" subsection).

We think Trump's big lie is consistent with conventional wisdom about the nature of the expressive costs that cause sensitivity bias (Blair et al. 2020), but at every stage of this work we encountered a new story about why it is out-of-scope. We think that this lack of consensus stems from the lack of direct evidence regarding the conditions under which list experiments work. Conventional wisdom has been established by extracting principles from cases in which direct question and list experiments differ, not empirical tests that manipulate the factors thought to be at play.[6]

Given the current state of knowledge, we think that the best one can do is select a variety of tools with an established track record of reducing expressive responding in some context. In the long term, gaining a better understanding of these techniques' mechanisms and scope conditions will be a challenging but important task (Graham and Huber 2021).

Data

We conducted five surveys on Amazon Mechanical Turk (MTurk) between November 2020 and August 2022. MTurk is a widely-used convenience sample vendor that tends to produce experimental treatment effects that are close to the general population (Mullinix et al. 2016; Coppock et al. 2018), including in studies specifically related to partisanship (Levendusky 2018; Skytte 2021) and partisan expressive responding (Bullock et al. 2015; Yair and Huber 2020). Table 1 lists the dates, sample size, partisan composition, and interventions included in each survey. Appendix F provides more information about the surveys, including eligibility criteria, randomization procedures, and preregistration documents for Surveys 2-5.

We selected our approaches during the months between Surveys 1 and 2, then fielded Surveys 2-4 in the order that best-suited our logistical and cost constraints. Survey 5 was a replication with modifications based on reader feedback and new evidence that request treatments may be too weak to eliminate expressive responding (Graham and Yair 2023). Consequently, the following sections proceed in an order that we believe makes conceptual

[6] A recent exception is Karpowitz et al. (2023).

Table 1: Survey information.

Survey	Dates	N	Partisanship Dem	Rep	Ind	Interventions
Survey 1	Nov. 28-30, 2020	1049	0	934	115	Betting on the future
Survey 2	May 10-23, 2021	2958	1754	934	270	Response substitution
Survey 3	July 7-31, 2021	4885	2278	2064	543	List experiment, betting on the future
Survey 4	Sep. 22-23, 2021	5005	2972	1739	294	Honesty requests
Survey 5	Aug. 11-12, 2022	4936	2915	1691	330	Honesty pledge
Total		18833	9919	7362	1552	

sense, not the order in which the surveys were conducted.

Honesty Encouragement

We begin by examining three related interventions designed to encourage respondents to report their beliefs honestly and accurately. The first two are requests to be honest. These are closely modelled after the first two studies reported by Berinsky (2018) and are similar to encouragements used by Prior et al. (2015) and Hanmer et al. (2014). The third intervention was a pledge to be honest. Although we are not aware of any existing studies of expressive responding that take this approach, pledges outperform requests as a means of inducing the desired behavior in other contexts (Clifford and Jerit 2016).

The request treatments were implemented in Survey 4. Subjects were randomly assigned to a control condition or to one of the two treatments. The *honesty request* asked respondents to honestly report their true beliefs. Before the question, the following text appeared: "Regardless of how you feel about the people and events mentioned in the question below, we want you to tell us what you believe to be true. Again, we ask that you try and ignore your personal feelings." The *subtle pipeline* treatment endeavors to strengthen this intervention by adding the suggestion that researchers may somehow learn about dishonest responding. Respondents read the text, "We sometimes find that people choose answers that they do not really believe so that they can say something good or bad about the people and events mentioned in the question," followed by the same text as the honesty request.

The pledge treatment was implemented in Survey 5. Subjects were randomly assigned to the treatment or a control condition. Treated subjects were presented with the following:

> The final question is about a different political topic. Regardless of how you feel about the people and events mentioned in the question, we want you to tell us what you believe to be true.
>
> Do you promise to answer the next question honestly?
>
> – Yes, I promise to answer honestly.
> – No.

Control subjects saw only the first sentence.

Following their assigned treatment, subjects advanced to a screen containing the dependent variable: "Do you think that Joe Biden only won the 2020 presidential election due to voter fraud, or would he have won either way?" Responses were recorded on a five-point Likert scale: "Definitely due to voter fraud," "Probably due to voter fraud," "Not sure," "Probably would have won either way," "Definitely would have won either way." We coded this to range from 0 to 1, where 0 means "definitely would have won either way" and 1 means "definitely due to voter fraud."

Results

To estimate the effect of the honesty encouragement treatments on endorsements of the big lie, we use OLS. The regression equation for Study 4 was $Y_i = \alpha + \beta_1 \text{Request}_i + \beta_2 \text{Pipeline}_i + \epsilon_i$; for Study 5, $Y_i = \alpha + \beta_1 \text{Pledge}_i + \epsilon_i$. In both equations, α estimates our subjects' baseline tendency to endorse the big lie and the β terms estimate treatment effects. As we expect expressive pressures to point in different directions depending on the subject's partisanship, we report results separately for Democrats, Republicans, and independents. In keeping with the preregistration, we use one-tailed tests throughout the paper, unless noted otherwise.

We also estimate treatment effects on partisan differences. We do this by subsetting our data to Democrats and Republicans only, then estimating

$$\begin{aligned} Y_i = \alpha + \beta_1 \text{Request treatment}_i + \beta_2 \text{Pipeline treatment}_i + \beta_3 \text{Republican}_i + \\ \beta_4 \text{Republican}_i \times \text{Request treatment}_i + \beta_5 \text{Republican}_i \times \text{Pipeline treatment}_i + \epsilon_i. \quad (1) \end{aligned}$$

Here, β_3 estimates the control group partisan difference and β_4 and β_5 estimate the two treatments' effect on partisan differences. If β_4 or β_5 take the opposite sign as β_3 and are statistically significant, we can infer that expressive responding occurred. We use the same approach for the pledge treatment.

Table 2 presents our estimates for the request and pipeline treatments. At baseline, the mean scale score was 0.404 among Republicans, 0.148 among Democrats, and 0.314 among independents. Although the level of endorsement among Democrats may appear high, such "counter-partisan beliefs" appear in every study of partisan belief differences, including other studies of partisan rumors (e.g., Berinsky 2018).

No evidence emerges that the honesty requests altered expressions of belief in the big lie. The request treatment's estimated effect was -0.004 for Democrats (s.e. = 0.009), -0.005 for Republicans (s.e. = 0.019), and 0.025 for independents (s.e. = 0.045). The subtle pipeline treatment's estimated effect was -0.003 for Democrats (s.e. = 0.009), 0.019 for Republicans (s.e. = 0.019), and 0.002 for independents (s.e. = 0.046).

Estimates of the request treatment's effect on partisan differences appear in the fourth column of Table 2. Consistent with the party-by-party results, we find no evidence of expressive responding. At baseline, the partisan difference was 0.256 scale points on the 0 to 1 scale. The average scale score was almost the same in the request treatment group ($\hat{\beta}_4 = 0.000$, s.e. $= 0.021$) and was slightly larger in the subtle pipeline treatment group ($\hat{\beta}_5 = 0.022$, s.e. $= 0.021$). Neither estimate is statistically significant.

The honesty pledge treatment yields suggestive evidence of a small amount of expressive

Table 2: Honesty request estimates.

	Dem.	Indep.	Repub.	Partisan diff.
Constant	0.148^{**}	0.314^{**}	0.404^{**}	0.148^{**}
	(0.006)	(0.033)	(0.013)	(0.006)
Request treatment	−0.004	0.025	−0.005	−0.004
	(0.009)	(0.045)	(0.019)	(0.009)
Pipeline treatment	−0.003	0.002	0.019	−0.003
	(0.009)	(0.046)	(0.019)	(0.009)
Republican				0.256^{**}
				(0.015)
Republican × request treatment				−0.000
				(0.021)
Republican × pipeline treatment				0.022
				(0.021)
Adj. R^2	−0.001	−0.006	−0.000	0.197
Num. obs.	2969	294	1737	4706

Note: First three columns display conditional average treatment effects by party. Fourth column displays estimates of (1); independents are excluded from this column. Robust standard errors in parentheses. One tailed tests preregistered. $^{*}p < 0.05$, $^{**}p < 0.01$.

Table 3: Honesty pledge estimates.

	Dem.	Indep.	Repub.	Partisan diff.
Constant	0.189^{**}	0.335^{**}	0.408^{**}	0.189^{**}
	(0.006)	(0.024)	(0.011)	(0.006)
Pledge treatment	−0.000	−0.011	−0.021	−0.000
	(0.008)	(0.033)	(0.015)	(0.008)
Republican				0.219^{**}
				(0.012)
Republican × pledge treatment				−0.021
				(0.017)
Adj. R^2	−0.000	−0.003	0.001	0.130
Num. obs.	2913	330	1691	4604

Note: First three columns display conditional average treatment effects by party. Fourth column interacts all terms with a Republican indicator; independents are excluded from this column. Robust standard errors in parentheses. One tailed tests preregistered. $^{*}p < 0.05$, $^{**}p < 0.01$.

responding among Republicans. Table 3 presents these estimates. The request's estimated effect on Republicans was -0.021 (s.e. $= 0.15$), or about 5 percent of the baseline. This comes close to, but does not attain, statistical significance (one-sided $p = 0.08$). The estimated effect on Democrats is almost exactly 0 (s.e. $= 0.08$). This means that the estimated effect on partisan differences is of the same magnitude as the estimated effect on Republicans (-0.021, s.e. $= 0.017$).

Response Substitution

Our second test for expressive responding considers the possibility that endorsements of the big lie are due to response substitution. We considered two sentiments to be especially likely candidates. First, some subjects may believe that election fraud occurred, but not enough to change the election result. Second, some may not believe the election was fraudulent at all, but want to express disappointment that Trump did not prevail. To test these possibilities, we randomly assigned respondents to Survey 2 to a control group or one of two treatment conditions. All subjects answered the same outcome variable used in the honesty experiments. Immediately before this, treated respondents answered one of the two questions designed to reduce response substitution.

The *fraud occurred* treatment examined the possibility that questions about the big lie serve as an expressive outlet for the belief that fraud occurred, regardless of whether it determined the outcome. Just before the outcome variable, respondents assigned to this condition were asked, "Which comes closest to your view?" with the options, "There was **no voter fraud** in the 2020 presidential election," "There was **a little voter fraud** in the 2020 presidential election," and "There was **a lot of voter fraud** in the 2020 presidential election." If this reduces measured belief in the big lie, one would conclude that some respondents want to express that fraud occurred but do not believe it decided the election.

The *wrong decision* treatment examined the possibility that questions about the big lie serve as an outlet for expressing disapproval of the election outcome. Just before the outcome variable, respondents assigned to this condition were asked "Which comes closest to your view?" with the response options "Electing Joe Biden was the **right decision** for the country" and "Electing Joe Biden was the **wrong decision** for the country." This is similar in spirit to Fahey's (2022) contemporaneous study. To the degree that this reduces measured belief in the big lie, one would conclude that some respondents want to express disapproval of the election result but do not think it was fraudulent.

Results

To estimate the effect of these treatments we use OLS to estimate

$$Y_i = \alpha + \beta_1 F_i + \beta_2 W_i + \beta_3 X_i + \epsilon_i, \tag{2}$$

where i indexes respondents, Y_i is belief in the big lie, F_i indicates assignment to the fraud occurred treatment, W_i indicates assignment to the wrong decision treatment, and X_i is a pre-treatment measure of belief in the big lie collected in a baseline survey.[7] To aid interpretation, we de-mean X_i within each party prior to estimation. Consequently, α can be interpreted as average endorsement of the big lie in the control group. β_1 and β_2 estimate the effect of the response substitution treatments.

Neither treatment yields evidence that response substitution affects measured belief in the big lie (Table 4). On the 0 to 1 scale, Republicans assigned to the fraud occurred treatment said that the big lie was 0.008 scale points more likely to be true (s.e. = 0.019). Republicans assigned to the wrong decision treatment also said that it was 0.008 scale points more likely to be true (s.e. = 0.017). The latter result is consistent with Fahey (2022). Democrats assigned to the fraud occurred treatment said the big lie was 0.010 scale points more likely to be true (s.e. = 0.011) on the 0 to 1 scale, while those assigned to the wrong decision treatment were 0.006 scale points less supportive of it (s.e. = 0.010). Independents

[7] Appendix C contains more information about the baseline survey and reports estimates without covariate adjustment, which are similar.

Table 4: Response substitution estimates.

	Dem.	Indep.	Repub.	Partisan diff.
Constant	0.130^{**}	0.355^{**}	0.506^{**}	0.034^{**}
	(0.007)	(0.019)	(0.014)	(0.007)
Fraud occurred treatment	0.010	-0.058^{*}	0.008	0.011
	(0.011)	(0.027)	(0.019)	(0.011)
Wrong decision treatment	−0.006	−0.015	0.008	−0.004
	(0.010)	(0.026)	(0.017)	(0.010)
Republican				0.117^{**}
				(0.018)
Republican × fraud occurred treatment				0.001
				(0.022)
Republican × wrong decision treatment				0.014
				(0.020)
Pre-treatment DV	0.553^{**}	0.870^{**}	0.792^{**}	0.684^{**}
	(0.029)	(0.032)	(0.021)	(0.019)
Adj. R^2	0.323	0.716	0.587	0.640
Num. obs.	1744	267	929	2673

Note: First three columns display estimates of (2). Fourth column interacts all terms with a Republican indicator; independents are excluded from this column. Robust standard errors in parentheses. One tailed tests preregistered. $^{*}p < 0.05$, $^{**}p < 0.01$.

in the fraud occurred treatment said that it was 0.058 scale points less likely to be true (s.e. = 0.027), while those in the wrong decision condition were 0.015 scale points less supportive (s.e. = 0.026). As we have no expectation that response substitution should systematically shift independents in one direction or the other, we attribute the statistically significant result to noise.

The fourth column estimates the effect on partisan differences. As before, we test this by interacting our treatment indicators with a Republican indicator. We find no evidence that the treatments affected partisan differences. Both estimates take the wrong sign and are statistically insignificant.

List Experiment

We next compare a list experiment estimate of the belief that Biden's victory was fraudulent to an identically worded direct question. If expressive responding is present, we expect that Republicans will be less likely to endorse the big lie in a list experiment than when asked directly. In Survey 3, we randomly assigned about one-fifth of our respondents to the direct question ($p = 0.21$) and split the remaining respondents between the two list experiment conditions ($p = 0.395$). In a simulation study, these probabilities that generated the smallest standard error for the difference in means between the direct question and list experiment estimates. Respondents in the list experiment treatment group answered the question in Figure 1a. Control respondents saw an identical list with the big lie removed and responded on a 0-4 scale.

List experiments do not ensure anonymity for individuals who disagree with all or none of the statements (Blair and Imai 2012). This threat can be minimized by selecting statements that are negatively correlated. Consequently, we paired "I voted in the election" with two statements that are unlikely to apply to people who voted: "I did not know where to vote" and "I requested an absentee ballot, but it did not arrive." The distribution of responses appears in Table 5. About 12.7 percent (control group) and 10.2 percent (treatment group) choose the highest or lowest option.

We compare the list experiment estimate to a direct question that matches the wording of the list experiment as closely as possible (Figure 1b). Though the list experiment and direct items are comparable to each other, note that the list experiment methodology necessitates that the direct question be binary, with no middle scale points to express uncertainty. Consequently, the group means in the list experiment differ somewhat from the group means displayed in Tables 2, 3, and 4.

Figure 1: Screen Shots of List Experiment

(a) List format (treatment condition).

Here is a list of statements about the 2020 U.S. presidential election. We want to know **how many** you agree with.

- I did not know where to vote.
- The Green Party came close to winning the election.
- Joe Biden only won the election due to voter fraud.
- I requested an absentee ballot, but it did not arrive.
- I voted in the election.

How many statements do you agree with?

0 1 2 3 4 5

(b) Direct question.

Do you agree or disagree with this statement about the 2020 U.S. presidential election?

Joe Biden only won the election due to voter fraud.

Disagree Agree

Table 5: Distribution of responses, list experiment.

		Response distribution					
		0	1	2	3	4	5
Control	N	193	1439	148	108	55	
	%	9.9	74.1	7.6	5.6	2.8	
Treatment	N	154	1119	442	87	81	43
	%	8.0	58.1	22.9	4.5	4.2	2.2

Results

We estimate the degree of expressive responding within party by comparing the list experiment and direct question estimates. The effect on partisan differences is the difference between the list experiment estimates for Democrats and Republicans. For all of these

Table 6: List experiment estimates.

Term	Dem.	Indep.	Repub.	Partisan diff.
Direct question estimate	0.086	0.250	0.550	0.464
	(0.013)	(0.041)	(0.024)	(0.027)
List experiment estimate	0.083	0.149	0.527	0.444
	(0.043)	(0.071)	(0.044)	(0.061)
Difference	-0.003	-0.101	-0.023	-0.020
	(0.045)	(0.082)	(0.050)	(0.067)
N	2278	543	2064	4342

Note: First three columns display list experiment estimates by party. Fourth column calculates the partisan difference by subtracting Democrats from Republicans; independents are excluded from this column. Bootstrap standard errors in parentheses. One tailed tests preregistered. $^{*}p < 0.05$, $^{**}p < 0.01$. Asterisks omitted from first two rows.

quantities, we bootstrap standard errors and confidence intervals and calculate p-values using the percentile method.

The list experiment finds little evidence of expressive responding (Table 6). Among Republicans assigned to the direct question condition, 55.0 percent agreed that Biden only won due to fraud. The list experiment estimates that 52.7 percent of Republicans agree with this statement, a difference of 2.3 pp (s.e. = 5.0). Among Democrats, the direct question estimate is 8.6 percent, compared with 8.3 percent in the list experiment (difference = 0.3, s.e. = 4.5). Among independents, the direct question estimate is 25.0 percent compared with 14.9 percent in the list experiment (difference = 10.1, s.e. = 8.2).

The estimated effect on partisan differences reinforces these conclusions. The direct question estimates a difference of 46.4 pp, compared with 44.4 pp in the list experiment. The point estimate suggests a decrease in partisan differences of 2.0 pp, which is far from statistical significance (s.e. = 6.7).

Betting on the Future

We next turn to our financial incentive design. Beliefs that are rooted in partisan misinformation challenge the classic financial incentive paradigm, which relies on payment for correct answers about facts that are not widely disputed (Bullock et al. 2015; Prior et al. 2015). Consequently, research that examines expressive responding about belief in false claims made by partisan actors usually avoids financial incentives (Berinsky 2018; Schaffner and Luks 2018; Malka and Adelman 2022; an exception is Peterson and Iyengar 2021).

To apply financial incentive treatments to the case of the big lie, we took advantage of the big lie's association with highly salient predictions about the future. Specifically, the period after Trump's election loss saw a series of widely disseminated predictions that evidence of fraud would enable Trump to retain power or be reinstated. Rather than having our subjects bet directly on whether the big lie is true, we allowed our subjects to bet on whether these predictions would bear out. Regardless of what subjects believed about our beliefs, this provided an incentive to rely only on their best guess about the truth.

The central drawback of this technique is that it does not directly measure belief in Trump's big lie, but rather tangent beliefs that depend in some way on belief in the big lie. For example, a genuine belief that Trump would be reinstated in August 2021, as in Study 2 below, likely depended on a belief that evidence of massive fraud would emerge. However, expressive responding could still occur due to a lack of genuine belief in some other component of the theory. For example, one might sincerely believe that the evidence will emerge, but not that it will be enough to get Trump reinstated. Thus, while our approach is well-suited to test partisans' willingness to put their money where their mouth is, it is not equipped to pinpoint precisely which belief drives whatever expressive responding is detected.

Study 1

Our first betting on the future study was conducted in late November 2020, shortly after the contested presidential election. At this time, Trump and his associates were predicting that evidence of fraud would enable him to overturn the results and retain power.

To leverage these circumstances, we recruited 939 Republican subjects. The sample also included 115 subjects who identified themselves as Republicans in March or May 2020, but as an independent or a Democrat in our survey (Survey 1, Table 1). To begin, all subjects were asked the following question: “On January 20, the winner of the presidential election will be inaugurated and begin his term. [Paragraph break.] Who do you expect to be President the next day, on January 21?” The response options were “Joe Biden” and “Donald Trump.” Next, all subjects were asked which of two tickets they would like to enter into a drawing for a $100 bonus, to be conducted on January 21, 2021. One ticket read “Win if Donald Trump is President on January 21, 2021” while the other read “Win if Joe Biden is President on January 21, 2021.” This within-person design enables us to estimate the frequency with which individuals change their prediction when money is on the line.

To estimate the difference between the two question formats, we use OLS to estimate

$$Y_{ik} = \alpha + \beta \text{Incentive}_{ik} + \epsilon_{ik} \tag{3}$$

where i indexes subjects, k indexes the two questions (no incentive or incentive), and Incentive_{ik} is an indicator for the incentivized question. Because we have two observations per subject, we cluster our standard errors at the subject level.

This test yields our only statistically significant evidence of expressive responding (Table 7). Among Republicans, 26.6 percent predicted that Trump would remain president when there was no money on the line. This fell to 20.9 percent when incentives were introduced, a decline of 5.7 percentage points (s.e. = 1.0; in this study we use two-tailed tests because it was not-preregistered). This suggests that about one-fifth of Republicans who initially claimed that Trump would prevail in his effort to overturn the election results did not actually think that this was the most likely outcome. Among those who did not identify as Republicans, 7.9 percent predicted that Trump would retain power when there was no money on the line, compared to 6.1 percent with the incentive (difference = 1.8, s.e. = 1.2).

The key potential weakness of Study 1 is the within-person design. It is possible that the effect of the incentive is attenuated by consistency pressure (a need to express the same

Table 7: Betting on the future: Study 1.

	Republican	All others
Constant	0.266**	0.079**
	(0.014)	(0.025)
Incentivized question	−0.057**	−0.018
	(0.010)	(0.012)
Adj. R^2	0.004	−0.003
Num. obs.	1864	228
Num. clusters	932	114

Note: Table displays estimates of (3) with clustered standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$ (two-tailed). Asterisks omitted from first two rows.

belief both times; Tourangeau and Rasinski 1988). It is also possible that effects are inflated: by the logic of response substitution, if the unincentivized question provides an opportunity to express a partisan sentiment, respondents may feel less motivated to express it a second time. To address this shortcoming, Study 2 included a paired within-between design.

Study 2

Our second betting on the future study was conducted in July 2021. At this time, rumors swirled in Republican circles that Trump would be reinstated by the end of August. Though the institutional mechanism varied, the prediction always started with the seismic impact of soon-to-be-released evidence to support the big lie.[8] Public-facing polls reported widespread belief among Republicans that Trump would be reinstated.[9] The rumors sparked concern at the Department of Homeland Security and Federal Bureau of Investigation.[10]

[8]The most popular version held that the Supreme Court would reinstate Trump through unspecified institutional means. See Ewan Palmer, "Why Mike Lindell Thinks Donald Trump Will Return as President in August," *Newsweek*, June 3, 2021, and Jason Leman, "Mike Lindell Insists There Are 'Two Pathways' to Change 2020 Election Results," *Newsweek*, July 11, 2021. Another version held that following the emergence of evidence of fraud, the U.S. House of Representatives would remove its Speaker, Nancy Pelosi, and elect Trump in her place. This would have placed Trump second in the line of presidential succession and in position to lead the impeachment of those ahead of him in the line of succession. See Aliya Shob, "A 7-point plan to reinstate Donald Trump as president 'in days, not weeks' was handed out at CPAC," *Business Insider*, July 10, 2021.

[9]Eli Yokley, "29% of GOP Voters Say It's Likely Trump Will Be Reinstated as President This Year," *The Morning Consult*, June 10, 2021.

[10]For example, see Betsy Woodruff Swan, "DHS is concerned about Trump reinstatement conspiracy theory, top official says," *Politico*, June 25, 2021. Marshall Cohen, "Justice Department says Trump's rein-

To leverage this second set of circumstances, we recruited a sample of 4,885 subjects, including 2,278 Democrats and 2,064 Republicans (Survey 3, Table 1). Respondents were first randomly assigned to one of two experimental conditions. Those in the control (unincentivized) condition were asked, “Which statement is most likely to be true?” Those in the treatment (incentivized) condition were asked to select which of two tickets they would like to enter into a drawing for a $500 bonus, to be conducted on September 1, 2021. Both conditions had the same response options: “Donald Trump will be restored as President of the United States by the end of August.” and “Donald Trump will **not** be restored as President of the United States by the end of August.” This gives us a between-person experiment on the effect of financial incentives. Next, subjects initially assigned to the control condition were asked the treatment version of the question. This gives us a within-person estimate comparable to our first study.

To estimate the causal effect of the incentive treatment, we use OLS to estimate the parameters in

$$Y_i = \alpha + \beta \text{Incentive}_i + \epsilon_i, \tag{4}$$

where Incentive_i indicates that the subject was randomly assigned to the financial incentive condition. We estimate the within-person design using the same strategy as our first study (Equation 3). We again estimate effects on partisan differences by interacting each term with a Republican indicator.

We find little evidence of expressive responding among Republicans (Table 8). In the no-incentive condition, 14.9 percent of Republicans predicted that Trump would be reinstated by the end of August. In the incentive condition 14.5 percent made the same prediction, a difference of 0.4 percent (s.e. = 1.6; Table 8a, third column). When the no-incentive respondents were subsequently asked the incentivized question, 13.8 predicted that Trump

statement talk could fuel more violence from his supporters, *CNN*, July 9, 2021.” Chris Strohm, “Conspiracy Theory About Trump Comeback Puts FBI on Alert for Violence,” *Bloomberg*, July 13, 2021.

Table 8: Betting on the future: Study 2.

(a) Experiment.

	Dem.	Indep.	Repub.	Partisan diff.
Constant	0.076**	0.042**	0.149**	0.076**
	(0.008)	(0.013)	(0.011)	(0.008)
Incentive treatment	0.007	0.007	−0.004	0.007
	(0.011)	(0.018)	(0.016)	(0.011)
Republican				0.073**
				(0.014)
Republican × incentive treatment				−0.011
				(0.019)
Adj. R^2	−0.000	−0.002	−0.000	0.011
Num. obs.	2278	543	2064	4342

(b) Within subjects.

	Dem.	Indep.	Repub.	Partisan diff.
Constant	0.076**	0.042**	0.149**	0.076**
	(0.008)	(0.013)	(0.011)	(0.008)
Incentive question	−0.003	0.019	−0.011	−0.003
	(0.005)	(0.012)	(0.007)	(0.005)
Republican				0.073**
				(0.014)
Republican × incentive question				−0.009
				(0.009)
Adj. R^2	−0.000	−0.000	−0.000	0.012
Num. obs.	2248	518	2096	4344
Num. clusters	1124	259	1048	2172

Note: Part (a) displays estimates of equation (4) with robust standard errors in parentheses. Part (b) displays estimates of equation (3) with clustered standard errors in parentheses. Fourth column interacts all terms with a Republican indicator; independents are excluded from this column. One-sided tests pre-registered. $^{*}p < 0.05$, $^{**}p < 0.01$.

would be reinstated, a difference of 1.1 percent (s.e. = 0.7; Table 8b, third column). This is on the borderline of statistical significance (one-tailed $p = 0.06$) and equal to less than 10 percent of the baseline. In sum, the between-person experiment yielded no evidence of expressive responding, while the within-person design suggested that a small amount of expressive responding may have been present. Likewise, no evidence of expressive responding emerges among Democrats or independents.

We similarly find little evidence of expressive responding when examining partisan differences. Relative to the baseline, the experimental estimate indicates that the partisan difference was 1.1 percentage points smaller in the incentive condition (s.e. = 1.9). The within-person estimate indicates that the difference was 0.9 percentage points smaller (s.e. = 0.9). Neither estimate is statistically significant.

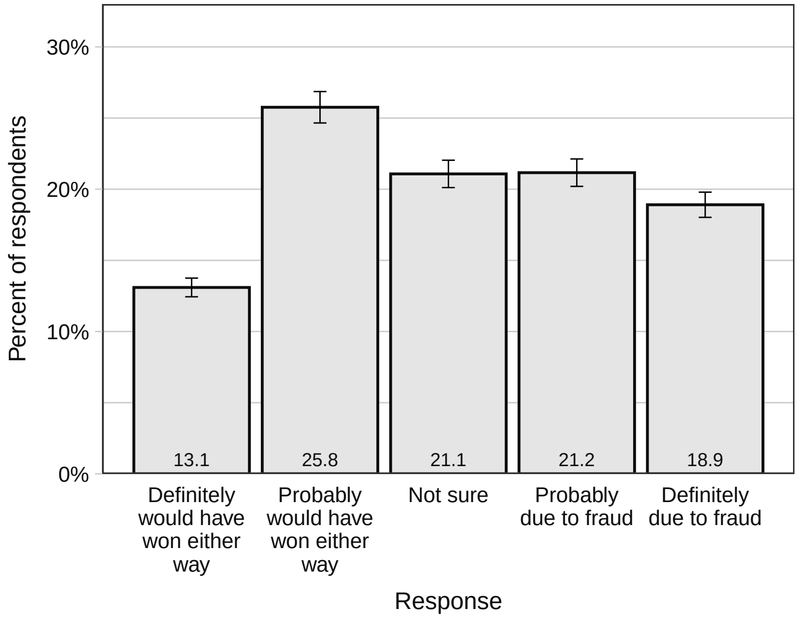
Confidence and Temporal Stability

Though we find limited evidence of expressive responding, there is another sense in which survey respondents may not "believe" their answers: they may make guesses even when they lack confidence. Research on political misperceptions suggests identifying true believers by measuring respondents' confidence in their answers (Kuklinski et al. 2000; Pasek et al. 2015; Graham 2020). Yet measured confidence can also be illusory: respondents who endorse falsehoods tend to be unstable in their responses over time, even when they at first report a high level of confidence in their answer (Graham 2023*b*). To examine the degree to which our apparently sincere respondents believe their answers, this section presents a supplemental analysis that takes advantage of Survey 2's two-wave design.[11] We find that Republicans who endorse the big lie are about evenly split between individuals who confidently believe it and individuals who find it plausible, but are not deeply convinced.

We first examine the pre-treatment distribution of Republican respondents' answers to the survey item designed to measure belief in the big lie (Figure 2). Recall that respondents

[11] The analysis in this section was not pre-registered, but is modelled after Graham's (2023*b*) critique.

Figure 2: Measured belief distribution among Republicans, Survey 2.



Note: Figure displays the distribution of responses from Study 2's baseline survey. Vertical bars represent 95 percent confidence intervals.

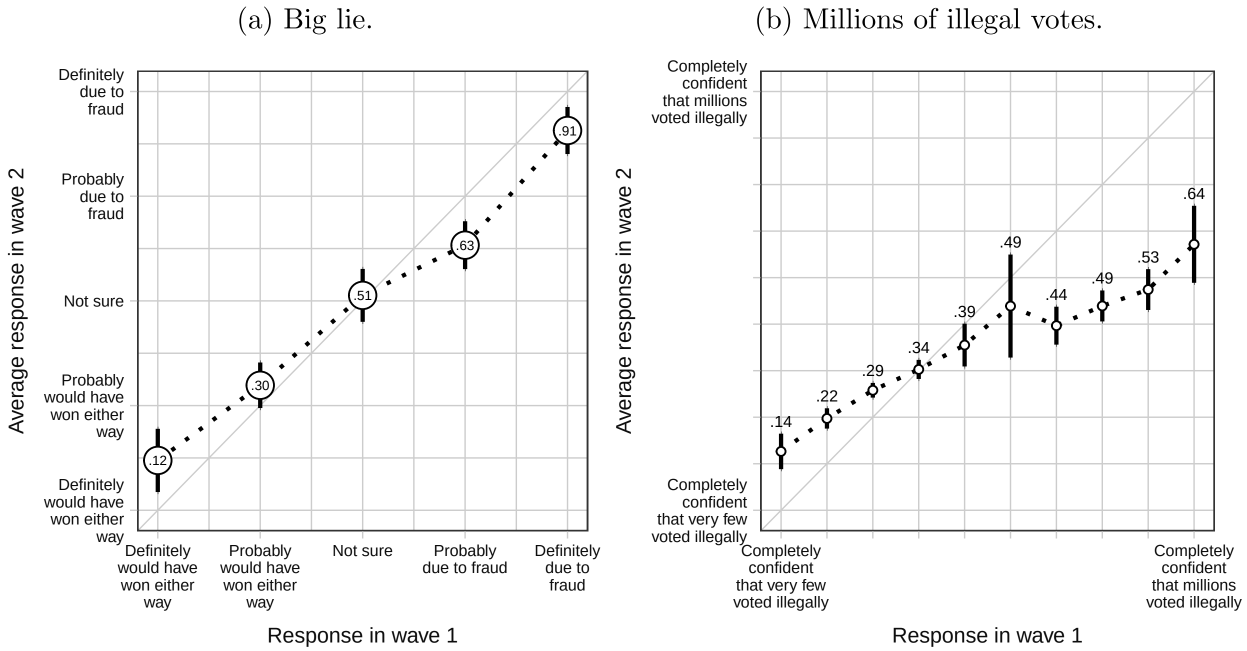
answered on a five-point scale labelled "Definitely would have won either way," "Probably would have won either way," "Not sure," "Probably due to fraud," and "Definitely due to fraud."[12] Republicans who endorsed the big lie were about evenly split between the "probably due to fraud" and "definitely due to fraud" categories. In other words, about half of those who endorse the big lie are confident that it is definitely true, while the other half find it plausible but are not deeply convinced.

Before placing too much weight on the meaning of these scale point labels, it is important to examine respondents' degree of commitment to their answers. To do so, we adopt Graham's (2023*b*) strategy of examining the average response in wave 2 of a panel survey conditional on the wave 1 response (Figure 3).[13] To the degree that respondents indicate the same belief in both waves (as indicated by the 45-degree line), one can take respondents' claims to be confident in their answers at face value. For this step of the analysis, we only

[12]Even when included in bipolar scales of this kind, probabilistic scale point labels capture meaningful information about respondent confidence (Graham 2023*b*, Appendix C.5).

[13]Figure 3 is modelled after the left panel of Graham's (2023*b*) Figure 1.

Figure 3: Temporal stability among Republicans, big lie vs. millions of illegal votes



Note: The x-axis displays the response in the first wave of a panel survey. The y-axis is the average response in the second wave, conditional on the response given in the first wave. Panel (a) panel presents these quantities using our data from Survey 2. Panel (b) presents the same analysis using the 2020 ANES Social Media Study's question about whether millions of illegal votes were cast in the 2016 election. Printed numbers are point estimates. Vertical bars represent 95 percent confidence intervals.

use the experimental control group.

We find a high degree of response stability. Figure 3a shows that on average, respondents to the second wave of the survey held very close to the beliefs they reported in the first wave. Among respondents who said in wave 1 that Biden's victory was "definitely due to fraud," the average scale score in wave 2 was 0.91. This is closer to "definitely due to fraud" (1) than it is to "probably due to fraud" (0.75). This is more stable than any of the measures of misperceptions examined by Graham (2023*b*). Similarly, among respondents who said in wave 1 that Biden's victory was "probably due to fraud," the average scale score in wave 2 was 0.63, solidly above the 0.5 score that indicates complete uncertainty. This indicates that measurement error makes only a modest contribution to Republicans' measured confidence in Trump's big lie.

For a more direct comparison to other measured misperceptions, Figure 3b uses the

2020 ANES Social Media Study to examine the temporal stability of endorsements of Trump's previously most notorious claim of election fraud, that millions of illegal votes were cast in the 2016 election. Relative to the big lie, we find substantially less stability among Republicans who confidently endorse the "millions of illegal votes" claim. For example, Republicans who endorsed it with complete confidence in wave 1 had an average wave 2 scale score of 0.64. Those choosing the next-highest scale point, "very confident," had an average wave 2 score of 0.53, which is close to complete indifference to Trump's claim. The big lie appears distinct from most measures of misperceptions—including Trump's previous claims of voter fraud—in that many people have outright accepted the falsehood at hand, as opposed to finding it plausible.

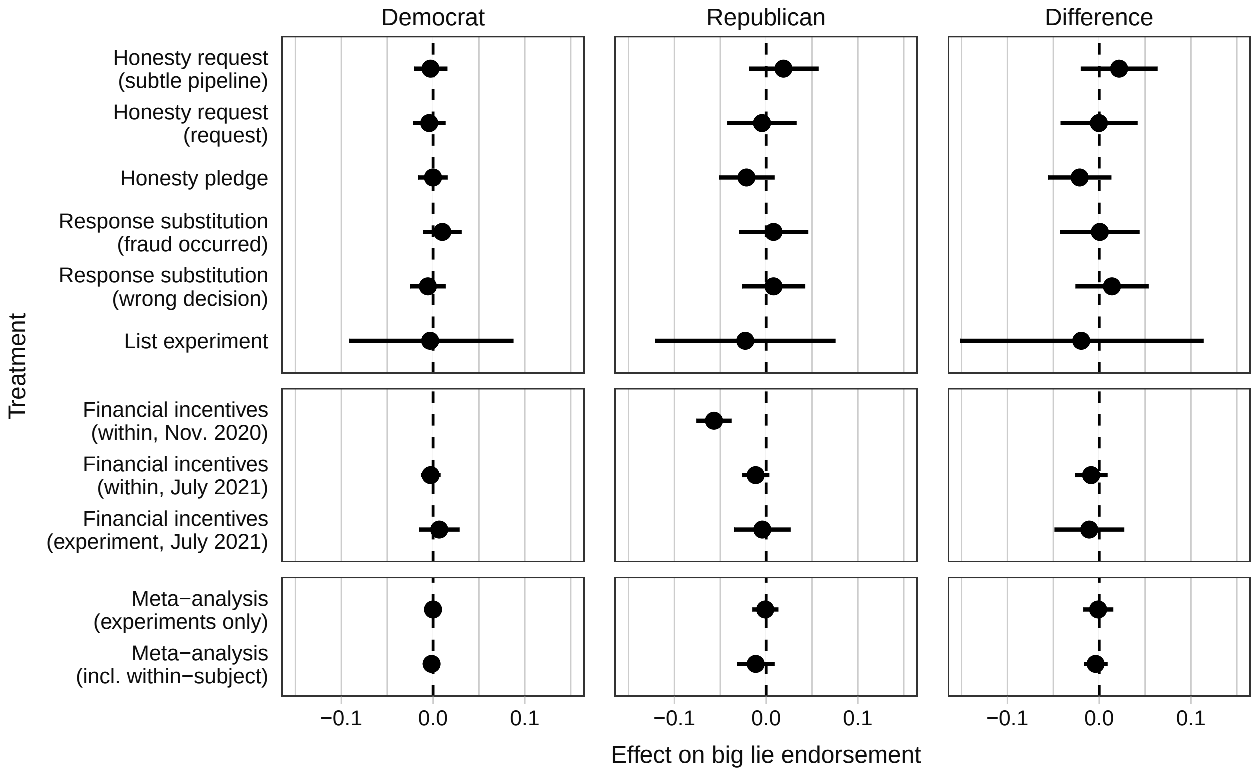
For Democrats and independents, Appendix E presents equivalent estimates of confidence and response stability. Independents who endorse the big lie are similar to Republicans in their degree of response stability. By contrast, Democrats who endorse the big lie in wave 1 tend to reject it in wave 2, exhibiting substantially less stability than Republicans. The typical Democrat who at first says that the big lie is "probably" or "definitely" true switches to saying that it is probably false. This indicates that the appearance that some Democrats have confidently accepted the big lie arises largely due to measurement error.

Summary

In this section, we present a holistic summary of out evidence. Figure 4 plots all of our estimates of the treatment effects on Democrats, Republicans, and partisan differences. As all of our ourcome variables were scaled to range between 0 and 1, we report each estimate in its natural units without any further standardization.

Our primary interest was in expressive responding among Republicans. Across our nine estimates, only one yields statistically significant evidence consistent with the expressive responding hypothesis (Figure 4, center panel). That estimate suggested that about 5.7 percent of Republicans misreported their best guess about whether Trump would be able

Figure 4: Summary of evidence for expressive responding.



to hang onto power after the 2020 election. This was equal to about 20 percent of the baseline rate. The other eight estimates, all based on data collected in 2021 or 2022, were substantively small (2.3 percentage points or less) and statistically insignificant. We think the phrase "limited at best" fairly captures our evidence for expressive responding among Repubicans. Not all of our estimates are null, but they suggest that at most, expressive responding is confined to a relatively small minority of those who endorse the big lie.

For a more precise summary of this evidence, we conducted an exploratory meta-analysis that combines the estimates from all five surveys using the random effects method. To accommodate the fact that our financial incentive designs make use of between- and within-person estimates, we conduct two versions, one that excludes the within-subject estimates ("experiments only") and another that excludes the experimental estimate ("including within-subjects"). The estimates are displayed in the bottom panel of Figure 4. Using only the experiments, our meta-analytic estimate for Republicans is almost exactly zero (estimate = 0.001, 95 percent CI = $(-0.015, 0.012)$). When the within-subject estimates of the effect of financial incentives are used instead, we find no evidence of more than a small effect (estimate = -0.012, 95% CI = $(-0.031, 0.008)$).

The summary figure also includes estimates for Democrats and partisan differences (Figure 4, left and right panels). Across the sixteen estimates from the individual studies, none were statistically significant. The same holds in the meta-analysis. Though one would expect weaker pressure to respond expressively among Democrats than among Republicans, rejecting a claim as central as the big lie is arguably a partisan act. Given this, the null findings for Democrats provide a bit of further evidence for the limited prevalence of expressive responding.

Finding little evidence of expressive responding, we turned to the question of whether Republicans endorse the big lie with confidence and remain temporally stable in their endorsements. We found that about half of Republicans who endorse the big lie are confident that it is true, and that these respondents are stable in their professions of confidence. This outperforms other measures of misperceptions, including measured belief in Trump's lies about 2016 election fraud.

Implications

Our evidence suggests that by and large, survey respondents are being sincere when they endorse "big lie" that Trump lost the 2020 U.S. presidential election due to voter fraud. These beliefs are split between confident acceptance and sincere suspicions (i.e., guesses by people who are not deeply convinced of the big lie but think it is more likely than not to be true).

These findings have implications for the study of democratic stability in the United States and around the world. Most immediately, they support the widely-held concern that public belief in the big lie poses a threat to American democracy. Even in a consolidated democracy like the United States, with a long tradition of free and fair elections and a robust ecosystem for validating and reporting on election results, party leaders are capable of convincing wide swaths of the public that an election was stolen without evidence. Whereas the traditional view was that consolidated democracies benefitted from a strong mass culture of support for democracy (Almond and Verba 1963), the aftermath of the 2020 election suggests that consolidated democracies have primarily benefitted from a strong elite culture of conducting free and fair elections and accepting the results.

Widespread acceptance of Trump's big lie complements existing research on the American electorate's reactions to violations of democratic values. For example, Graham and Svolik (2020) find that polarization undermines voters' willingness to punish undemocratic candidates by raising the stakes of elections, and Krishnarajan (2022) finds that partisans make excuses for their party, construing violations of democratic values as consistent with democracy. Our findings suggest another pathway: many partisans are willing to believe outright lies told by copartisan opinion leaders. In this case, the substance of those lies enables Trump and his allies to dress their attempts to subvert a free and fair election in the clothes of defending election integrity. For such voters, democratic transgressions go unpunished not because voters prioritize other things (Graham and Svolik 2020) or conjure their own justifications (Krishnarajan 2022), but because they believe a version of events in which there is no transgression to justify. This suggests that partisan voters' well-documented susceptibility to elite cues (e.g., Lenz 2012; Barber and Pope 2019; Pink et al. 2021) can be weaponized as a threat to democratic stability.

In terms of partisan belief differences and acceptance of misinformation, our findings suggest that the United States has entered new territory. Existing analysis of large question batteries generally finds partisan differences in factual beliefs to be surprisingly small, on the order of 5 to 15 percentage points (Jerit and Barabas 2012; Graham 2020; Roush and Sood 2023). These belief differences are often exaggerated by expressive responding (Bullock et al. 2015) and primarily reflect differences in knowledge and ignorance, not outright belief in misinformation (Graham 2023*b*). In contrast, we find partisan differences equal to about

40 percent of the scale, with little evidence of exaggeration due to expressive responding and substantial evidence of outright acceptance. Public-facing polls—which tend to use binary questions, loaded language, and more representative samples—generally find even larger differences. This indicates that when a falsehood is relentlessly pushed by politicians and partisan media, levels of belief and partisan difference can reach levels that were rarely observed in earlier research.

For the larger study of public opinion, the contrast between our findings and other research highlights the misleading nature of one-size-fits-all interpretations of survey data. Though we found minimal evidence of expressive responding, robust and replicable has been found in many other cases (Bullock et al. 2015; Prior et al. 2015; Khanna and Sood 2017; Schaffner and Luks 2018; Peterson and Iyengar 2021; Yair and Huber 2020; Ross and Levy 2023; Graham and Yair 2023). Similarly, our finding that endorsements of Trump's 2020 lie are more temporally stable than his 2016 lie echoes other evidence that temporal stability varies substantially between survey items (Converse 1964; Schuman and Presser 1981; Graham 2023*b*). This indicates that rather than rely on broad generalizations about the sense in which survey respondents believe their answers, researchers should inform their interpretations with item-level validation. Absent such evidence, researchers should refrain from strong judgments about the veracity with which respondents believe their answers. In this sense, observers were right to worry that expressive responding *could* influence measured belief in the big lie, even as our evidence suggests that it does not.

To promote nuanced, evidence-based interpretation of survey responses, the research community should make a standard practice out of the sort of comprehensive validation we have carried out here. Rather than "going wide" by asking ten or twenty different questions about the same topic, researchers should "go deep" by allocating resources toward understanding the measures they consider to be most important. At present, such evaluations tend to be carried out in reaction to prominent narratives in public opinion discourse, leaving hard evidence in the uncomfortable position of having to confirm or correct the narrative.

Ideally, prevailing interpretations of survey data would be informed by validation exercises. Today, the relationship is precisely the opposite. Strong interpretations of survey data serve as the motivation for validation exercises, functioning as a precondition for the collection of hard evidence rather than emerging as a function of that evidence.

In sum, by providing the most comprehensive evidence to date that measured belief in Trump's big lie is minimally affected by expressive responding, our effort sheds new light on threats to democratic stability and highlights the benefits of comprehensive, case-by-case validation of survey items. Measured belief that the 2020 election was decided by fraud is mostly genuine, and is a genuine threat to democratic stability in the United States.

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Appendix to

Expressive Responding and Trump's Big Lie

Contents

A Honesty Encouragement

A.1 Balance tests

In Survey 4, simple random assignment was used to assign subjects to control or one of the two treatments ($p = 1/3$; Gerber and Green 2012). In Survey 5, simple random assignment was used to assign subjects to control or the pledge treatment ($p = 1/2$).

Table A.1: Balance test, request treatment versus control (Survey 4).

Variable	Z=0	Z=1	Diff	SE	Std. Diff	z	p
white	0.786	0.780	-0.006	0.014	-0.014	-0.417	0.676
black	0.131	0.143	0.012	0.012	0.035	1.017	0.309
asian	0.060	0.061	0.001	0.008	0.004	0.112	0.911
hispanic	0.000	0.000	0.000	0.000	NaN	0.000	1.000
female	0.454	0.434	-0.020	0.017	-0.040	-1.149	0.251
pid7	3.340	3.355	0.015	0.084	0.006	0.180	0.857
educ_n	0.950	0.949	-0.001	0.007	-0.006	-0.183	0.855
age	39.342	39.022	-0.319	0.415	-0.027	-0.769	0.442
female(missing)	0.001	0.000	-0.001	0.001	-0.034	-0.997	0.319

Overall: Chi-squared statistic= 4.847(df=8,p=0.774)

Table A.2: Balance test, pipeline treatment versus control (Survey 4).

Variable	Z=0	Z=1	Diff	SE	Std. Diff	z	p
white	0.786	0.782	-0.004	0.014	-0.009	-0.253	0.800
black	0.131	0.134	0.003	0.012	0.009	0.248	0.804
asian	0.060	0.058	-0.002	0.008	-0.008	-0.234	0.815
hispanic	0.000	0.000	0.000	0.000	NaN	0.000	1.000
female	0.454	0.437	-0.017	0.017	-0.033	-0.966	0.334
pid7	3.340	3.377	0.037	0.084	0.015	0.438	0.662
educ_n	0.950	0.945	-0.005	0.007	-0.026	-0.764	0.445
age	39.342	39.303	-0.039	0.414	-0.003	-0.093	0.926
female(missing)	0.001	0.000	-0.001	0.001	-0.034	-0.996	0.319

Overall: Chi-squared statistic= 2.938(df=8,p=0.938)

Table A.3: Balance test, pledge treatment (Survey 5).

Variable	Z=0	Z=1	Diff	SE	Std. Diff	z	p
white	0.851	0.838	-0.013	0.010	-0.037	-1.284	0.199
black	0.075	0.085	0.010	0.008	0.037	1.300	0.194
asian	0.053	0.052	-0.001	0.006	-0.004	-0.135	0.893
hispanic	0.252	0.271	0.018	0.013	0.042	1.473	0.141
female	0.480	0.467	-0.013	0.014	-0.026	-0.911	0.363
pid7	3.319	3.328	0.009	0.069	0.004	0.131	0.895
educ_n	0.760	0.766	0.006	0.006	0.029	1.033	0.302
age	40.007	38.879	-1.128	0.342	-0.094	-3.297	0.001

Overall: Chi-squared statistic= 15.194(df=8,p=0.055)

Note: Diff refers to the difference in means for a covariate. SE denotes the standard error of the difference in means. Std. Diff refers to the standardized difference in means.

A.2 Supplemental results

Table A.4: Estimates with treatment conditions pooled, honesty encouragement.

	Dem.	Indep.	Repub.	Partisan Diff.
Constant	0.148**	0.314**	0.404**	0.148**
	(0.006)	(0.033)	(0.013)	(0.006)
Either treatment	−0.004	0.014	0.007	−0.004
	(0.008)	(0.040)	(0.017)	(0.008)
Republican				0.256**
				(0.015)
Republican × either treatment				0.011
				(0.018)
Adj. R^2	−0.000	−0.003	−0.000	0.197
Num. obs.	2969	294	1737	4706

Note: Table replicates main text Table 2 with the two treatment conditions pooled. Robust standard errors in parentheses. One tailed tests preregistered. $^{*}p < 0.05$, $^{**}p < 0.01$.

B List Experiment

B.1 Balance tests

Table B.1: Balance test, treatment versus control lists.

Variable	Z=0	Z=1	Diff	SE	Std. Diff	z	p
white	0.717	0.710	-0.006	0.015	-0.014	-0.442	0.659
black	0.091	0.087	-0.005	0.009	-0.017	-0.525	0.600
asian	0.068	0.071	0.003	0.008	0.011	0.336	0.737
hispanic	0.060	0.059	-0.001	0.008	-0.004	-0.127	0.899
female	0.528	0.528	0.001	0.016	0.001	0.033	0.973
pid7	4.232	4.090	-0.142	0.072	-0.063	-1.977	0.048
educ_n	0.542	0.543	0.001	0.006	0.005	0.164	0.870
age	41.555	41.135	-0.420	0.412	-0.033	-1.021	0.307
hispanic(missing)	0.035	0.045	0.010	0.006	0.050	1.542	0.123
female(missing)	0.004	0.005	0.002	0.002	0.024	0.749	0.454
pid7(missing)	0.002	0.002	0.001	0.001	0.013	0.391	0.696
educ_n(missing)	0.227	0.212	-0.015	0.013	-0.037	-1.157	0.247
age(missing)	0.031	0.040	0.009	0.006	0.046	1.445	0.148

Overall: Chi-squared statistic= 12.546(df=13,p=0.483)

Table B.2: Balance test, treatment list versus direct question.

Variable	Z=0	Z=1	Diff	SE	Std. Diff	z	p
white	0.696	0.710	0.014	0.018	0.032	0.815	0.415
black	0.087	0.087	0.000	0.011	-0.001	-0.031	0.975
asian	0.088	0.071	-0.017	0.010	-0.063	-1.633	0.102
hispanic	0.057	0.059	0.002	0.009	0.008	0.199	0.842
female	0.520	0.528	0.008	0.019	0.017	0.426	0.670
pid7	4.111	4.090	-0.020	0.087	-0.009	-0.235	0.815
educ_n	0.551	0.543	-0.009	0.007	-0.050	-1.290	0.197
age	41.500	41.135	-0.365	0.487	-0.029	-0.750	0.453
hispanic(missing)	0.043	0.045	0.001	0.008	0.005	0.141	0.888
female(missing)	0.012	0.005	-0.007	0.003	-0.077	-1.994	0.046
pid7(missing)	0.000	0.002	0.002	0.001	0.056	1.450	0.147
educ_n(missing)	0.245	0.212	-0.033	0.016	-0.079	-2.036	0.042
age(missing)	0.032	0.040	0.008	0.007	0.044	1.134	0.257

Overall: Chi-squared statistic= 16.987(df=13,p=0.2)
Note: Diff refers to the difference in means for a covariate. SE denotes the standard error of the difference in means. Std. Diff refers to the standardized difference in means.

Table B.3: Balance test, control list versus direct question.

Variable	Z=0	Z=1	Diff	SE	Std. Diff	z	p
white	0.696	0.717	0.021	0.018	0.046	1.184	0.236
black	0.087	0.091	0.004	0.011	0.016	0.403	0.687
asian	0.088	0.068	-0.020	0.010	-0.075	-1.923	0.054
hispanic	0.057	0.060	0.003	0.009	0.012	0.304	0.761
female	0.520	0.528	0.008	0.019	0.015	0.399	0.690
pid7	4.111	4.232	0.121	0.086	0.055	1.408	0.159
educ_n	0.551	0.542	-0.010	0.007	-0.055	-1.419	0.156
age	41.500	41.555	0.056	0.497	0.004	0.112	0.911
hispanic(missing)	0.043	0.035	-0.009	0.007	-0.045	-1.156	0.247
female(missing)	0.012	0.004	-0.008	0.003	-0.103	-2.669	0.008
pid7(missing)	0.000	0.002	0.002	0.001	0.048	1.249	0.212
educ_n(missing)	0.245	0.227	-0.018	0.016	-0.041	-1.069	0.285
age(missing)	0.032	0.031	0.000	0.007	-0.002	-0.043	0.966

Overall: Chi-squared statistic= 16.659(df=12,p=0.163)

Note: Diff refers to the difference in means for a covariate. SE denotes the standard error of the difference in means. Std. Diff refers to the standardized difference in means.

C Response Substitution

C.1 Balance tests

Simple random assignment was used to assign subjects to control or one of the two treatments ($p = 1/3$).

Table C.1: Balance test, fraud occurred treatment versus control.

Variable	Z=0	Z=1	Diff	SE	Std. Diff	z	p
white	0.730	0.763	0.033	0.020	0.075	1.661	0.097
black	0.121	0.103	-0.018	0.014	-0.056	-1.250	0.211
asian	0.113	0.107	-0.007	0.014	-0.021	-0.464	0.642
hispanic	0.129	0.128	-0.001	0.015	-0.002	-0.035	0.972
female	0.468	0.496	0.029	0.023	0.057	1.268	0.205
pid7	4.857	4.651	-0.206	0.098	-0.095	-2.104	0.035
educ_n	0.703	0.697	-0.006	0.011	-0.023	-0.518	0.605
age	39.307	40.300	0.993	0.554	0.081	1.792	0.073
hispanic(missing)	0.001	0.000	-0.001	0.001	-0.045	-1.002	0.316
female(missing)	0.004	0.006	0.002	0.003	0.028	0.627	0.530
educ_n(missing)	0.016	0.017	0.001	0.006	0.007	0.164	0.870
age(missing)	0.002	0.000	-0.002	0.001	-0.064	-1.417	0.156

Overall: Chi-squared statistic= 13.69(df=12,p=0.321)

Table C.2: Balance test, wrong decision treatment versus control.

Variable	Z=0	Z=1	Diff	SE	Std. Diff	z	p
white	0.730	0.771	0.040	0.020	0.093	2.061	0.039
black	0.121	0.093	-0.028	0.014	-0.090	-1.991	0.046
asian	0.113	0.102	-0.011	0.014	-0.037	-0.817	0.414
hispanic	0.129	0.136	0.007	0.015	0.020	0.449	0.653
female	0.468	0.480	0.012	0.023	0.025	0.545	0.586
pid7	4.857	4.607	-0.250	0.099	-0.115	-2.540	0.011
educ_n	0.703	0.698	-0.005	0.011	-0.020	-0.452	0.651
age	39.307	39.984	0.676	0.542	0.056	1.248	0.212
hispanic(missing)	0.001	0.000	-0.001	0.001	-0.045	-1.001	0.317
female(missing)	0.004	0.002	-0.002	0.002	-0.037	-0.820	0.412
educ_n(missing)	0.016	0.016	0.000	0.006	0.000	-0.006	0.995
age(missing)	0.002	0.000	-0.002	0.001	-0.064	-1.416	0.157

Overall: Chi-squared statistic= 14.615(df=12,p=0.263)

Note: Diff refers to the difference in means for a covariate. SE denotes the standard error of the difference in means. Std. Diff refers to the standardized difference in means.

C.2 Additional results

This section contains the following tables, all of which are versions of main text Table 4.

- Table C.3 presents estimates without covariate adjustment.
- Table C.4 presents estimates with the treatment conditions pooled.
- Table C.5 compares the two response substitution treatments to one another. The reference group is the fraud occurred treatment.

Table C.3: Response substitution estimates without covariate adjustment.

	Dem.	Indep.	Repub.	Partisan Diff.
Constant	0.128**	0.356**	0.501**	0.128**
	(0.008)	(0.033)	(0.020)	(0.008)
Fraud occurred treatment	0.006	−0.074	0.034	0.006
	(0.013)	(0.048)	(0.028)	(0.013)
Wrong decision treatment	−0.013	0.020	0.021	−0.013
	(0.012)	(0.048)	(0.028)	(0.012)
Republican				0.373**
				(0.022)
Republican × fraud occurred treatment				0.027
				(0.031)
Republican × wrong decision treatment				0.033
				(0.030)
Adj. R^2	0.000	0.008	−0.001	0.331
Num. obs.	1745	268	929	2674

Note: Table replicates main text Table 4 without covariate adjustment (i.e., dropping the pre-treatment measure of the dependent variable). $^{*}p < 0.05$, $^{**}p < 0.01$.

Table C.4: Estimates with treatment conditions pooled, response substitution.

	Dem.	Indep.	Repub.	Partisan Diff.
Constant	0.130**	0.355**	0.506**	0.034**
	(0.007)	(0.019)	(0.014)	(0.007)
Either treatment	0.002	−0.036	0.008	0.004
	(0.009)	(0.023)	(0.016)	(0.009)
Republican				0.117**
				(0.018)
Republican × either treatment				0.007
				(0.019)
Pre-treatment DV	0.553**	0.875**	0.792**	0.684**
	(0.029)	(0.032)	(0.021)	(0.019)
Adj. R^2	0.323	0.714	0.587	0.640
Num. obs.	1744	267	929	2673

Note: Table replicates main text Table 4 with the two treatment conditions pooled. Robust standard errors in parentheses. One tailed tests preregistered. $^{*}p < 0.05$, $^{**}p < 0.01$.

Table C.5: Response substitution: test for differences between treatments.

	Dem.	Indep.	Repub.	Partisan Diff.
Constant	0.133**	0.313**	0.528**	0.041**
	(0.008)	(0.020)	(0.013)	(0.008)
Wrong decision treatment	−0.016	0.041	0.000	−0.015
	(0.010)	(0.026)	(0.017)	(0.010)
Republican				0.105**
				(0.019)
Republican × wrong decision treatment				0.013
				(0.020)
Pre-treatment DV	0.592**	0.889**	0.806**	0.713**
	(0.036)	(0.037)	(0.025)	(0.022)
Adj. R^2	0.359	0.741	0.598	0.663
Num. obs.	1131	180	650	1781

Note: Table tests for differences in effects between the two response substitution treatments. In all other respects it is comparable to main text Table 4. $^{*}p < 0.05$, $^{**}p < 0.01$.

D Betting on the Future

D.1 Balance test

Simple random assignment was used to assign between the incentive and no-incentive conditions ($p = 1/2$).

Table D.1: Balance test, betting on the future study 2, treatment versus control.

Variable	Z=0	Z=1	Diff	SE	Std. Diff	z	p
white	0.705	0.715	0.010	0.013	0.022	0.773	0.439
black	0.088	0.089	0.001	0.008	0.004	0.136	0.892
asian	0.075	0.072	-0.004	0.007	-0.014	-0.488	0.625
hispanic	0.066	0.052	-0.013	0.007	-0.056	-1.973	0.049
female	0.529	0.524	-0.005	0.014	-0.010	-0.335	0.738
pid7	4.119	4.182	0.063	0.064	0.028	0.986	0.324
educ_n	0.543	0.545	0.002	0.005	0.010	0.354	0.724
age	41.419	41.337	-0.083	0.364	-0.006	-0.226	0.821
hispanic(missing)	0.037	0.044	0.006	0.006	0.031	1.084	0.278
female(missing)	0.004	0.008	0.004	0.002	0.047	1.647	0.099
pid7(missing)	0.001	0.002	0.001	0.001	0.032	1.121	0.262
educ_n(missing)	0.212	0.237	0.025	0.012	0.059	2.060	0.039
age(missing)	0.033	0.037	0.004	0.005	0.020	0.710	0.478

Overall: Chi-squared statistic= 15.538(df=13,p=0.275)

D.2 Additional results

In the main text, we use regression to estimate the difference between the unincentivized and incentivized questions, with errors clostered at the respondent level (Tables 7 and 8). However, our PAP states that we will estimate the difference by subtracting the two measures and taking the average. These procedures yield identical results. We verify this in Table E.2. The estimates are identical to the second row of Tables 7 and 8.

Table D.2: Average within-person change, betting on the future.

Study	Party	Estimate	SE	t-stat
Study 1	Neither	-0.018	(0.012)	-1.421
	Republican	-0.057	(0.010)	-5.850
Study 3	Democrat	-0.003	(0.005)	-0.507
	Independent	0.016	(0.011)	1.417
	Republican	-0.012	(0.007)	-1.550

E Confidence and Temporal Stability

E.1 Additional results

This section contains a tabular version of the estimates plotted in main text Figures 2 and 3, as well as the equivalent estimates for Democrats and independents.

Table E.1: Estimates displayed in Figure 2.

Party	Response	Estimate	SE	95% CI	N
Rep.	Definitely would have won either way (0)	0.131	0.003	(0.124, 0.138)	151
	Probably would have won either way (0.25)	0.258	0.006	(0.247, 0.269)	297
	Not sure (0.5)	0.211	0.005	(0.201, 0.220)	243
	Probably due to fraud (0.75)	0.212	0.005	(0.202, 0.221)	244
	Definitely due to fraud (1)	0.189	0.005	(0.180, 0.198)	218
Dem.	Definitely would have won either way (0)	0.648	0.005	(0.639, 0.658)	1374
	Probably would have won either way (0.25)	0.204	0.004	(0.197, 0.211)	432
	Not sure (0.5)	0.092	0.002	(0.088, 0.096)	195
	Probably due to fraud (0.75)	0.045	0.001	(0.043, 0.047)	96
	Definitely due to fraud (1)	0.010	0.000	(0.010, 0.011)	22
Indep.	Definitely would have won either way (0)	0.283	0.011	(0.261, 0.305)	92
	Probably would have won either way (0.25)	0.277	0.011	(0.255, 0.299)	90
	Not sure (0.5)	0.252	0.010	(0.232, 0.273)	82
	Probably due to fraud (0.75)	0.114	0.006	(0.103, 0.125)	37
	Definitely due to fraud (1)	0.074	0.004	(0.066, 0.081)	24

Table E.2: Estimates displayed in Figure 3a.

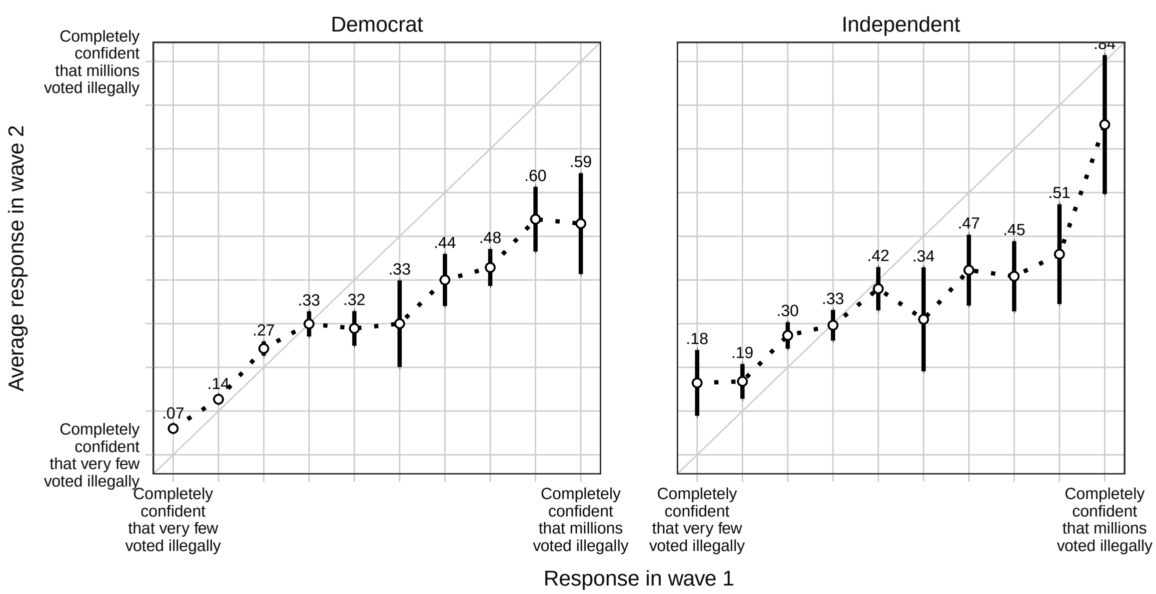
Party	Response	Estimate	SE	95% CI	N
Rep.	Definitely would have won either way (0)	0.119	0.037	(0.044, 0.195)	42
	Probably would have won either way (0.25)	0.299	0.027	(0.244, 0.353)	67
	Not sure (0.5)	0.513	0.032	(0.450, 0.576)	57
	Probably due to fraud (0.75)	0.633	0.029	(0.576, 0.690)	62
	Definitely due to fraud (1)	0.907	0.028	(0.851, 0.963)	51
Dem.	Definitely would have won either way (0)	0.046	0.007	(0.032, 0.060)	398
	Probably would have won either way (0.25)	0.235	0.018	(0.199, 0.271)	133
	Not sure (0.5)	0.358	0.032	(0.295, 0.421)	51
	Probably due to fraud (0.75)	0.391	0.058	(0.270, 0.513)	23
	Definitely due to fraud (1)	0.219	0.088	(0.012, 0.426)	8
Indep.	Definitely would have won either way (0)	0.065	0.036	(-0.009, 0.140)	23
	Probably would have won either way (0.25)	0.269	0.039	(0.189, 0.350)	26
	Not sure (0.5)	0.467	0.033	(0.400, 0.535)	23
	Probably due to fraud (0.75)	0.687	0.078	(0.502, 0.873)	8
	Definitely due to fraud (1)	0.893	0.074	(0.711, 1.075)	7

E.2 Comparison to 2016 fraud claim

To benchmark our results, we examined a topically similar false claim: Trump's allegation that millions of illegal votes were cast in the 2016 U.S. presidential election. A question designed to measure belief in this claim was included in the 2020 ANES Social Media Study. In both survey waves, the question asked, "Which of these do you think is most likely to be true?" with the response options, "Millions of people voted illegally in the 2016 election" and "Few people voted illegally in the 2016 election." Next, respondents were asked "How confident are you about that?" and presented with a 5-point scale with the labels "not at all," "a little," "moderately," "very," and "completely." We recoded these responses to a 0-1 scale where 0 represents completely confident rejection of the claim and 1 represents completely confident acceptance.

Using these data, we computed the same temporal stability statistics. The main results appear in Figure 3b and are discussed in the main text. As a further point of comparison, we produce the same analysis for Democrats and independents. Unlike the case of the big lie, stability among Democrats and independents is similar to what we observed among Republicans. This provides further evidence that Republicans did not accept Trump's "millions of illegal votes" lie to the same degree they accepted the big lie about 2020.

Figure E.1: Temporal stability among Democrats and independents, millions of illegal votes



Note: This figure is identical to main text Figure 3b, but with estimates for Democrats and indepenents instead of Republicans.

Table E.3 presents the estimates from Figures 3b and E.1 in tabular form.

Table E.3: Estimates displayed in Figure 3b.

Party	Response	Estimate	SE	95% CI	N
Rep.	Completely confident that few voted illegally	0.141	0.021	(0.098, 0.183)	83
	Very confident that few voted illegally	0.219	0.012	(0.195, 0.244)	307
	Moderately confident that few voted illegally	0.287	0.009	(0.269, 0.304)	599
	A little confident that few voted illegally	0.336	0.012	(0.314, 0.359)	332
	Not at all confident that few voted illegally	0.395	0.026	(0.343, 0.446)	69
	Not at all confident that millions voted illegally	0.488	0.058	(0.365, 0.611)	18
	A little confident that millions voted illegally	0.441	0.023	(0.396, 0.486)	122
	Moderately confident that millions voted illegally	0.488	0.019	(0.451, 0.525)	271
	Very confident that millions voted illegally	0.527	0.025	(0.478, 0.576)	191
	Completely confident that millions voted illegally	0.635	0.046	(0.543, 0.727)	74
Dem.	Completely confident that few voted illegally	0.067	0.005	(0.057, 0.077)	756
	Very confident that few voted illegally	0.141	0.006	(0.130, 0.152)	725
	Moderately confident that few voted illegally	0.270	0.009	(0.252, 0.288)	512
	A little confident that few voted illegally	0.333	0.016	(0.301, 0.365)	195
	Not at all confident that few voted illegally	0.321	0.022	(0.277, 0.365)	92
	Not at all confident that millions voted illegally	0.333	0.052	(0.223, 0.443)	19
	A little confident that millions voted illegally	0.444	0.033	(0.378, 0.511)	57
	Moderately confident that millions voted illegally	0.476	0.024	(0.429, 0.523)	133
	Very confident that millions voted illegally	0.599	0.041	(0.517, 0.681)	64
	Completely confident that millions voted illegally	0.588	0.063	(0.460, 0.716)	38
Indep.	Completely confident that few voted illegally	0.183	0.042	(0.099, 0.266)	45
	Very confident that few voted illegally	0.187	0.022	(0.142, 0.231)	78
	Moderately confident that few voted illegally	0.303	0.017	(0.270, 0.337)	171
	A little confident that few voted illegally	0.329	0.020	(0.290, 0.368)	83
	Not at all confident that few voted illegally	0.422	0.027	(0.367, 0.477)	45
	Not at all confident that millions voted illegally	0.344	0.058	(0.212, 0.477)	10
	A little confident that millions voted illegally	0.469	0.045	(0.379, 0.560)	40
	Moderately confident that millions voted illegally	0.454	0.044	(0.365, 0.543)	47
	Very confident that millions voted illegally	0.510	0.061	(0.383, 0.637)	22
	Completely confident that millions voted illegally	0.840	0.077	(0.663, 1.016)	9

F Survey Information

Survey 1

Platform: MTurk.

Dates: November 28-30, 2020.

Sample size: 1,049.

Screeners: Captcha verification, resides in the United States, at least one previous task completed, at least 95 percent approval on previous tasks.

Consent: Subjects read an IRB-approved consent form, then voluntarily consented to participate in a research study.

Refusal rate: 0 percent.

Compensation: $0.50.

Preanalysis plan: None.

Survey 2

Platform: MTurk.

Dates: May 10-23, 2021.

Sample size: 3,599 (first wave); 2,958 (second wave).

Screeners: Captcha verification, resides in the United States, at least one previous task completed, at least 95 percent approval on previous tasks.

Consent: Subjects read an IRB-approved consent form, then voluntarily consented to participate in a research study.

Refusal rate: 0.2 percent.

Compensation: $0.60.

Preanalysis plan: This preanalysis plan covered multiple papers, some of which are still under peer review. An anonymous version is available at https://aspredicted.org/blind.php?x=GDZ_UAN and at the end of this section. It will be made public after all relevant papers are published.

The pre-registered hypotheses are tested in the following locations:

- *Hypothesis 1: partisan differences.* Tested in main text Table 4. Robustness check in Table C.3.
- *Hypothesis 1a: expressive responding by Democrats.* Tested in main text Table 4. Robustness check in Table C.3.
- *Hypothesis 1b: expressive responding by Republicans.* Tested in main text Table 4. Robustness check in Table C.3.
- *Hypothesis 2: comparison between treatments.* Tested in Table C.5.

Survey 3

Platform: MTurk.

Dates: July 7-31, 2021.

Sample size: 4,885.

Screeners: Captcha verification, resides in the United States, at least one previous task completed, at least 95 percent approval on previous tasks.

Consent: Subjects read an IRB-approved consent form, then voluntarily consented to participate in a research study.

Refusal rate: 0.4 percent.

Compensation: $0.50.

Preanalysis plan: Available at https://aspredicted.org/94vx6.pdf and at the end of this section. The pre-registered hypotheses are tested in the following locations:

- *Hypothesis 1: list experiment reduces Republicans' measured belief in the big lie.* Tested in main text Table 6.
- *Hypothesis 1a: list experiment reduces partisan differences regarding the big lie.* Tested in main text Table 6.
- *Hypothesis 2: financial incentives reduce Republicans' tendency to predict Trump's reinstatement.* Tested in main text Table 8a and 8b.
- *Hypothesis 2a: financial incentives reduce partisan differences regarding Trump's reinstatement.* Tested in main text Table 8a and 8b.

We deviated from the PAP in two respects. First, for the list experiment, the PAP states that we will use block random assignment. However, this failed when we launched the survey. As a backup, the survey automatically reverted to using simple random assignment. Second, for betting on the future, the PAP states that we will conduct the within-person analysis by scoring respondents as a -1, 0, or 1, then taking the average. We instead used a different procedure that yields identical estimates (see Appendix D.2).

Survey 4

Platform: MTurk.

Dates: September 22-23, 2021.

Sample size: 5,005.

Screeners: Captcha verification, resides in the United States, at least one previous task completed, at least 95 percent approval on previous tasks.

Consent: Subjects read an IRB-approved consent form, then voluntarily consented to participate in a research study.

Refusal rate: 0.1 percent.

Compensation: $0.75.

Preanalysis plan: Available at https://aspredicted.org/nf3p7.pdf and at the end of this section. The pre-registered hypotheses are tested in the following locations:

- *Hypothesis 1: honesty encouragement reduces Republicans' measured belief in the big lie.* Tested in main text Table 2.
- *Hypothesis 1a: honesty encouragement reduces partisan differences.* Tested in main text Table 2.

Survey 5

Platform: MTurk.

Dates: August 11-12, 2021.

Sample size: 4,936.

Screeners: Captcha verification, resides in the United States, at least one previous task completed, at least 95 percent approval on previous tasks.

Consent: Subjects read an IRB-approved consent form, then voluntarily consented to participate in a research study.

Refusal rate: 0.1 percent.

Compensation: $1.00.

Preanalysis plan: Available at https://aspredicted.org/gt5ce.pdf and at the end of this section. The pre-registered hypotheses are tested in the following locations:

- *Hypothesis 1: honesty encouragement reduces Republicans' measured belief in the big lie.* Tested in main text Table 3.
- *Hypothesis 1a: honesty encouragement reduces partisan differences.* Tested in main text Table 3.

As Predicted:*Response substitution: Economy, vaccinations, and voter fraud* (#65446)

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1) Have any data been collected for this study already?
No, no data have been collected for this study yet.

2) What's the main question being asked or hypothesis being tested in this study?
We examine whether partisan gaps in response to survey items concerning political issues are caused by "response substitution" on behalf of partisan respondents. "Response substitution" in the survey context can be considered a systematic measurement error, as respondents provide "an answer to a question that reflects attitudes or beliefs that they want to convey but that the researcher has not asked about" (Gal and Rucker 2011, 186) in response to a given survey item. In our study, we test whether reducing "response substitution" indeed reduces the partisan gap in responses to politically contested items. More specifically, we will test whether allowing respondents to answer "an unasked question" (i.e., convey "the attitudes or beliefs that they want to convey") prior to the item of interest changes their response to the item of interest, thereby reducing the partisan gap in the latter item.

As detailed below, we will examine response substitution in three topic areas: economic evaluations, vaccination campaigns, and voter fraud in the 2020 election. Though we may examine these topics in separate manuscripts, we are registering them together because the studies all draw on the same theoretical framework. In all areas we will test the following hypothesis. "Treatment" always refers to allowing the respondent to answer an unasked question.
H1: Treatment will reduce the difference in average responses between Democrats and Republicans.

To provide context for H1, we will also test the following hypotheses.
H1a: Treatment will reduce pro-Democrat responses among Democrats.
H1b: Treatment will reduce pro-Republican responses among Republicans.
When it comes to voter fraud, we may privilege our test of H1b over H1 and H1a. See section 8 for a brief discussion of the relative substantive importance of these hypotheses as they apply to each topic.

For the two topics with more than one treatment (i.e., all but the vaccine topic), we will also compare the effect of the two treatments.
H2: Different treatments have different effects.

3) Describe the key dependent variable(s) specifying how they will be measured.
Economic evaluations (7-point Likert)
Question text: What do you think about the state of the economy these days in the United States? Would you say the state of the economy is good or bad?
Valence of responses: Good = pro-Democrat, bad = pro-Republican

Vaccine evaluations (7-point Likert)
Question text: What do you think about COVID-19 vaccination in the United States? Would you say the country is doing a good job or a bad job?
Valence of responses: Good = pro-Democrat, bad = pro-Republican

Voter fraud (5-point Likert)
Question text: Would you say that Joe Biden only won the 2020 presidential election due to voter fraud, or do you think he would have won

either way?
Valence of responses: Either way = pro-Democrat, due to fraud = pro-Republican

4) How many and which conditions will participants be assigned to?
For all three topics, respondents will be assigned to the treatment arms with equal probability using simple random assignment. Control conditions display only the dependent variable (as listed above), while treatment conditions precede the dependent variable with items that we suspect may function as "unasked questions." The conditions are as follows:

Economic evaluations
• Control
• Approval condition (unasked question concerns approval of Biden's performance)
• Responsibility condition (unasked question concerns whether Biden or Trump had more influence on the current state of the economy)

Vaccine evaluations
• Control
• Responsibility condition (unasked question concerns whether Biden or Trump had more influence on the vaccine rollout)

Voter fraud
• Control
• Fraud beliefs condition (unasked question concerns whether fraud occurred)
• Right decision condition (unasked question concerns whether electing Biden was the right or wrong decision for the country)

5) Specify exactly which analyses you will conduct to examine the main question/hypothesis.
For each of the individual topics, we will estimate all of our treatment effects using OLS regressions with robust standard errors.

To test H1, we will use OLS to estimate the parameters in a linear model:
(1) DV = B0 + B1×FirstTreatment + B2×SecondTreatment + B3×Republican + B4×FirstTreatment×Republican + B5×SecondTreatment×Republican + B6×PreTreatmentDV + epsilon

where:
• DV – the dependent variable in each topic, with higher values denoting responses that are more favorable to Republicans (see section 3).
• FirstTreatment – a dummy variable for our first treatment.
• SecondTreatment – a dummy variable for our second treatment.
• Republican – a dummy variable for a Republican respondent.
• PreTreatmentDV – the pre-treatment measure of the DV collected in the baseline survey.

For the vaccine topic, B2 and B5 will be excluded as there is only one treatment. Similarly, for topics in which we fail to confirm hypothesis 2, we will report a pooled estimate using a model that compares the control condition with the two treatments combined.

We expect that B1 and B2 will take the opposite sign as B4 and B5 and that B4 and B5 will be statistically significant. This would indicate that the treatment(s) reduced the partisan difference.

To illustrate where the estimates come from (e.g., to say that response substitution seemed to primarily occur among Democrats or Republicans), we will examine the separate party means and treatment effects.
To test H1a and H1b, we will use data for Democrats and Republicans only to estimate (1)
(2) DV = B0 + B1×FirstTreatment + B2×SecondTreatment + B3×PreTreatmentDV + epsilon
where all terms are defined above.

To test H2, we will use only the data on the treatment groups to estimate:
(3) DV = B0 + B1×SecondTreatment + B2×SecondTreatment×Republican + B3×PreTreatmentDV + epsilon
where all terms are defined above. We have no clear expectations as to whether B2 should be positive or negative.

For the hypothesis stated with clear directional expectations (i.e., all but H2), we will conduct one-tailed tests.

6) Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.
We will exclude from our hypothesis tests "pure" independents ("leaning" independents will be included in the analyses as either Democrats or Republicans).

7) How many observations will be collected or what will determine sample size?

No need to justify decision, but be precise about exactly how the number will be determined.

We will recruit 3,600 respondents from MTurk into a baseline/wave 1 survey that measures background characteristics and a pre-treatment measure of the economic, vaccine, and voter fraud DVs. We will recontact 3,000 of these respondents for the main/wave 2 survey, which will include the treatments.

8) Anything else you would like to pre-register?
(e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)

Although we are pre-registering the same set of tests in the same empirical framework for all three topics, we note above that our emphasis on the components of H1 may differ based on the context of each topic area. For the economic and vaccine topics, we do not have strong expectations about whether response substitution among Democrats or Republicans would be more important. We therefore plan to emphasize H1, which tests for the narrowing of partisan differences that are expected to occur if both H1a and H1b hold. Due to the voter fraud topic's political context, we think that response substitution is most important if it occurs among Republicans, and therefore plan to pay close attention to H1b.

As Predicted: *Belief in voter fraud + Trump reinstatement (July 2021)* (#70229)

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1) Have any data been collected for this study already?
No, no data have been collected for this study yet.

2) What's the main question being asked or hypothesis being tested in this study?
As detailed below, we will look for evidence of expressive responding in two topic areas: belief that voter fraud determined the results of the 2020 election, and belief that Donald Trump will be reinstated as the US president in August 2021.

For voter fraud, we will test the following hypothesis:
H1: An anonymity treatment (a list experiment) will reduce Republicans' reported belief that Biden only won due to election fraud.

For the Trump reinstatement prediction, we will test the following hypothesis:
H2: Financial incentives will reduce Republicans' tendency to predict that Trump will be reinstated as president.

To provide context, we will also test the following hypothesis:
H1a/H2a: Treatment (anonymity or financial incentives) will reduce the average difference in responses between Democrats and Republicans.

3) Describe the key dependent variable(s) specifying how they will be measured.
Voter fraud:
• Direct question: Do you agree or disagree with this statement about the 2020 U.S. presidential election? Joe Biden only won the election due to voter fraud. [Agree, disagree]
• List experiment, control condition: Here is a list of statements about the 2020 U.S. presidential election. We would like to know how many you agree with. [I voted in the election.; I did not know where to vote.; I requested an absentee ballot, but it did not arrive.; The Green Party came close to winning the election.]
• List experiment, treatment condition: Same as control with the addition of the following statement: Joe Biden only won the election due to voter fraud.

Trump reinstatement:
• Direct question: Which statement is more likely to be true?
• Incentivized question: Which ticket would you like to enter into the drawing?
Response options for both questions: Donald Trump will be restored as President of the United States by the end of August.; Donald Trump will not be restored as President of the United States by the end of August.

Before answering the dependent variable, respondents in the incentivized condition will see some explanatory text stating that they will be allowed to enter a drawing for a bonus that will be conducted on September 1, 2021.

4) How many and which conditions will participants be assigned to?
For the voter fraud list experiment, respondents will be assigned to one of three conditions using block random assignment conducted prior to recruitment. Treatment probabilities were selected using a simulation study to minimize the standard error of the estimated difference between the direct question and the list experiment.
• Direct question (p=0.21)

• List experiment, no fraud statement (p=0.395)
• List experiment with fraud statement (p=0.395)

For the Trump reinstatement experiment, respondents will be assigned to one of two conditions using block random assignment:
• Control: direct question / no incentive (p=1/2)
• Treatment: financial incentive (p=1/2)
After answering the direct question, control respondents will be routed to the treatment condition. This will allow us to conduct both experimental analysis and a within-subjects analysis.

5) Specify exactly which analyses you will conduct to examine the main question/hypothesis.
For the voter fraud topic, we will estimate our treatment effect by comparing the difference in means from the list experiment to the mean of the direct question measure. If the difference in means from the list experiment is smaller, this would indicate expressive responding. We will test for statistical significance using a t-test, with p=0.05 (one-sided) as a guideline for statistical significance when testing H1. In all comparisons between the list experiment and direct questions, we will bootstrap p-values using the percentile method. We will conduct 10,000 simulations with the seed set to 0.

For the Trump reinstatement experiment, we will conduct a difference in means test. Specifically, per H2 we will examine whether the percentage of Republicans who will state in the "direct" question that they believe that Trump will be reinstated in August will be greater than the percentage of Republicans who will place a bet on Trump being reinstated in August. We will test for statistical significance using OLS regression, with p=0.05 (one-sided) as a guideline for statistical significance.

For the Trump reinstatement within-subjects analysis, we will subtract the direct question from the incentivized question, yielding a variable that takes the values -1 ('switch' from reinstated to not reinstated), 0 (no change), 1 ('switch' from not reinstated to reinstated). The within-person effect is the mean of this variable. A negative average among Republicans provides support for H2, with p=0.05 (one-sided) as a guideline for statistical significance.

To test for the effect on partisan differences (H1a/H2a), we estimate the difference in treatment effects between Democrats and Republicans using an interaction between the treatment and a dummy for Republican respondents.

6) Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.
We will exclude "pure" independents from our test of the partisan difference hypotheses (H1a/H2a). "Leaning" independents will be included in the analyses as either Democrats or Republicans.

7) How many observations will be collected or what will determine sample size?
No need to justify decision, but be precise about exactly how the number will be determined.
We will make the survey available to 8,647 respondents on MTurk whose partisanship is already known to the researcher. Of these, about 50 percent are Republicans, 10 percent are independents, and 40 percent are Democrats. We will end the survey when we reach 6,000 respondents or on July 31, whichever comes first. If the recontact rate is below 50 percent on July 31, we will extend the sampling period for the list experiment by two weeks.

8) Anything else you would like to pre-register?
(e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)

As Predicted: *Belief in election fraud: Honesty treatments* (#72630)

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1) Have any data been collected for this study already?
No, no data have been collected for this study yet.

2) What's the main question being asked or hypothesis being tested in this study?
As detailed below, we will look for evidence of expressive responding in the belief that voter fraud determined the results of the 2020 election. Specifically, we will test the following hypothesis:
H1: An honesty treatment will reduce Republicans' reported belief that Biden only won due to election fraud.

To provide context, we will also test the following hypothesis:
H1a: The honesty treatment will reduce the average difference in responses between Democrats and Republicans.

3) Describe the key dependent variable(s) specifying how they will be measured.
[1] Do you think that Joe Biden only won the 2020 presidential election due to voter fraud, or do you think he would have won either way?
• Definitely due to voter fraud
• Probably due to voter fraud
• Not sure
• Probably would have won either way
• Definitely would have won either way

We will rescale this variable such that higher values denote more support for the response that is congenial to Republicans (i.e., 'Definitely due to voter fraud')

4) How many and which conditions will participants be assigned to?
Respondents will be assigned to one of three conditions using simple random assignment.

• First treatment (request): Regardless of how you feel about the people and events mentioned in the question below, we want you to tell us what you believe to be true. Again, we ask that you try and ignore your personal feelings. [Respondents will then answer the dependent variable]

• Second treatment (pipeline): We sometimes find that people choose answers that they do not really believe so that they can say something good or bad about the people and events mentioned in the question. Regardless of how you feel about the people and events mentioned in the question below, please tell us what you believe to be true. [Respondents will then answer the dependent variable]

• Control: none [only the dependent variable.]

5) Specify exactly which analyses you will conduct to examine the main question/hypothesis.
We will estimate our treatment effects using OLS regressions with robust standard errors.

To test H1, we will use OLS to estimate the parameters in a linear model among republican respondents only. This model will separately estimate the effect of the two treatments:
(1) DV = B0 + B1× FirstTreatment + B2×SecondTreatment + epsilon

And to test H1a, we will use OLS to estimate the parameters in a linear model:
(2) DV = B0 + B1×FirstTreatment + B2×SecondTreatment + B3×Republican + B4×FirstTreatment×Republican + B5×SecondTreatment×Republican + epsilon

where:
• DV – the dependent variable in each topic, with higher values denoting responses that are more favorable to Republicans (see section 3).
• FirstTreatment – a dummy variable for our first treatment.
• SecondTreatment – a dummy variable for our second treatment.
• Republican – a dummy variable for a Republican respondent.

In Equation (1), we expect both B1 and B2 to be negative and statistically significant. This would indicate that each treatment reduced reported belief in voter fraud among Republicans.
In Equation (2), we expect that B1 and B2 will take the opposite sign as B4 and B5, and that B4 and B5 will be statistically significant. This would indicate that each treatment reduced the partisan difference.

As an additional test of H1 and H1a, respectively, we will use OLS models that combine the two treatments:
(3) DV = B0 + B1×AnyTreatment + epsilon

(4) DV = B0 + B1×AnyTreatment + B2×Republican + B3×AnyTreatment×Republican + epsilon

where:
• AnyTreatment – a dummy variable for any of the two treatment conditions.

In Equation (3), we expect that B1 will be negative and statistically significant. This would indicate that the treatments (pooled) reduced reported belief in voter fraud among Republican respondents.
And in Equation (4), we expect that B1 will take the opposite sign as B3 and that B3 will be statistically significant. This would indicate that the treatments (pooled) reduced the partisan difference.

All hypotheses are stated with clear directional expectations. Accordingly, we will conduct one-tailed tests.

6) Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.
We will exclude "pure" independents from our test of the partisan difference hypotheses (H1a). "Leaning" independents will be included in the analyses as either Democrats or Republicans.

7) How many observations will be collected or what will determine sample size?
No need to justify decision, but be precise about exactly how the number will be determined.
We will recruit 5,000 respondents from MTurk.

8) Anything else you would like to pre-register?
(e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)

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Belief in election fraud: Honesty pledge (#104206)

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1) Have any data been collected for this study already?

No, no data have been collected for this study yet.

2) What's the main question being asked or hypothesis being tested in this study?

As detailed below, we will look for evidence of expressive responding in the belief that voter fraud determined the results of the 2020 election. Specifically, we will test the following hypothesis:
H1: An honesty treatment will reduce Republicans' reported belief that Biden only won due to election fraud.

To provide context, we will also test the following hypothesis:
H1a: The honesty treatment will reduce the average difference in responses between Democrats and Republicans.

3) Describe the key dependent variable(s) specifying how they will be measured.

Do you think that Joe Biden only won the 2020 presidential election due to voter fraud, or do you think he would have won either way?

- Definitely due to voter fraud
- Probably due to voter fraud
- Not sure
- Probably would have won either way
- Definitely would have won either way

4) How many and which conditions will participants be assigned to?

Respondents will be assigned to one of two conditions using simple random assignment.

- Treatment: on the page before the question, respondents read a short generic transition sentence and are asked to promise to answer the next question honestly.
- Control: on the page before the question, respondents only read the short generic transition sentence.

5) Specify exactly which analyses you will conduct to examine the main question/hypothesis.

We will estimate our treatment effects using OLS regressions with robust standard errors.

To test H1, we will use OLS to estimate the parameters in a linear model among Republican respondents only:
(1) DV = B0 + B1× Treatment + epsilon

And to test H1a, we will use OLS to estimate the parameters in a linear model:
(2) DV = B0 + B1×Treatment + B2×Republican + B3×Treatment×Republican + epsilon

where:

- DV – the dependent variable in each topic, with higher values denoting responses that are more favorable to Republicans (see section 3).
- Treatment – a dummy variable for treatment.
- Republican – a dummy variable for a Republican respondent.

In Equation (1), we expect B1 to be negative and statistically significant. This would indicate that treatment reduced reported belief in voter fraud among Republicans.
In Equation (2), we expect that B1 and B3 will take opposite signs and that B3 will be statistically significant. This would indicate that treatment reduced the partisan difference.

The hypotheses are stated with clear directional expectations. Accordingly, we will conduct one-tailed tests.

6) Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.

We will exclude "pure" independents from our test of the partisan difference hypotheses (H1a). "Leaning" independents will be included in the analyses as either Democrats or Republicans.

7) How many observations will be collected or what will determine sample size? No need to justify decision, but be precise about exactly how the number will be determined.
5,000

8) Anything else you would like to pre-register? (e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)
Although we are most interested in effects among Republicans, we will also test H1 among Democrats and independents.