The Liar's Dividend: Can Politicians Use Deepfakes and Fake News to Evade Accountability?

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Abstract

This study addresses the phenomenon of *misinformation about misinformation*, or politicians "crying wolf" over fake news. Strategic and false allegations that stories are fake news or deepfakes may benefit politicians by helping them maintain support in the face of information damaging to their reputation. We posit that this concept, known as the "liar's dividend," works through two theoretical channels: by invoking informational uncertainty or by encouraging oppositional rallying of core supporters. To evaluate the implications of the liar's dividend, we use three survey experiments detailing hypothetical politician responses to video or text news stories depicting real politician scandals. We find that allegations of misinformation raise politician support, while potentially undermining trust in media. Moreover, these false claims produce greater dividends for politicians than longstanding alternative responses to scandal, such as remaining silent or apologizing. Finally, false allegations of misinformation pay off less for videos ("deepfakes") than text stories ("fake news").

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"The result of a consistent and total substitution of lies for factual truth is not that the lie will now be accepted as truth and truth be defamed as a lie, but that the sense by which we take our bearings in the real world—and the category of truth versus falsehood is among the mental means to this end—is being destroyed." —Hannah Arendt in *The Origins of Totalitarianism* (1973)

Misinformation in political discourse can negatively impact political accountability, trust, and social cohesion (Jerit and Zhao, 2020; Vaccari and Chadwick, 2020*a*). Concerns about misinformation are only deepening with the emergence of new methods to generate and disseminate falsified media, methods that are transforming and extending traditional strategies of promoting misinformation. While scholars have debated the direct effects of misinformation in terms of its ability to deceive and persuade, misinformation can serve a variety of purposes beyond direct persuasion, working through emotional and symbolic means and shifting the foundations of the broader informational environment itself. This study devotes attention to these indirect effects and provides novel experimental evidence related to one such subtle and concerning consequence of misinformation: the liar's dividend.

In particular, we seek to understand whether politicians and other public figures can leverage an environment of misinformation and distrust to their benefit by falsely claiming that damaging true information about themselves (e.g., a scandal) is fake. That is, we explore whether politicians can maintain support by spreading *misinformation about misinformation*—falsely claiming that true events and stories are merely "fake news" or "deepfakes." If such lies are used successfully, they provide a benefit, or a "liar's dividend," increasing the liar's authority, reelection prospects, or reputation (Chesney and Citron, 2019). However, they do so through deception and risk further undermining political discourse, social cohesion, and public trust in the media and larger informational environment.

We investigate the liar's dividend through three experimental studies using text and video from four real politician scandals in the United States. We follow the politician scandals with rebuttals from the politicians alleging that the stories are mere misinformation. The politician allegations make use of two strategies. First, politicians may seek to undermine confidence in the informational environment, a channel we term "informational uncertainty." Alternatively, they may exploit affective polarization and partisan animus to draw supporters to their defense, which we term "oppositional rallying." We evaluate the extent to which these strategies bolster support for the politicians and undermine trust in the media environment generally. We also assess whether lying pays off more for video ("deepfakes") versus text ("fake news")[1] stories and whether allegations of misinformation are more effective than alternative politician responses: apologizing or simply denying (without alleging misinformation).

We find that false allegations of misinformation do pay a liar's dividend. Allegations invoking both informational uncertainty and oppositional rallying lead to increases in politician support, and these effects may be concentrated on political moderates and co-partisans with the politician, respectively. Allegations of misinformation also generate larger support gains for politicians than simply ignoring the scandal (non-response) or apologizing, arguably a normatively preferable strategy. Yet, these gains come at the cost of deceiving the public and undermining trust in media. Finally, the results provide some reassurance: politician attempts to discredit scandals caught on video are much less successful, suggesting that politicians are still likely to be held accountable when audio-visual evidence is available.

In what follows, we provide context on the direct and indirect harms of misinformation, highlighting new challenges and features of the political and informational environment. Next, we present a theory of the liar's dividend and further define the informational uncertainty and oppositional rallying strategies. After describing our pre-registered experimental de-

[1] We define fake news as stories "which have no factual basis" but are published so as to create an impression of legitimacy, generally with the "intention of misinforming" (Tandoc Jr, Lim and Ling, 2018). While our study was motivated by the diffusion of allegations of misinformation specifically using the terminology "fake news," it's important to clarify that colloquial usage of this term is imprecise, politically loaded, and not limited to text-based media. While we use the term "fake news" at points to contextualize the study, we discuss our approach to treating this nuance more carefully in the section on research design.

signs,[2] we present results and review the implications of our findings for current public and scholarly conversations regarding misinformation.

1 Direct and Indirect Harms of Misinformation

Policymakers, scholars, and members of the public have raised fears about the impacts of misinformation on social and political cohesion, on institutional trust, and on maintaining a basis of shared truth. These fears are fueled by more frequent, everyday encounters with misinformation: 89% of Americans report encountering made-up news at least sometimes, and Americans are more likely to identify made-up news as a critical problem than climate change, racism, and illegal immigration (Mitchell et al., 2019). The political implications of misinformation are particularly troubling, as both foreign and domestic actors have seized upon vulnerabilities in the current informational environment to perpetuate falsehoods. Notably, 25% of tweets spread during the 2016 US presidential elections were fake or misleading (Bovet and Makse, 2019), and subsequent politically-oriented misinformation culminated in a violent insurrection after the 2020 election (Election Integrity Partnership, 2021). These recent events highlight the potential for misinformation to deepen social and political fractures by exacerbating polarization, undermining accountability and rational deliberation, and decreasing trust in institutions and media as part of a vicious cycle (Anderson, Rainie and Vogels, 2021).

While the use of misinformation for political ends is as old as politics itself (Arendt, 1973; O'Shaughnessy, 2004), new trends are upending the informational environment. One such transformative development is the emergence of new sophisticated methods to produce digitally-altered or fabricated audio, images, or videos, known as "deepfakes," which result from advances in artificial intelligence techniques such as Generative Adversarial Networks (GANs). Deepfakes are produced using approaches such as facial swapping, facial animation,

[2] Our pre-analysis plan is available at: https://osf.io/qpxr8/.

and the creation of entirely synthetic images or audio; notably, less sophisticated techniques (so-called "cheapfakes" or "shallowfakes") involving basic splicing, editing, or decontextualizing of media present similar risks (Reuters, 2019; Tandoc Jr, Lim and Ling, 2018). While advanced media creation and manipulation capabilities were previously restricted to professional artists and studios through time-consuming and expensive efforts, it is increasingly possible for non-sophisticated actors to generate highly-convincing fake video, images, and audio rapidly and at low cost (Karnouskos, 2020; Ovadya, 2021). Concerns surrounding deepfakes have now permeated society: 90% of the public say altered video and images cause confusion (Mitchell et al., 2019), news media and technical experts report severe challenges in determining the authenticity of content (Ker, 2019; Toews, 2020), and politicians have raised alarm as well.

While some experts previously suggested that the impact of deepfakes would be limited, examples of problematic uses are now accumulating. For example, deepfakes have been used to discourage supporters of opposing parties from voting in an Indian election (Christopher, 2020) and to create fake accounts on Twitter and YouTube in support of foreign propaganda efforts (Kan, 2020). Of particular relevance for this study, deepfakes have been used to depict specific politicians engaging in controversial acts or making offensive statements. For example, videos have allegedly exposed sex scandals involving Malaysian deputy minister Shamsul Iskander and Brazilian governor João Doria, though—critically—there remains an unsettled debate in both cases regarding whether the videos are deepfakes or authentic (Toews, 2020). Still other deepfakes have featured U.S. presidents Donald Trump and Barack Obama and French president Emmanuel Macron, and a cheapfake of Joe Biden was created and shared by a prominent Republican Representative Steve Scalise (New York Times Editorial Board, 2020). In perhaps the most concerning political case to date, an allegation that a video depicting Gabon's president as healthy was a deepfake helped to spur an unsuccessful military coup (Cahlan, 2020). Given many these examples, one striking implication is that the *mere existence* or allegation of deepfakes may lead to significant social and political harms, even when the authenticity of the content is disputed or disproved.

Notwithstanding increased attention and the seemingly consequential examples above, there is scholarly disagreement over the direct effectiveness of misinformation, conceived of primarily in terms of the ability of the information to persuade. Analogous to the minimal effects hypothesis in the context of political campaigns (Kalla and Broockman, 2018), some scholars have argued that the impact of fake news may be modest. According to this perspective, consumption of misinformation may be limited depending on individuals' media diets, restricted to those with strong partisan preferences, and moderated by individuals' ability to adjust for bias in news sources (Little, 2018). Moreover, individual fake news messages may not be especially persuasive on their own in the face of the multitude of informational signals people receive and because fake news consumption is only a small portion of overall news and information diets (Guess, Nyhan and Reifler, 2020; Watts, Rothschild and Mobius, 2021). However, while it is possible that the direct persuasive effects of fake news may be less than feared, there is much unknown about the multiple possible direct and indirect impacts of misinformation, especially in the medium-to-long-term (Lazer et al., 2018).

Indeed, it has long been understood that misinformation can serve a variety of purposes beyond direct persuasion about the truth of particular claims. For example, in the context of authoritarian regimes, misinformation has been used as means to signal the power of regimes or encourage performance of loyalty (Huang, 2015; O'Shaughnessy, 2004; Wedeen, 2015). Misinformation can also promote confusion and skepticism. Deepfakes in particular seem especially likely to drive such indirect harms on the informational environment, as individuals may feel they are no longer able to trust their eyes and ears, engendering broader distrust in all content—whether authentic or falsified (Ternovski, Kalla and Aronow, 2022). In this sense, while deepfakes "might not always fool viewers into believing in something false," they may exacerbate uncertainty and distrust, "further eroding our ability to meaningfully discuss public affairs" and discern truth from fiction (Vaccari and Chadwick, 2020*b*).

Appreciating that these effects may be intentional rather than merely incidental is essential if we are to understand the full implications of misinformation. As such, this paper examines indirect effects of misinformation and additionally considers whether new tools to promote misinformation (deepfakes) exacerbate or otherwise alter extant challenges.

2 A Theory of the Liar's Dividend

In light of the importance of indirect effects, this paper is concerned with a form of misinformation that owes its existence (in part) to fake news. That is, the widespread awareness of fake news has opened the door to *false allegations of fake news*, whereby politicians or other public figures can—potentially credibly—claim that real news stories are merely fake news or deepfakes, leading to what Chesney and Citron (2019) term the "liar's dividend." While this tactic of denial and deflection has been made prominent by U.S. President Donald Trump, calls of "fake news" have now been echoed by politicians in Russia, Brazil, China, Turkey, Libya, Poland, Hungary, Thailand, Somalia, Myanmar, Syria, and Malaysia (Erlanger, 2017). This form of misinformation has been used to target political opponents and to deny critical media coverage, even when objective observers and experts find the reporting to be credible. As a few notable examples, former Spanish Foreign Minister Alfonso Dastis claimed that images of police violence in Catalonia in 2017 were "fake photos" (Oppenheim, 2017) and American Mayor Jim Fouts called audio tapes of him making derogatory comments toward women and black people "phony, engineered tapes" (Wang, 2017), despite expert confirmation.

That the systematic usage of *misinformation about misinformation*—alleging "fake news" or "deepfakes" in response to real stories—has grown in recent years suggests that public figures find this strategy to be effective or beneficial, against the expectations of a minimal effects hypothesis. In particular, politicians may believe such a strategy can be employed to avoid accountability for political abuses or scandals. We therefore hypothesize that this strategy pays off by safeguarding politician reputations: members of the public are less likely to penalize politicians for scandals when they "cry wolf" over fake news and deepfakes. In particular, we expect this strategy to be more effective than three alternative politician communication strategies: 1) non-response, representing an attempt to ignore a scandal and let it blow over, 2) apologizing, arguably a normatively preferable response, or 3) simply denying a scandal without invoking misinformation.

Liar's Dividend Hypothesis: *In the face of scandal, allegations of misinformation (fake news or deepfakes) will increase average support for politicians.*[3]

We propose that an allegation of a deepfake or fake news might improve politician support through two potential pathways. First, the public may find allegations of "fake news" to be credible due to uncertainty regarding the truth of signals in what many members of the public may perceive as a distorted media environment—a channel we term "informational uncertainty." Here, the payoffs of allegations of fake news result from misinformation's truth-undermining effects, or "the principle that any information could be fake" (Ciancaglini et al., 2020). The concern is not that "people will be deceived, but that they will come to regard everything as deception" (Schwartz, 2018), particularly because it is easy to challenge the veracity of evidence in a fractured political environment (Hao, 2019), and harder to disprove these kinds of allegations (Galston, 2020). If consumers of information believe they have no credible signals about truth or falsity of political claims, the result may be increased uncertainty, as individuals lack sufficient information to establish a basic ground truth or make informed choices (Vaccari and Chadwick, 2020*a*). Thus, even when individuals are motivated to hold accurate beliefs, *informational uncertainty* undermines their capacity to do so.

To illustrate how informational uncertainty operates in the case of the liar's dividend, consider the statement of Spanish Minister Alfonso Dastis, who attempted to discredit photos of

[3] In the pre-registered pre-analysis plan (PAP), this corresponds to H1.

violence in Catalonia: "I'm sure you have seen what you have seen, but I have seen fake photos that date back to 2012. So, I think we have got to be patient, and look at the situation" (Oppenheim, 2017). The uncertainty induced by a statement like this (perhaps intentionally) may leave citizens unclear about how to update their evaluation of the politician or scandal. More generally, after learning of an embarrassing moment or political scandal, a member of the public will be more likely to downgrade their evaluation of the politician. However, if the politician then issues a statement disclaiming the story as a deepfake or fake news, then some members of the public may be more uncertain about what is true, decreasing belief in the scandalous story and increasing average support for the politician. Furthermore, we expect these effects to be concentrated amongst individuals in the middle of the political spectrum, representing individuals less likely to be strong supporters or opponents of partisan politicians.

The proposed channel of informational uncertainty is perhaps most active when individuals are motivated to hold true beliefs and engage in rational updating of beliefs and subsequent evaluations of politicians. Yet scholars note that individuals may also be motivated by partisan "directional" goals and engage in motivated rather than accuracy-driven reasoning (Taber and Lodge, 2006). In an environment of heightened polarization, low social trust, and without credible and shared informational signals to support rational processing, individuals may be especially prone to abandoning accuracy motivations in favor of directional ones (Druckman, 2012; Pennycook et al., 2021).

These elements of the political environment are highlighted by the second causal channel, which we term *oppositional rallying*. To avoid cognitive dissonance in the face of identity-incongruent information (a damaging news story about a preferred politician or party), core supporters or strong co-partisans may be receptive to congenial information, and may employ motivated reasoning (Bullock et al., 2015) to maintain support. The allegation of a deepfake or fake news can provide just this sort of cover—an excuse or reason for supporters to rally around the politician, disregarding the negative coverage and preserving their positive evaluations of the politician. Such a response may reflect genuine changes in belief, or instead, expressive responding and partisan cheerleading (Peterson and Iyengar, 2021). Further, this channel often explicitly invokes references to political opponents, as allegations of misinformation may strategically make use of a "devil shift" (Sabatier, Hunter and McLaughlin, 1987) where politicians signal not only their own innocence, but also the guilt of political opponents and media, allowing supporters to rally against the opposition. As such, we expect this channel to be particularly strong when individuals feel that their preferred politician or party is the target of unfair and hostile treatment by the opposition.

As an example of this strategy, American Mayor Jim Fouts alleged that his opponents were attempting to "hijack [the annual MLK Day] ceremony by releasing more vile, vitriolic, phony tapes against me" and that such an "effort...is designed to distract from my efforts of inclusion for all" (Wang, 2017). A politician who employs the strategy of oppositional rallying may thus explicitly signal to supporters because they seek to prime partisan directional motives. We therefore expect this mechanism to be most influential when individuals have strong positive associations with a specific politician (Flynn, Nyhan and Reifler, 2017), though strong party identification alone may be sufficient to drive these effects, given increasing affective polarization and a heightened connection between partisanship and identity (West and Iyengar, 2020). Thus, we expect effects to be stronger for strong co-partisans, who are more likely to reward allegations that employ the oppositional rallying channel with greater support for their preferred politician (Craig and Cossette, 2020).[4]

2.1 Mediating Factors and Further Consequences

Given the expanded use and awareness of manipulated or synthetic video including deepfakes, our study also considers whether the dynamics surrounding misinformation and the

[4]Subsidiary predictions related to Informational Uncertainty and Oppositional Rallying are discussed in the PAP under H1.1 and H1.2, respectively.

liar's dividend differ for text-based versus video-based content. There is much unknown about the extent to which deepfakes constitute a major societal risk as compared to text-based fake news, and our study aims to provide helpful evidence to answer this question. On the one hand, given a "psychological predisposition to believe in audio-visual content and a truth-default tendency," individuals are more likely to find this information credible (Ciancaglini et al., 2020). A "realism heuristic" implies that individuals find audio-visual content more closely resembles real-world experience and thus may be more naturally assimilated than text-based content (Vaccari and Chadwick, 2020*a*). This finding also extends to recent experimental work on misinformation, comparing video against text and audio formats (Sundar, Molina and Cho, 2021).

On the other hand, other recent studies call into question the extent to which deepfakes are more credible and persuasive than misinformation conveyed through text (Barari, Lucas and Munger, 2021), though video-based misinformation may be more effective for changing beliefs (Wittenberg et al., 2021). Relatedly, there is a long-standing debate about the extent to which "vivid" content—referring to the ability of information to provoke emotions and interest—is actually more persuasive (Taylor and Thompson, 1982). Notably, however, a recent meta-analysis of vividness which incorporates pictorial and video representations suggests that vivid information impacts both attitudes and behavior (Blondé and Girandola, 2016). In the context of the liar's dividend, on balance, we hypothesize that respondents will believe that video depicting politician scandals is harder to fake than text, such that allegations that these videos are deepfakes will be perceived as less credible, translating into a smaller payoffs for politicians.

Deepfakes Hypothesis: *Allegations of misinformation will lead to smaller improvements in average support for politicians when the underlying stories are video ("deepfakes") as compared to text ("fake news").*[5]

[5]Corresponds to H2 in the PAP.

An environment of distrust in media and institutions, partly created by misinformation, constitutes a fertile ground for the liar's dividend. In light of this, the consequences of alleging misinformation may extend beyond the immediate gains in politician support. In particular, allegations of misinformation may denigrate or otherwise undermine news media, reducing trust. These allegations can create the conditions for avoiding accountability not only for today's scandal or bad news story, but for tomorrow's as well. To investigate this possibility, we examine whether allegations of misinformation decrease average trust in media. We expect that this reduction in trust might be driven by both pathways behind the liar's dividend. For the informational uncertainty channel, politicians explicitly invoke distrust and confusion in the informational environment, likely driving individuals to increase their uncertainty over the accuracy of news coverage (Lee, 2010). For the oppositional rallying channel, individuals might be prompted to view the media as a biased, hostile actor itself or as simply a tool for transmitting opinion-laden attacks by political opponents.

Trust in Media Hypothesis: *Allegations of misinformation will lead to decreased trust in media.*[6]

3 Experimental Design

To address the hypotheses presented above, we conducted three online survey experiments based on pre-registered designs[7] with a total of 8,017 respondents.[8] All three studies consider how Americans react to politicians' allegations of misinformation in response to scandalous news stories. We randomly assigned participants, irrespective of political party, to a real scandal involving one of four politicians—two Democrat and two Republican—making statements that are arguably insensitive, embarrassing, or otherwise counter to their mes-

[6] Corresponds to H3 in the PAP.

[7] As a note, this paper incorporates some language previously included in our pre-analysis plans and amendments.

[8] We chose the sample size for the first study based on minimum detectable effect (MDE) calculations using results from a pilot study in August 2020 (N = 916); for the second and third studies, we performed power analyses using results from the prior studies. MDE calculations are available in SI Section A.4.

sage, identity, or agenda.[9]

Of note, Thompson (2000) defines scandals as "actions or events involving certain kinds of transgressions which become known to others and are sufficiently serious to elicit a public response." While the events studied here—surrounding offensive comments—are different from other types of scandals such as financial corruption or sex-based scandals, a number of news sources indeed characterize these as scandals. In particular, all four scandals relate to identity politics: three scandals pertain to race and ethnicity, while one scandal centers on gender and abortion. It is thus important to understand that characteristics of the scandal are likely to influence evaluative effects for politicians (Sikorski, 2018) and have some bearing on the generalizability of our findings.

In Studies 1 and 2, after viewing the politician scandal, participants were then also randomly assigned to one of three politician responses: no response (control), an allegation of misinformation priming informational uncertainty, or an allegation of misinformation priming oppositional rallying.[10] Thus, in Studies 1 and 2, the control non-response represents a politician strategy of ignoring the scandal in hopes that it will blow over. In Study 3, we consider how allegations of misinformation invoking informational uncertainty compare to two other politician response strategies: an apology and a simple denial without an allegation of misinformation. We included the simple denial and apology treatments in Study 3 to assess whether the current informational environment makes claims of misinformation even more effective than alternative longstanding politician responses to scandal.

For the video, text, and allegation treatments that we describe next, we aimed to reduce

[9]The stories are of former politicians in order to ensure minimal impacts on current officials. Based on pilot results presented in SI Section A.8, we identified four stories that respondents viewed as similarly embarrassing and plausibly digitally faked. We also selected clips that were as consistent as possible given available options in terms of length, content, and context.

[10]While we contextualized the study in the context of recent discourse surrounding "fake news," this term is both problematic and polarizing. Indeed, in our pilot study (see SI Section A.8), we confirmed that this terminology has a strong partisan connotation. As such, in place of "fake news," our treatments employ the more conservative terminology of "false and misleading," a phrase also commonly used by political actors when disclaiming misinformation.

media source cues (for example, by cropping news banners from videos) to 1) maintain symmetry across treatments and improve internal validity, and to 2) focus on respondent identification with the politician and party rather than the particular media source. While we recognize that such a strategy removes an element of realism in normal news consumption, we thought this approach best balanced concerns about internal versus external validity. Reassuringly, experimental designs with sparser details, albeit less naturalistic, tend to enable researchers to identify the existence of an effect and do not necessarily imply less generalizability (Brutger et al., forthcoming).[11] Further, the use of multiple stories and averaging of results across politicians helps to ensure that our findings are not limited to a single media source, politician, scandal, or political party.

The specific allegations are inspired by real politician statements and are designed to invoke considerations related to informational uncertainty and oppositional rallying, they are not strictly derived from statements made by the depicted politicians themselves. The informational uncertainty allegation draws from comments such as those made by Foreign Minister Dastis and by Syrian President Bashar al-Assad, who in an attempt to discredit an Amnesty International report said: "You can forge anything these days... We are living in a fake news era" (Erlanger, 2017). Along these lines, participants in the informational uncertainty treatment group saw the following allegation:

> **[Politician Name] Responds That Story is False and Misleading, People Should Be Skeptical**.
>
> In response to the recent allegations, [Republican | Democrat] [Politician Name] asserted that the story is false and misleading. He claimed that [the video is a deepfake, a computer-edited video that uses fake audio and images | the story is not based on true information]. When asked about the incident, he said that

[11] We believe that studies including media cues would be relevant to examining the interaction between media source effects and politician allegations of misinformation. Since this is one of the first empirical tests of the liar's dividend, we leave these additional explorations for further research.

> it's well known that there's a lot of misleading information, so people should be skeptical about what they hear. [Last Name] stated that "You can't know what's true these days with so much misinformation out there."

For the oppositional rallying allegation, we drew inspiration from statements like that of Mayor Fouts, along with comments by then-president Donald Trump on Twitter in response to growing criticism over his handling of the pandemic: "The Fake News Media and their partner, the Democrat Party, is doing everything within its semi-considerable power (it used to be greater!) to inflame the CoronaVirus situation." Participants in the oppositional rallying treatment group saw:

> **[Politician Name] Responds That Story is False and Misleading, Attack by Opponent**.
>
> In response to the recent allegations, [Republican | Democrat] [Politician Name] asserted that the story is false and misleading. He claimed that [the video is a deepfake, a computer-edited video that uses fake audio and images | the story is not based on true information]. When asked about the incident, he said that the story is an attack by the opposition, and that people should not pay attention to it. [Last Name] stated that, "My opponent would say anything to hurt me, but my supporters know who's really on their side."

An important aspect of our study is that it addresses sensitive social and political issues in the context of misinformation, an already fraught topic in that interaction with misinformation can harm participants. As such, we carefully considered ethics in the design and administration of our surveys. Foremost, our study unavoidably involved deception, given the focus of our research questions surrounding political misinformation and the liar's dividend. Our approach to minimizing deception as much as possible was to use real videos and stories of politicians, rather than, for example, generating a new deepfake or false story.

To enable the comparison of different politician communication strategies in the context of misinformation, the research team did attribute various responses to the politicians (e.g., a denial or apology) that they did not actually make. Given this deception, we debriefed all participants at the end of the study. Second, to avoid exacerbating participant feelings of distrust and uncertainty, our debrief included links to resources on media literacy and digital literacy, such as knowing how to spot false news stories.[12] Third, we wanted to avoid the risk that participation in the study would influence real-life political behavior such as voting. Therefore, we chose to use stories about inactive politicians, i.e., individuals who are not currently in office or running for office. We also expected that a lower degree of attachment to these less prominent individuals would be less likely to stoke partisan animosity or otherwise influence real-world behavior. Fourth, all participants gave consent prior to participation and were compensated through Lucid Theorem's survey partners. During the consent, participants were warned that some of the information was offensive, that some information would be withheld, and that additional information about the goals of the study would be provided at the end. Two separate Institutional Review Boards ultimately approved of the study's approach to research ethics and deception.

We use a set of four outcome measures to assess whether respondents supported the politician ("I would support the politician", "I would defend the politician against critics," "I would vote for the politician," and "I would donate to the politician"). We measure respondents' belief in the underlying story using two outcome questions ("I believe the story about the politician" and "I think that the story about the politician is true") and respondents' trust in media using two outcome questions ("I trust the media" and "I believe that the media reports the news fairly").[13] All outcome questions use a bipolar 5-point Likert scale with respondents indicating their agreement from "Strongly disagree" to "Strongly agree." With the goal of

[12]The full instrument including the participant debrief is available on SI Section A.1.

[13]Our measures of general media trust resemble those used by, for example, ANES (NES, 2022), Gallup (Brenan, 2021), and the Reuters Institute for the Study of Journalism at Oxford (Newman et al., 2019), and psychometric studies conceptually and empirically support the use of measures of generalized media trust (Prochazka and Schweiger, 2019).

reducing variance and improving content validity, we use multiple questions and create preregistered indices for each outcome.[14]

To test our hypotheses, we regress the appropriate outcome measure (e.g., the politician support index or trust in media index) on treatment (the reference group is the group of participants who did not receive a response message from the politician) and a set of covariates (partisanship, gender, race/ethnicity, age, education, household income, region, media literacy, and digital literacy).[15] Our hypotheses and regression specifications, including covariates, are preregistered and are available at https://bit.ly/3EidCi6. For the primary regressions used to test our hypotheses, we report standard nominal 2-sided p-values based on robust standard errors. We also engage in exploratory analysis, and within hypothesis families with multiple additional exploratory tests, we use the Benjamini-Hochberg method to correct for multiple testing and present corrected p-values (using a false discovery rate of 0.05), following the approach of Bohlken, Iakwad and Nellis (2018). Results from the exploratory analyses with nominal and adjusted p-values are presented in SI Section A.7.

The samples for all studies were recruited using the Lucid Theorem platform and are demographically proportionate to the U.S. adult population in terms of gender, race/ethnicity, age, and region.[16] We also find no evidence of covariate imbalance in our samples.[17] We include two attention screener questions to allow for the analysis of results stratified by level of attentiveness of respondents (shown in SI Section A.3); our main analyses do not exclude inattentive respondents (Berinsky, Margolis and Sances, 2014; Berinsky et al., 2019). Overall,

[14]The indices are constructed following a pre-registered procedure used by Kling, Liebman and Katz (2007) which involves averaging z-scores for the component outcome questions.

[15]Our estimates pool the four politicians and reflect a weighted average across them. Results with politician fixed effects are very similar, as shown in SI Section A.6. Considerations related to the construction of the news media literacy and digital literacy measures are presented in SI Section A.3. Covariate-unadjusted main results are included in SI Section A.6.

[16]Research supports the use of Lucid for social science research, as it has been used successfully to replicate prior experimental results, and because its survey takers more closely match U.S. political and psychological profiles than alternate platforms such as MTurk (Coppock and McClellan, 2019).

[17]See SI Section A.5 for covariate balance information and results of F-tests evaluating whether the covariates jointly predict treatment assignment.

our findings are stronger among more attentive participants (see SI Section A.7).

4 Study 1

We conducted our first study in February 2021 with 2,503 respondents. Study 1 includes the elements of the research design presented in Figure 1, and incorporates differences in the media format through which the scandalous news stories are presented. This creates a 2x3 factorial design with variation in both the presentation of the politician scandal (video[18] or text) and the subsequent politician response (no response, an allegation invoking informational uncertainty, or an allegation invoking oppositional rallying). Thus, the design of Study 1 allows for examination of the Deepfakes Hypothesis as well as the Liar's Dividend Hypothesis through exploring differences in responses to politician allegations after video versus text-based treatments. In order to ensure consistency across the text and video treatments, we create transcripts of the video clips to produce the text-based treatments. We present results pooling across video and text treatments and then separately by media format.

4.1 Results

Figure 2 presents standardized treatment effects from Study 1 in order to assess the impact of allegations of misinformation on politician support. Overall, the results provide strong support for the Liar's Dividend Hypothesis. Figure 2 shows that allegations of misinformation (either invoking informational uncertainty or oppositional rallying) increase politician support by 0.07 and 0.16 standard deviations for text and video (combined) and for text only, respectively. For allegations priming informational uncertainty in particular, politician support increases by 0.09 (text and video) and 0.18 (text) standard deviations, and for oppositional rallying, politician support increases by 0.06 (text and video) and 0.14 (text)

[18] We used a pilot study to assess whether participants could successfully see and hear the videos, and 98% of subjects reported no difficulty. Nevertheless, we also added subtitles to the videos and used a timer to encourage participants to engage with the treatments.

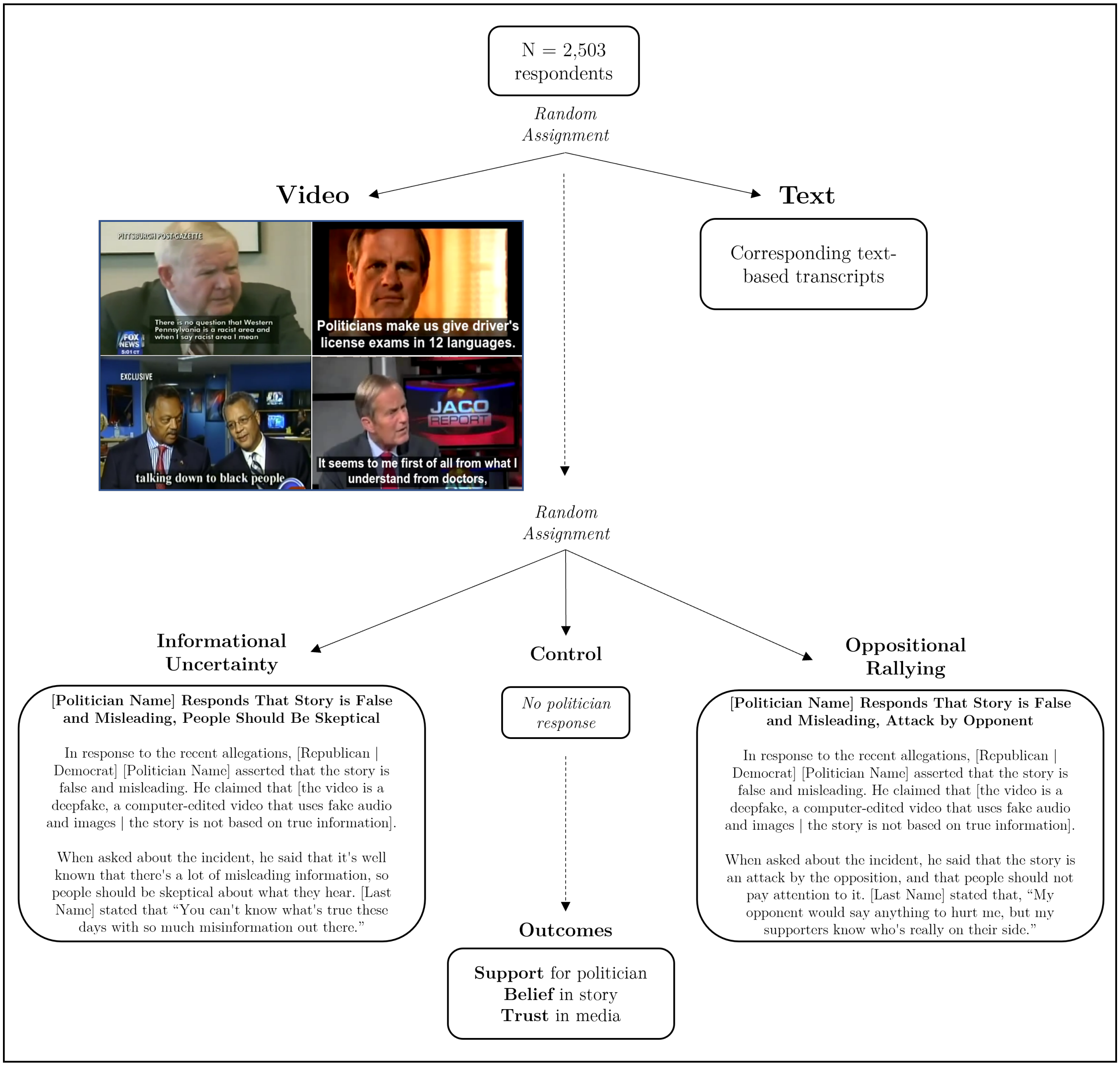

Figure 1: Study 1 Design

standard deviations. All of these effects are statistically significant at the conventional 0.05 alpha level, except for oppositional rallying, which only has significant effects for text. Notably, these effects are even larger for three of the support measures used to create the index—willingness to support, defend, and vote for the politician—while reticence to donate to the politician attenuates combined support as measured by the index (see Figure A5 in SI Section A.6).

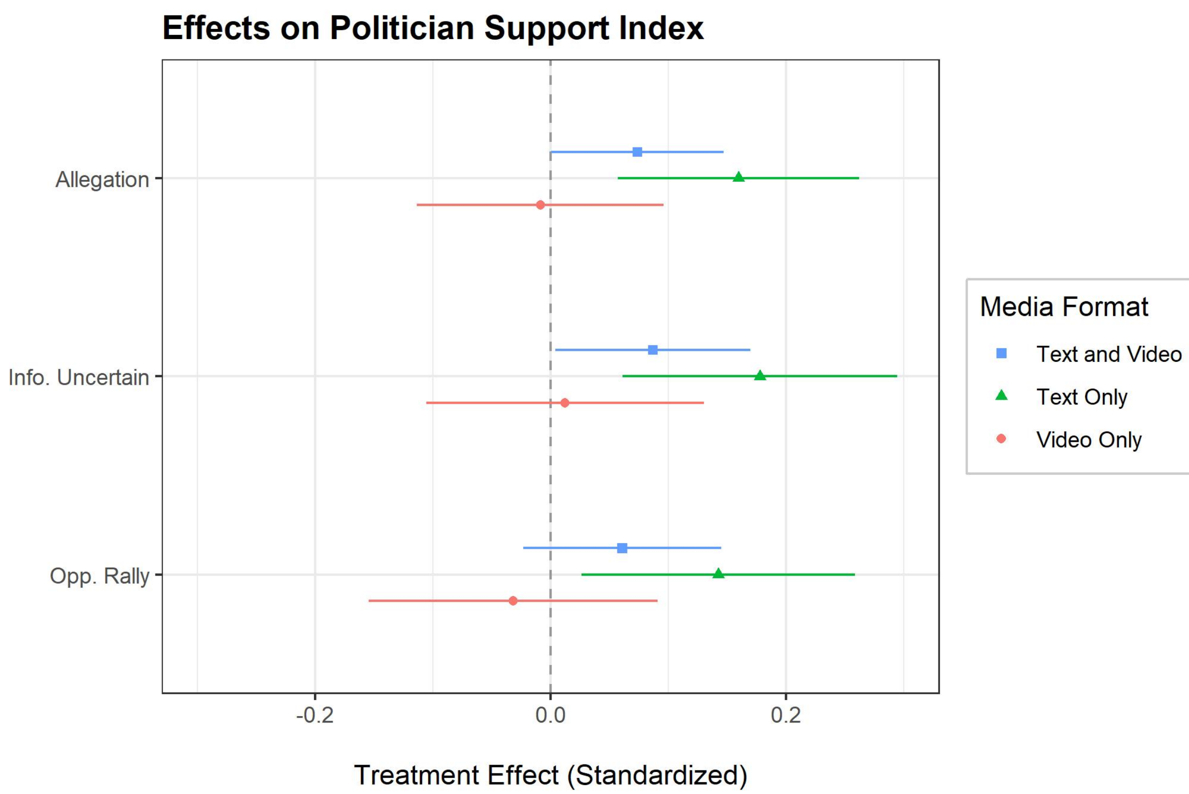

Figure 2: Liar's Dividend Results for Study 1

Notes: All figures display 95% confidence intervals based on robust standard errors. "Allegation" refers to a pooled treatment group with either Informational Uncertainty or Oppositional Rallying allegations, and the reference group is composed of respondents who received a non-response from the politician. Full table of results with covariates available as SI Table A4.

These effects are meaningful, with effect sizes of 0.1 considered 'small' and 0.2 'medium' in the political psychology literature (Funder and Ozer, 2019). For context, the largest standardized treatment effects for a single component outcome measure—e.g., "I would support the politician"—correspond to an *unstandardized* 0.25 point increase in support along the

5-point Likert scale. Another way of making sense of these effects is to examine the impact of the allegations of misinformation on critics of the politicians. In the control group, around 44% of respondents were critics, measured as the percentage of respondents who disagreed or strongly disagreed that they would "support the politician." In contrast, in the text-scandal treatment groups, allegations of misinformation substantially decreased the percentage of critics to around 32-34%, a 10-12 percentage point reduction in the number of critics.

Across all types of allegation (pooled or considering the distinct channels separately), video evidence of scandals reduces the effectiveness of politician allegations for generating support gains. We find that when politicians allege "deepfake," they do not receive a liar's dividend. Individuals may find video sufficiently persuasive or allegations insufficiently persuasive such that a politician's reputation does not recover from a scandalous video story. In contrast, as discussed above, there is a payoff for allegations of misinformation in response to text-based stories (addressing the Deepfakes Hypothesis, pre-registered as H2). Indeed, the treatment effects for politician support are substantially larger in the case of text stories versus video, and this difference is statistically significant for both informational uncertainty ($p = 0.048$) and oppositional rallying ($p = 0.042$).[19] These results are somewhat reassuring. While scholars and the public are justifiably concerned about misinformation perpetuated through the use of ultra-realistic deepfakes, an interesting irony is that video content may be so believable that politicians gain little ground when trying to pretend that real video content is faked. Yet, to the extent that public figures find themselves increasingly needing to rebut real deepfakes, they may find there is no truth-teller's dividend either.

[19] Arguably, the treatment wording for the video condition is slightly stronger than the treatment for text-based misinformation, meaning that our finding of null effects for allegations of deepfakes is conservative, if anything.

5 Study 2

In Study 2, we replicate key elements of Study 1 to increase our confidence in the robustness of the original findings. Study 2 differs from the prior study by focusing on text exclusively (no video treatment) because the effects of allegations of misinformation on support appear to operate primarily through text. Additionally, by pooling across text conditions from Study 1 and Study 2, we increase our statistical power and ability to explore relevant heterogeneity by partisan identity.

For Study 2, we recruited 2,518 additional participants in April 2021 via Lucid. Participants were randomly assigned to one of the four text-based politician scandals, followed by: no response from the politician (control) or the informational uncertainty allegation.[20] After seeing one of the two responses to the politician scandal, participants answered the same outcome questions as in Study 1 to preserve the integrity of the replication for the informational uncertainty treatment. We followed up this component of Study 2 with a secondary experiment embedded in the same survey and used to separately assess the oppositional rallying treatment. In particular, Study 2 participants were also assigned to a *second* politician scandal followed by either the control condition or oppositional rallying allegation, and accompanied by the same outcome questions.[21]

Similar to Study 1, we test our hypotheses by regressing the outcomes of interest on treatment and the same set of pre-registered covariates. For ease of comparability, we report estimates from Study 2 along with text-only estimates from Study 1 and pooled estimates. The pooled

[20] We also included another treatment: the informational uncertainty allegation rebutted by a subsequent fact-checking statement. The results indicate that fact-checking may eliminate the liar's dividend. However, we also found that most subjects were uninterested in clicking to access resources about media and digital literacy, potentially raising a concern about individuals' willingness to seek out and consume fact-checking information. We move the discussion of this pre-registered hypothesis (PAP Amendment 1, fact-checking hypothesis) to the SI due to space constraints. Results are available in SI Section A.7.

[21] The wording introducing the oppositional rallying treatment was slightly modified to avoid raising survey taker suspicion that the study was manufactured by researchers. Moreover, because the secondary experiment comes after another experiment, priming effects are a concern and this component of the study should not be considered a perfect replication.

estimates are precision-weighted averages of treatment effects from each study using fixed effects specifications and allow us to make use of the larger sample of respondents across both studies.[22]

5.1 Results

Figure 3 shows the results from both studies and the pooled estimates. Across both studies, there is again strong support for the Liar's Dividend Hypothesis. Participants who were exposed to allegations of misinformation reported higher average levels of willingness to support the politicians. While there is some variation in effect sizes across studies (the effect of informational uncertainty in Study 2 is smaller in magnitude, with a p-value of 0.08), estimates are all in the same direction and are statistically indistinguishable from each other. Moreover, we find clear evidence of impacts on support through the oppositional rallying channel, ranging from 0.14 to 0.16 standard deviations across studies. Overall, given that these dividends are produced through a single politician allegation, the gains in politician support are substantial.[23]

Misinformation about misinformation does seem to produce a liar's dividend in terms of gains in politician support. Yet, how are these gains produced? In the case of oppositional rallying, we hypothesized that allegations of misinformation invoking friends and foes would prime partisan political identity and stir up negative sentiments towards perceived political opponents. As a result, we expected allegations invoking oppositional rallying to produce the strongest effects for sympathetic co-partisans of the politician. Alternatively, in the case of informational uncertainty, we expected allegations invoking this strategy to produce stronger effects on moderates, whose lack of partisan attachments may make them more susceptible

[22] Results for specifications using random effects are nearly identical. Results are also largely the same if we combine samples and perform a single regression as opposed to combining separate studies' estimates through precision weighting.

[23] When we incorporate the additional 1,254 respondents who received the video scandals in the first wave, results are generally consistent, though smaller in magnitude. SI Section A.6 presents the findings from the combined sample of 5,021 from Studies 1 and 2.

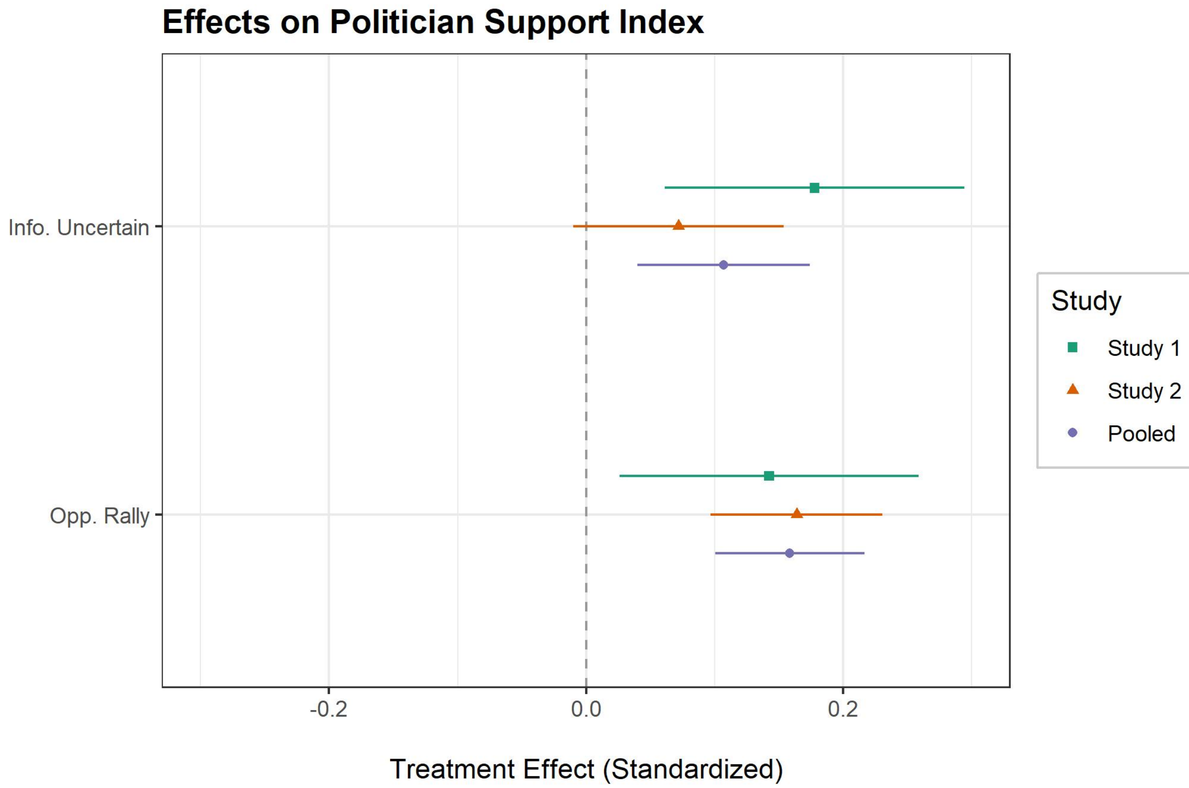

Figure 3: Liar's Dividend Results for Study 2

Notes: We use only text treatments for comparability across Studies 1 and 2. Full table of results with covariates available as SI Table A5.

to feelings of uncertainty.[24]

Figure 4 displays heterogeneous effects of both theoretical channels of the liar's dividend compared to control. Effects are disaggregated by the co-partisanship[25] of respondents with the politician in their respective treatment, and are produced by pooling respondents across studies and focusing on text scandals for comparability.

In line with our expectations, we find that politician allegations meant to shift the focus to

[24]We include a set of exploratory analyses from Study 2 in SI Section A.7 to assess how belief operates in the context of the liar's dividend. In short, the relationship between belief and politician support is complex and begs further research.

[25]The way in which we code co-partisanship deviates from our pre-analysis plan. Rather than comparing strong co-partisans (respondents that are co-partisans with their treatment politicians, excluding leaners) to all other respondents, we instead compare co-partisans, anti-partisans, and moderates in order to better identify distinct subgroups of respondents.

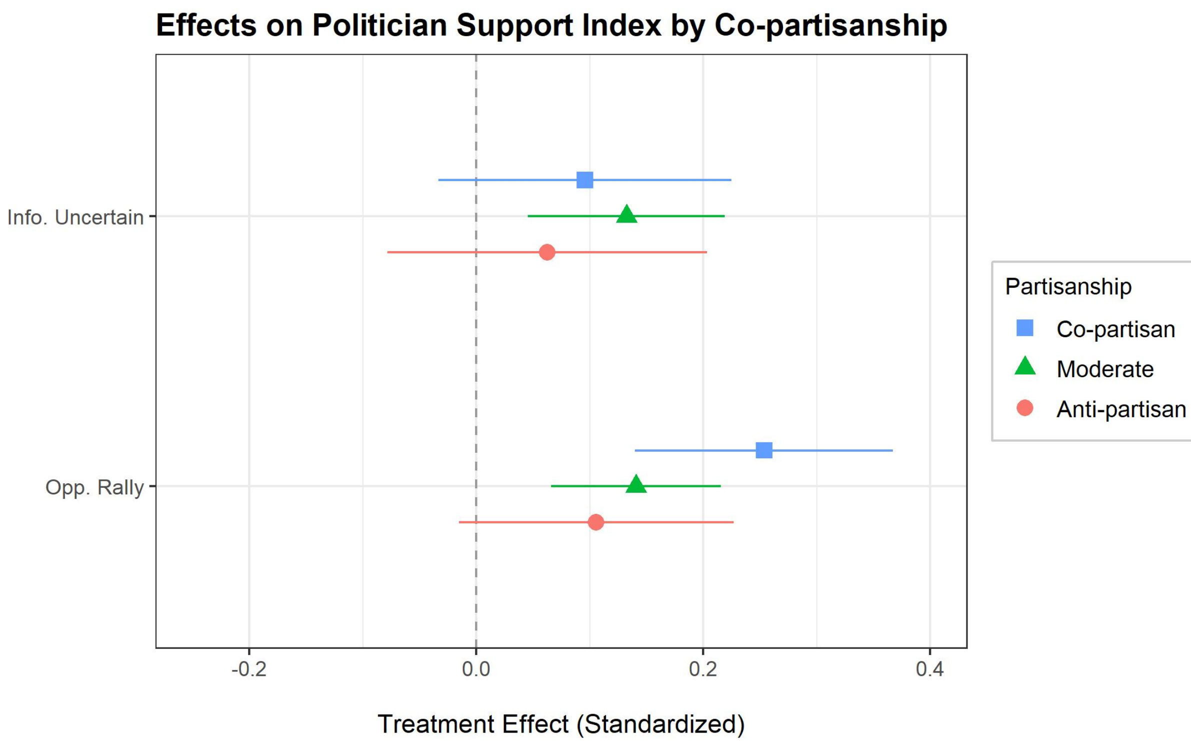

Figure 4: Heterogeneous Effects of Oppositional Rallying and Informational Uncertainty

Notes: Co-partisans are respondents whose self-reported partisanship matches that of the politician whose scandal they saw/read. Anti-partisan respondents are from the opposing political party to treatment politicians. Moderates are independents. For example, self-identified Strong Democrats, Democrats, and Lean Democrats are identified as co-partisans with the Democrat politicians and anti-partisans with the Republican politicians depicted in the treatments. Those who identify as independents are classified as moderates regardless of the politician party. Full table of results with covariates available as SI Table A6.

opponents trigger more support among individuals who harbor stronger co-partisan feelings. That is, oppositional rallying produces effects that are larger in magnitude for co-partisans of politicians, on the order of 0.25 standard deviations and borderline statistically different ($p = 0.081$) from the effects for anti-partisans. Notably, there are also apparent increases in support for moderates, and even borderline statistically significant ($p = 0.087$) gains for anti-partisans, suggesting that oppositional rallying has even more widespread appeal than anticipated, for example, with no evident backlash effect for anti-partisans. Meanwhile, results from Figure 4 suggest that moderates are more greatly impacted by informational uncertainty than their more partisan peers. While the general pattern for informational uncertainty aligns with our expectations, the differences between moderates and other subgroups are not statistically significant.

Furthermore, we expected informational uncertainty to also influence belief in the story about the politician (pre-registered H1.1), lowering belief in the scandal and resulting in higher politician support. Oddly, however, our experimental results do not indicate that allegations priming informational uncertainty influence belief in the story. As shown in SI Section A.6, we find in both Studies 1 and 2 that politician allegations have largely insignificant impacts on belief in the scandal. To make sense of these counterintuitive results, SI Section A.7 provides further exploratory evidence assessing the complex relationship between belief and support. In particular, drawing on additional survey questions, we find descriptive evidence that self-reported belief in the politicians' allegations correlates with the feeling that "it's hard to know what's true these days" and that respondents who believed the allegations agreed that this affected their support for politicians. Yet, we also find that belief in the politician allegation is not correlated with belief in the underlying scandal. This may be evidence of a belief-support disconnect, expressive reporting, or something else. Overall, there appear to be substantial inconsistencies in the ways in which individuals process their beliefs, presenting a challenge for understanding the mechanism behind allegations invoking informational uncertainty.

In sum, both hypothesized channels do produce a liar's dividend, with preliminary evidence of differences between political subgroups. Yet, further research is needed to better understand how subgroups are affected by different politician messaging strategies, as well as how politicians may strategically design their messages to target particular audiences. Also, our findings from both studies suggest some evidence of a belief-support disconnect, which merits further investigation.

5.2 Trust in Media

Beyond the immediate dividends to politicians, does misinformation about misinformation produce additional, more indirect consequences on society as a whole? To answer this question, we examine whether a politician allegation changes participants' trust in media. Table 1 presents results that address the Trust in Media Hypothesis. In Study 1, we observe that politician allegations using either strategy in response to text-based scandals (Allegation) lead to small reductions in trust in news media on average, though this result is not statistically significant. For Study 2, we observe slightly greater reductions in trust in news media when allegations of informational uncertainty (Info. Uncertain) are used in particular, with effects on the order of 0.07 standard deviations ($p = 0.075$).

	Dependent variable:	
	Trust in Media	
	(1)	(2)
Allegation	−0.044	
	(0.052)	
Info. Uncertain		−0.072*
		(0.041)
Observations	1,249	2,518
R^2	0.239	0.265
Study	Study 1 (Text-only)	Study 2

*p<0.1; **p<0.05; ***p<0.01

Table 1: Impacts on Trust in Media Index

Notes: With robust SEs and including covariates. Full table with covariates available as SI Table A7.

While we find small, borderline significant impacts on trust in media in the context of a survey experiment, we cannot evaluate the extent to which these effects persist, compound, or decay over time in real-world contexts. Nevertheless, it is somewhat disconcerting that even a single instance of misinformation about misinformation might lead to decreased overall trust in news media, a concern further highlighted by our findings in Study 3 below.

6 Study 3

Results from Studies 1 and 2 indicate that politicians gain a liar's dividend when alleging misinformation rather than remaining silent after scandal. Yet, remaining silent in the face of scandal and attempting to allow a controversy to blow over is only one among several possible politician messaging strategies. It is possible that any active reply by a politician would proffer benefits compared to a non-response. To address this possibility, Study 3 compares allegations of misinformation with two additional politician responses: a simple denial and an apology. These latter strategies have been studied previously as prominent types of politician reactions to transgressions (Gonzales et al., 1995) and have been found to mitigate reputational damage (Brenton, 2011). Compared to these tried-and-true approaches, then, Study 3 allows us to assess whether allegations of misinformation are effective in boosting support specifically *because* they invoke an environment saturated with informational uncertainty. That is, is there something novel about today's informational environment, due to technological, social, or political conditions, that renders allegations of misinformation especially effective?

For this study, we recruited 2,996 new participants in October 2021 via Lucid. Participants were again randomly assigned to one of the four text-based politician scandals that we used in the previous studies, followed, via random assignment, by one of three responses: the informational uncertainty allegation from the prior two studies, a simple denial that does not invoke misinformation, or an apology. We chose to use the informational uncertainty allegation (as opposed to the one invoking oppositional rallying) because it most directly references the indirect harms to the informational environment due to misinformation and thus is most salient for answering the question articulated above.

We structured the denial and apology allegations statements to be as similar as possible to the allegation of misinformation, to preserve symmetry across treatments and thus isolate the unique aspects of each politician communication strategy.[26] The denial allegation included below is based on the form of flat-out denials common, for example, to politician sex scandals, such as Bill Clinton's infamous denial:

> **[Politician Name] Denies that Events in Story Occurred**.
>
> In response to the recent allegations, [Republican | Democrat] [Politician Name] firmly denied the story. When asked about the incident, he said that it never occurred. [Last Name] stated that "That did not happen. I never said that."

The apology statement provides an alternative in which the politician acknowledges truth to the story and accepts responsibility. This allows us to assess whether members of the public are more receptive to politicians who accept responsibility, arguably a normatively preferable response. The wording for this treatment is based off of the real reaction by John Murtha to the scandal used in our experiment. After critical news coverage, Murtha released a statement saying "I apologize for making the comment that Western Pennsylvania is a racist area." The apology treatment is as follows:

> **[Politician Name] Acknowledges Story and Offers Apology**.
>
> In response to the recent allegations, [Republican | Democrat] [Politician Name] acknowledged the story and apologized. When asked about the incident, he said that it did occur. [Last Name] stated that "Yes, I did say that, and I apologize

[26] All three treatments are structured similarly, though the simple denial and apology treatments are slightly shorter than the informational uncertainty treatment. In balancing internal and external validity goals, we determined that increasing the length of the alternative treatments to achieve further symmetry risked introducing other sources of variation and would be perceived as less believable. Additionally, across all three studies, we used timers to require participants to spend at least ten seconds viewing each scandal as well as each politician allegation before moving on. Notwithstanding slight differences in video or text length, this ensured that participants spent both a sufficient and similar amount of time engaging with all treatments.

for making those comments."

6.1 Results

Figure 5 displays the support gains that accrue to politicians from alleging misinformation relative to other communication strategies in the face of scandal. Unlike the prior two studies, the control group is not politician non-response. Instead, allegations of misinformation are compared to an apology or simple denial.

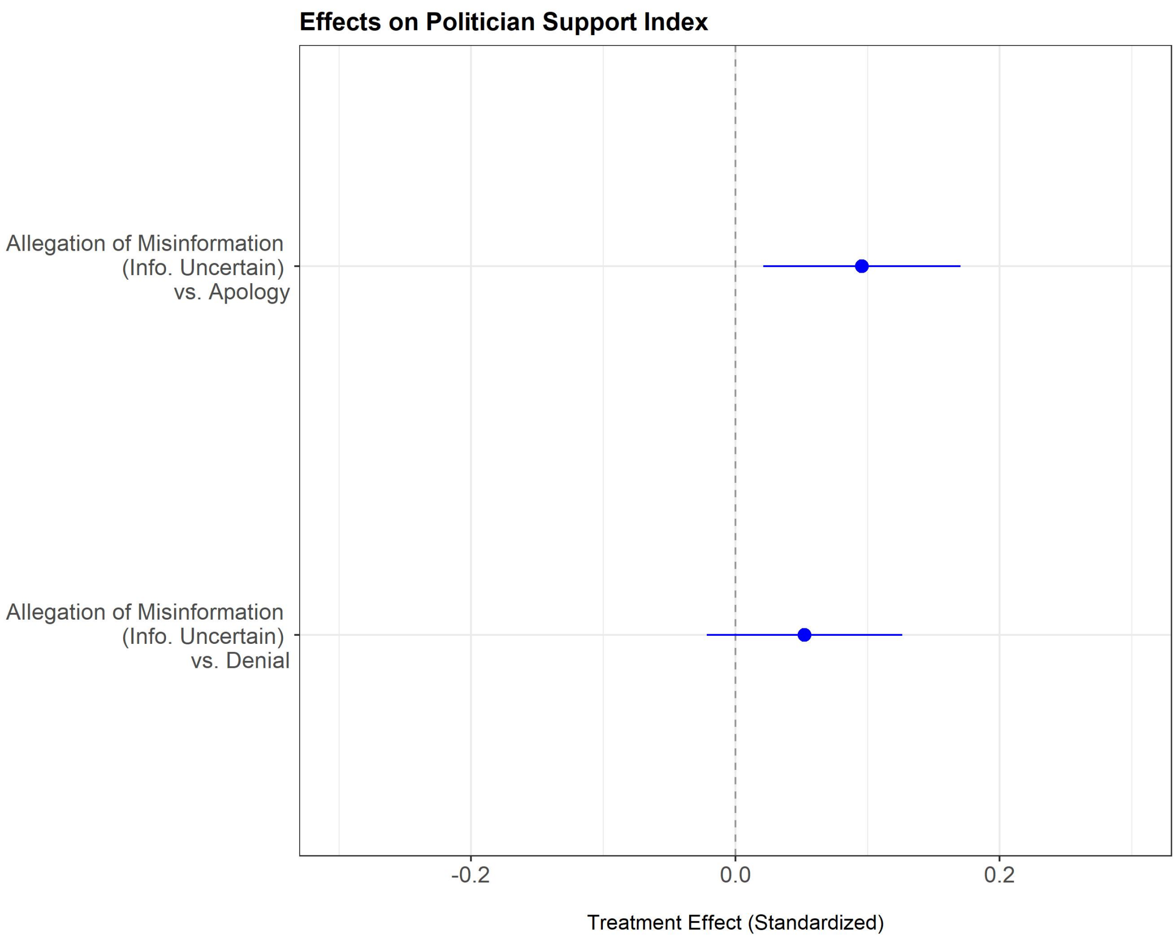

Figure 5: Liar's Dividend Results for Study 3: Allegations of Misinformation Compared to Alternative Politician Communication Strategies

Notes: Full table of results with covariates available as SI Table A8.

We find some evidence that allegations of misinformation invoking informational uncertainty are more effective than alternative politician responses. In particular, allegations of misinformation are more effective than apologizing (0.10 standard deviations, $p = 0.012$). However, while support gains from allegations of misinformation are larger in magnitude than support gains due to more simple denials, this difference is not significant at conventional levels (0.06 standard deviations, $p = 0.116$). This finding could imply that a liar's dividend in today's informational environment is not meaningfully larger than dividends that would have accrued to liars in the past. Yet another possibility is that even simple denials are more effective in today's informational ecosystem, a possibility that this study cannot directly address. Additionally, while both apologies and simple denials are common politician responses to scandal, an open question is how allegations of misinformation compare to still *other* types of responses or variations of the treatments used here.

Indeed, the results are most concerning when comparing allegations of misinformation to apologies, and raise the concern that politicians can benefit by falsely alleging misinformation rather than taking responsibility for a scandal. This extends recent scholarship finding that politicians benefit more from denying scandals than from conceding and offering to take corrective action (Johnson, 2018). Relatedly, while our results indicate that simple denials are not statistically more effective than apologies ($p = 0.344$), *denials that employ the extra step of alleging misinformation* are indeed more beneficial to politicians than apologies. In combination, these findings caution that political accountability in today's informational environment is especially difficult. Public figures may be incentivized to cry wolf over misinformation even when doing so undermines principles of political accountability.

To shed more light on this challenge, Table 2 presents compares the effects of allegations of misinformation versus apologies on politician support, belief in the underlying scandal, and trust in media. As indicated in the coefficient plot, allegations of misinformation drive support gains for politicians on the order of 0.1 standard deviations. Yet these benefits to politicians are socially costly: they require deceiving the public and undermine trust in media, creating the conditions for more uncertainty and less accountability. Different from studies 1 and 2, belief in the story declines by a sizable 0.31 standard deviations when the public is misled in this way, likely because the apology response explicitly acknowledges the truth of the scandal. Finally, trust in media declines by 0.12 standard deviations.[27] The liar's dividend therefore comes at a substantial social cost, involving a zero-sum trade-off between politicians who benefit and social welfare which declines.

	Support Index	Belief Index	Trust Index
	(1)	(2)	(3)
Info. Uncertain	0.103**	−0.311***	−0.120***
	(0.040)	(0.041)	(0.038)
N	1,994	1,994	1,994
R^2	0.082	0.081	0.223
F Statistic (df = 26; 1967)	6.728***	6.650***	21.688***

*p < .1; **p < .05; ***p < .01

Table 2: Allegations of Misinformation Versus Apologies

Notes: With robust SEs, including covariates, and using Study 3 data. Full table with covariates available as SI Table A9.

7 Conclusion

This study is the first to provide experimental evidence of the liar's dividend. Using real politician scandals presented to participants, we find that unscrupulous politicians willing to falsely allege misinformation may be rewarded with a reputational boost in the face of an otherwise damaging story. Alleging misinformation bolsters politician support more than remaining silent and allowing a scandal to blow over. It is also significantly more effective than apologizing—a preferable behavior for promoting trust and political accountability—and it is at least as effective as a more simple denial. Indeed, these strategies and their effects may be enabled by developments in technological tools for generating and disseminating misinformation (e.g., deepfakes, social media platforms) and by the broader sociopolitical

[27] Compared to simple denials, allegations of misinformation marginally decrease belief (standardized effect $= -0.07, p = 0.08$) and have no effect on trust in media (standardized effect $= -0.04, p = 0.34$).

environment in which frequent instances of real misinformation render even false allegations credible.

Interestingly, while the liar's dividend concept was originally developed in the context of concerns over the implications of deepfakes, we find that crying wolf about fake news is far more likely to pay off. Scholars have debated the extent to which deepfakes are more believable and persuasive than text-based misinformation (Barari, Lucas and Munger, 2021; Wittenberg et al., 2021). Our results provide compelling evidence that video and text do operate differently in the context of allegations of misinformation. In particular, attempts to discredit video appear to be much less persuasive. Deepfakes may not (yet) pose the particular indirect threat suggested by the liar's dividend, but they remain highly novel additions to the informational environment, and warrant much more research to unpack their direct and indirect effects.

We also sought to better understand the strategies employed in allegations of misinformation and the channels through which they affect individuals' attitudes. Drawing on real-world attempts to allege misinformation by public figures and relevant scholarly literature, this study proposes and evaluates two such strategies, which we term informational uncertainty and oppositional rallying. We find that both strategies are effective in raising politician support, and preliminary evidence suggests they may work in distinct ways. Politicians employing the oppositional rallying strategy receive more support from co-partisans, likely the intended targets of these messages in the first place, as they seek to exploit polarization and foment political animus. Meanwhile, informational uncertainty's effects may appear concentrated on political moderates and, under some circumstances, influence belief in the scandal. Yet, the evidence on both counts is mixed: the differences between partisan groups are not statistically distinguishable and the effects on belief are unstable across studies. Further research is needed to unveil the underpinnings of the informational uncertainty effect we document in our three studies.

Also importantly, our study examines a certain type of political scandal, surrounding offensive comments largely related to race, ethnicity, gender, and identity. While some may consider these to be relatively minor gaffes, there are reasons to think that both making and responding to these kinds of comments is becoming more prevalent, such that this constitutes an important feature of modern political discourse worth understanding. An open question is whether other types of scandals, including potentially more severe ones, make the payout of the liar's dividend even greater. Additionally, for ethical reasons, this study is centered on inactive politicians and scandals that are not especially politically salient today. The liar's dividend may pay out even more for current high-profile political leaders, reinforced when political actors, organizations, and certain media sources act in concert to amplify misinformation and undermine trust. Yet, as members of the public may have stronger attachments and more information about currently active politicians, it is also possible that public attitudes may be more polarized and less malleable.

Overall, how concerned should we be about these findings? On the one hand, we find that false allegations of misinformation are not effective in the case of video. Further, even if based on real scandals and videos, our results established in an experimental context may overstate the effects that occur in real-world settings, especially if effects decay over time or are countered by fact-checking. On the other hand, many of our analyses are deliberately designed to be conservative. For example, we include inattentive respondents in our main results but find substantially larger effects for attentive participants. We also find larger effects when we omit more demanding support outcomes from our index like "I would donate to the politician," an outcome we included understanding that large effects are unlikely. Even when using our conservative estimation approach, we witness harmful impacts for political accountability including a decline in trust in media when allegations of misinformation are employed rather than apologizing. Might the indirect effects of misinformation be even more consequential for political accountability and trust than the direct effects? Those political figures attempting to reap the liar's dividend certainly hope so.

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A Supporting Information for:

"The Liar's Dividend: Can Politicians Use Deepfakes and Fake News to Evade Accountability?"

Contents

A.1 Study 1 Survey

This section describes the treatments and outcomes used in the Study 1 survey. Covariate and screener questions are presented separately in SI Section A.3.

A.1.1 Treatments

Respondents randomly received information about a scandal with 1) one of four politicians (two Republican and two Democrat) and 2) either a video clip or text transcript:

A news report has come out [showing | with] the following [video clip | story excerpt] about [Republican | Democrat] politician [Tim James | Todd Akin | John Murtha | Jesse Jackson].

Please [watch the following video clip | read the excerpt below].

[Republican | Democrat] [Tim James | Todd Akin | John Murtha | Jesse Jackson] Accused of Making Offensive Remarks

Tim James: https://youtu.be/Onvy6nzsa1s or text transcript: "Politicians make us give driver's license exams in 12 languages. This is Alabama. We speak English. If you want to live here, learn it! We're only giving that test in English."
Todd Akin: https://youtu.be/WIwu04J6lsc or text transcript: "What about in the case of rape? Should it be legal or not? It seems to me first of all from what I understand from doctors, that's really rare. If it's a legitimate rape, the female body has ways to try to shut that whole thing down."
John Murtha: https://youtu.be/3z_ZHHZI-Jg or text transcript: "There is no question that Western Pennsylvania is a racist area and when I say racist area I mean older people are hesitant. They are slow in seeing change, real change."
Jesse Jackson: https://youtu.be/YkhAAZVza5k or text transcript: "See, Barack been, um, talking down to black people on this faith based... I wanna cut his n*ts off."

Next, respondents randomly received one of the following politician response messages:

- Control: *No politician response message*
- Informational Uncertainty: **[Politician Name] Responds That Story is False and Misleading, People Should Be Skeptical**. In response to the recent allegations, [Republican | Democrat] [Politician Name] asserted that the story is false and misleading. He claimed that [the video is a deepfake, a computer-edited video that uses fake audio and images | the story is not based on true information]. When asked about the incident, he said that it's well known that there's a lot of misleading information, so people should be skeptical about what they hear. [Last Name] stated that "You can't know what's true these days with so much misinformation out there."
- Oppositional Rallying: **[Politician Name] Responds That Story is False and Misleading, Attack by Opponent**. In response to the recent allegations, [Republican | Democrat] [Politician Name] asserted that the story is false and misleading. He claimed that [the video

is a deepfake, a computer-edited video that uses fake audio and images | the story is not based on true information]. When asked about the incident, he said that the story is an attack by the opposition, and that people should not pay attention to it. [Last Name] stated that, "My opponent would say anything to hurt me, but my supporters know who's really on their side."

A.1.2 Outcome Measures

Next, respondents were presented with a set of 8 outcome questions for which they were asked to rate the extent of their agreement or disagreement. All outcome questions use a 5-point Likert scale from "Strongly Disagree" to "Strongly Agree."

1. I **believe the story** about the politician.
2. I think that the story about the politician **is true**.
3. I would **support the politician**.
4. I would **defend the politician** against critics.
5. I would **vote for the politician**.
6. I would **donate to the politician**.
7. I **trust the media**.
8. I believe that the **media reports the news fairly**.

Outcome questions 1 and 2 were combined to create an index for belief in the story about the politician. Outcome questions 3-6 were combined to create an index for politician support. Outcome questions 7 and 8 were combined to create an index for trust in media. To create the indices, we followed the procedure used by Kling, Liebman and Katz (2007) by averaging z-scores for the component outcome questions.

A.1.3 Debrief

Finally, all respondents were shown a debrief paragraph providing information about the survey and clarifying any deception/misinformation:

The information provided to you about the politician is part of a study on false/fake news and "deepfakes," or digitally altered video, and the impacts that they have on trust in politics and the media. While the video or story presented to you about the politician is real, the reply by the politician was created by a team of researchers and therefore does not represent an actual statement made by the politician. To learn more about how to identify fake news stories and fake videos, see the following resources from the International Federation of Library Associations and Institutions and the MIT Media Lab Detect DeepFakes Project: https://www.ifla.org/publications/node/11174 and https://www.media.mit.edu/projects/detect-fakes/overview.

A.2 Study 2 Survey

This section describes the new fact-checking treatment and additional exploratory outcome and covariate questions used in the Study 2 survey.

A.2.1 Fact-Checking Treatment

A non-partisan fact-checking organization has weighed in on the story and the politician's response to it. Please read the statement by the fact-checking organization carefully before moving on.

Fact Check: [Politician Name] was recently accused of making offensive comments but disputes the truthfulness of the story. We find evidence that [Politician Name] did make the comments as originally reported.

A.2.2 Additional Exploratory Outcome and Covariate Questions

- Experiment 1: Control vs. IU vs. IU + fact-checking.
  - I think that the politician's remarks, as reported in the news story, were offensive. [Strongly disagree to Strongly agree]
  - It's hard to know what's true these days. [Strongly disagree to Strongly agree]
  - I believe the politician's response that the news story is false. [Strongly disagree to Strongly agree] [IU group and fact-checking group]
  - To what extent did the politician's response that the story was false affect your support for the politician? [Strongly decreased my support to Strongly increased my support] [IU group and fact-checking group]
  - I would share the politician's response with family and friends. [No - because I don't support it, No - although I support it, Yes - but not because I support it, Yes - because I support it] [IU group and fact-checking group]
  - I believe the fact-checking organization's statement that the news story is true. [Strongly disagree to Strongly agree] [Fact-checking group only]
  - To what extent did the fact-checking organization's statement that the story was true affect your support for the politician? [Strongly disagree to Strongly agree] [Fact-checking group only]
- Experiment 2: Control vs. OR.
  - I think that the politician's remarks, as reported in the news story, were offensive. [Strongly disagree to Strongly agree]
- Additional Questions to Help with Assessing the IU Mechanism.
  - How concerned are you, if at all, about made-up news and information? [Not at all concerned, Slightly concerned, Concerned, Very concerned]
  - How confident are you in your own ability to recognize news that is made up? [Not at all confident, Slightly confident, Confident, Very confident]
  - How big of a problem do you think "cancel culture" is in the U.S. today? [Not a problem, A minor problem, A problem, A major problem]
  - Do you agree or disagree that people should be more careful with language to avoiding offending people? [Strongly disagree to Strongly agree]
  - Which most closely matches your view? When a public figure makes an offensive statement, they should be: [Given a second chance, Held accountable]
- Additional Exploratory Outcome Questions.
  - How often can you trust the government to do what is right? [Almost none of the time to Almost always]
  - How often can you trust the information you get from political leaders and public officials? [Almost none of the time to Almost always]
  - How often can you trust other people? [Almost none of the time to Almost always]
  - How often can you trust [opposing political party]? [Almost none of the time to Almost always] [Randomized for political moderates]
  - We measure whether participants click on a link provided in the survey debrief to learn more about how to identify fake news stories.

A.3 Survey Screeners and Covariate Questions

A.3.1 Screener Questions

We include two screener questions near the beginning of the survey to allow for analysis of results stratified by level of attentiveness of respondents. In particular, we use two screening questions employed by Berinsky, Margolis and Sances (2014) that test respondents' attention by asking them to select specific answer choices regardless of how they would answer those questions normally. We create an attentiveness index which ranges from 0-2, corresponding to the number of correct answers. Note that this may provide slightly different results compared to the item response theory model used by Berinsky et al. (2019), but should be highly correlated.

These screener questions function much in the same way as manipulation or attention checks, and are important because inattentive survey takers may fail to receive the treatment and answer questions accurately, likely increasing noise and diluting the strength of effects (Oppenheimer, Meyvis and Davidenko, 2009). We follow the advice of Berinsky et al. (2019) to employ multiple screener questions targeted at identifying both high attention and low attention respondents. However, we do not discard results from respondents who fail the screeners, because doing so could threaten internal and external validity if characteristics that predict attention (such as levels of education) may also predict responses on our outcome questions. Results stratified by level of attentiveness are available in SI Section A.7.

A.3.2 Demographic Questions

We received the following demographic information directly from respondents or through Lucid, coded as described below. All demographic questions that were directly asked were included at the end of the survey, other than race and education, which were used as filler questions between the screeners and which we considered unlikely to introduce priming effects.

- Partisanship is coded as a factor variable with seven levels: strong Democrat, Democrat, lean Democrat, Independent, lean Republican, Republican, and strong Republican.[1]
- Gender is coded as a factor variable with male and female..
- Age is coded as a factor variable with five levels based on the Pew Research Center generation age ranges. (https://www.pewresearch.org/topics/generations-and-age/)
- Race/ethnicity is coded as a factor variable with White, Black or African American, and Other as the three race/ethnicity categories.
- Education is coded as a factor variable with four levels: high school graduate or less, some college or technical or Associate degree, Bachelor's degree, and graduate degree.
- Income is coded as a factor variable with three levels from low to high income: $< \$30,000$, $\$30 - \$74,999$, and $\$75,000+$.
- Region is coded as a factor variable with four levels: Northeast, South, Midwest, and West.

A.3.3 News Media and Digital Literacy

To assess potential protective factors against misinformation, we include items for news media literacy and digital literacy. The media literacy questions used to create a news media literacy

[1] We ask this question post-treatment as we are more concerned about priming effects than post-treatment bias, and because our pilot study indicated that respondents' answers to the partisanship question were not affected by treatment (p-value from F-statistic = .962).

index each have a single correct response from a set of four possible answers. The questions come from the Reuters Institute for the Study of Journalism at Oxford University (Newman et al., 2019). The three questions measure: respondents' factual knowledge of how news sources are funded, how press releases are produced, and how news on social media is curated. Correct responses are summed to place respondents on a 0-3 scale for news literacy. Two of the three questions were adapted from a measure of news media literacy by Maksl, Ashley and Craft (2015) in the Journal of Media Literacy Education. The Reuters Institute has shown that higher news literacy on the 0-3 scale is correlated with measures important for assessing external validity, such as higher consumption of news stories from newspaper sources, discernment when selecting news stories, and consumption of unbiased credible news sources.

We assess digital literacy through a single measure of self-reported participant familiarity with deepfakes, as participant responses to allegations implicating deepfakes are likely moderated by their prior technical familiarity. As shown by Hargittai (2005), self-reported measures of digital literacy are valid indicators of people's factual knowledge and digital literacy skills for a wide variety of digital literacy domains.[2]

The three media literacy questions and one digital literacy question are as follows:

1. Which of the following news outlets does NOT primarily depend on advertising for financial support? [Fox News, PBS (correct response), New York Times, USA Today, Don't know]
2. Which of the following is typically responsible for writing a press release? [A reporter for a news organization, A producer for a news organization, A lawyer for a news aggregator, A spokesperson for an organization (correct response), Don't know]
3. How are most of the individual decisions about what news stories to show people on Facebook made? [At random, By computer analysis of what stories might interest you (correct response), By editors and journalists that work for news outlets, By editors and journalists that work for Facebook, Don't know]
4. Computer algorithms can now be used to create ultra-realistic fake video content. How much had you heard about this before today? ["Not at all" to "A great deal."]

A.4 Ethical Considerations

Misinformation is a fraught topic, one that spells potential harms for individuals and society. It is for precisely these reasons that scholars need to study misinformation. In the context of our research, we sought to understand if certain types of political misinformation—as well as mitigations—were effective in influencing individuals. As described in the main text, while we chose to use real politician scandals rather than fabricated stories in order to minimize deception, we did generate a set of politician responses and attributed all such responses to the four politicians under study. This was essential for allowing for valid comparisons of public responses to different political communication strategies, something that is not otherwise feasible given the infrequent and ad-hoc occurrence of liar's dividend type claims in natural settings. In turn, we did debrief participants and provide media and digital literacy resources, as well as warned participants about this debrief during the

[2] We have opted to include these demographic questions post-treatment because we are concerned about potential priming effects, and the results of our pilot study suggest that the media literacy and digital literacy questions are not significantly impacted by treatment (p-values from global F-tests: .66 and .18, respectively).

consent process. All participants consented, we used approved consent language from our institutions' Institutional Review Boards to make the study's design and risks accessible, and we did not target any vulnerable groups. We also received feedback from other misinformation researchers on the ethical dimensions of the study prior to administration.

Also importantly, all participants were compensated for participation in the three studies, regardless of overall survey completion or satisfaction of attention check questions. Per Lucid Theorem policies, the platform is paid one dollar per participant, and this rate is fixed. As our survey only took between three and five minutes for the large majority of participants, the effective pay rate for the participants—all American adults—is likely above minimum wage rates and standard market rates for online survey participants. However, as Lucid uses a variety of suppliers to recruit individuals, and does not have access to the specifics of compensation for each supplier, we do not know how much each participant was ultimately compensated. See: https://luc.id/wp-content/uploads/2019/10/Lucid-IRB-Methodology.pdf for a discussion of Lucid's fixed rate approach and use of suppliers. Of note, two separate Institutional Review Boards approved this study, cognizant of our approach to deception and mitigation of any resulting harms.

A.5 MDE Calculations and Multiple Testing

We use simulations based on a pilot study of 916 respondents on MTurk to calculate minimum detectable effects (MDE) along a range of possible sample sizes for our main outcome of interest: support. As suggested by DeclareDesign (2019), the calculation of MDEs using pilot results is an improvement on power calculations because the latter are based on noisy effect estimates.

With sample sizes of 2,500-3,000 for each study, our study has sufficient power to detect standardized effects as small as 0.15 to 0.17 for our main hypothesis for each study. With a combined 5,021 respondents across Studies 1 and 2 (the research design allows these studies to be pooled), we have sufficient power to detect standardized effects for our main hypothesis as small as 0.12. However, our study may lack power to definitively evaluate all hypotheses of interest. These considerations informed our decision to perform a replication of key findings from the Study 1 survey and increase our total sample size.

For our primary regressions used to test our hypotheses, we will report standard nominal p-values based on robust standard errors. However, within hypothesis families with multiple additional exploratory tests, we use the Benjamini-Hochberg method to correct for multiple testing and present corrected p-values, following the approach of Bohlken, Iakwad and Nellis (2018). We use a false discovery rate of 0.05. As defined in our pre-analysis plan, the Liar's Dividend Hypothesis has two exploratory tests (each with two p-values of interest), the Informational Uncertainty Hypothesis has three exploratory tests (one p-value each), and the Oppositional Rallying Hypothesis has two exploratory tests (one p-value each) for which we will perform corrections. Results from the exploratory analyses, including nominal and adjusted p-values, are presented in SI Section A.7.

A.6 Covariates and Balance

Table A1, Table A2, and Table A3 help to evaluate covariate balance for Studies 1, 2, and 3, respectively. Within treatment groups, proportions in each covariate category are reported, along with mean scores for media literacy and digital literacy.

Variable Level	Control Text	Control Video	IU Text	IU Video	OR Text	OR Video
Strong Democrat	0.18	0.14	0.18	0.15	0.15	0.16
Democrat	0.18	0.14	0.17	0.17	0.17	0.17
Lean Democrat	0.10	0.10	0.08	0.09	0.11	0.08
Independent	0.24	0.30	0.24	0.29	0.27	0.28
Lean Republican	0.12	0.11	0.13	0.10	0.10	0.11
Republican	0.09	0.08	0.09	0.08	0.09	0.11
Strong Republican	0.09	0.13	0.11	0.11	0.10	0.09
Male	0.49	0.47	0.48	0.48	0.46	0.54
Female	0.51	0.53	0.52	0.52	0.54	0.46
White	0.74	0.70	0.72	0.72	0.73	0.68
Black	0.11	0.11	0.11	0.10	0.11	0.10
Hispanic	0.07	0.08	0.08	0.09	0.07	0.10
Asian	0.06	0.07	0.05	0.06	0.07	0.09
Other race/ethnicity	0.02	0.03	0.03	0.02	0.02	0.03
Gen Z	0.13	0.10	0.14	0.13	0.11	0.14
Millennials	0.29	0.30	0.26	0.33	0.34	0.34
Gen X	0.25	0.29	0.28	0.28	0.27	0.24
Boomers	0.29	0.26	0.28	0.24	0.24	0.24
Silent	0.04	0.04	0.04	0.03	0.03	0.04
High school graduate or less	0.27	0.28	0.25	0.26	0.24	0.26
Some college	0.34	0.30	0.32	0.34	0.34	0.31
Bachelor's degree	0.23	0.28	0.26	0.24	0.26	0.25
Graduate degree	0.16	0.14	0.17	0.16	0.16	0.17
Low income	0.32	0.30	0.33	0.32	0.29	0.30
Middle income	0.40	0.42	0.38	0.36	0.39	0.41
High income	0.27	0.28	0.29	0.31	0.33	0.28
Northeast	0.21	0.22	0.22	0.21	0.22	0.19
Midwest	0.19	0.19	0.20	0.18	0.17	0.24
South	0.38	0.37	0.37	0.41	0.41	0.32
West	0.22	0.23	0.22	0.19	0.21	0.25
Media literacy	1.03	1.04	1.09	1.09	1.02	1.06
Digital literacy	2.73	2.79	2.80	2.87	2.69	2.88

Table A1: Covariate Balance for Study 1

Variable Level	Cont. + Cont.	Cont. + OR	FC + Cont.	FC + OR	IU + Cont.	IU + OR
Strong Democrat	0.18	0.16	0.17	0.18	0.15	0.18
Democrat	0.14	0.18	0.15	0.16	0.18	0.18
Lean Democrat	0.12	0.09	0.10	0.12	0.10	0.10
Independent	0.26	0.27	0.29	0.20	0.27	0.26
Lean Republican	0.11	0.12	0.11	0.10	0.11	0.08
Republican	0.11	0.09	0.08	0.14	0.11	0.09
Strong Republican	0.08	0.09	0.11	0.11	0.08	0.11
Male	0.48	0.48	0.47	0.53	0.50	0.49
Female	0.52	0.52	0.53	0.47	0.50	0.51
White	0.70	0.75	0.75	0.73	0.71	0.74
Black	0.14	0.10	0.10	0.12	0.13	0.10
Hispanic	0.06	0.06	0.06	0.09	0.07	0.07
Asian	0.07	0.05	0.06	0.04	0.05	0.07
Other race/ethnicity	0.03	0.03	0.03	0.03	0.02	0.03
Gen Z	0.12	0.10	0.15	0.13	0.14	0.11
Millennials	0.32	0.32	0.30	0.27	0.29	0.30
Gen X	0.27	0.23	0.26	0.29	0.24	0.25
Boomers	0.25	0.31	0.25	0.26	0.28	0.29
Silent	0.04	0.04	0.03	0.05	0.05	0.05
High school graduate or less	0.25	0.28	0.27	0.22	0.26	0.27
Some college	0.29	0.29	0.32	0.35	0.32	0.33
Bachelor's degree	0.27	0.20	0.20	0.25	0.22	0.22
Graduate degree	0.19	0.22	0.21	0.17	0.19	0.18
Low income	0.28	0.30	0.30	0.26	0.34	0.32
Middle income	0.37	0.40	0.37	0.42	0.37	0.35
High income	0.34	0.31	0.32	0.32	0.30	0.33
Northeast	0.22	0.20	0.21	0.18	0.24	0.22
Midwest	0.21	0.18	0.20	0.20	0.16	0.18
South	0.35	0.37	0.40	0.40	0.40	0.36
West	0.22	0.25	0.20	0.21	0.21	0.24
Media literacy	0.94	0.98	0.86	0.97	0.92	0.93
Digital literacy	2.78	2.84	2.82	2.97	2.91	2.81

Table A2: Covariate Balance for Study 2

Variable Level	Info. Uncertain	Simple Denial	Apology
Independent	0.27	0.27	0.28
Strong Democrat	0.14	0.18	0.16
Democrat	0.15	0.14	0.16
Lean Democrat	0.12	0.11	0.11
Lean Republican	0.11	0.10	0.11
Republican	0.09	0.10	0.08
Strong Republican	0.11	0.10	0.09
Male	0.49	0.49	0.49
Female	0.51	0.51	0.51
White	0.76	0.70	0.71
Black	0.11	0.13	0.13
Hispanic	0.08	0.09	0.09
Asian	0.04	0.05	0.05
Other	0.01	0.02	0.02
Gen Z	0.10	0.11	0.10
Millennials	0.30	0.31	0.32
Gen X	0.28	0.27	0.24
Boomers	0.28	0.28	0.30
Silent	0.04	0.04	0.03
High school graduate or less	0.26	0.30	0.24
Some college	0.35	0.35	0.36
Bachelor's degree	0.27	0.24	0.26
Graduate degree	0.12	0.12	0.13
Middle income	0.38	0.37	0.36
Low income	0.31	0.37	0.34
High income	0.30	0.27	0.30
Northeast	0.23	0.20	0.19
Midwest	0.17	0.19	0.20
South	0.38	0.38	0.36
West	0.22	0.23	0.25
Media literacy	1.05	1.07	1.06
Digital literacy	2.84	2.91	2.85

Table A3: Covariate Balance for Study 3

To evaluate the success of randomization and to further assess covariate balance for each study, we perform F-tests of global significance by regressing an indicator for each treatment group on the covariates. For Study 1, the p-values of the F-tests for assignment to control, informational uncertainty, oppositional rallying, and video (versus text) treatments are 0.97, 0.91, 0.92, and 0.69, respectively. Thus, we fail to reject the null hypothesis that the covariates jointly do not predict treatment assignment for Study 1. For Study 2, the p-values of the F-tests for assignment to control, informational uncertainty, fact-checking, and oppositional rallying (versus control in Study 2 experiment two) treatments are 0.77, 0.77, 0.36, and 0.86, respectively. Finally, for Study 3, the p-values of the F-tests for assignment to apology, simple denial, and allegation of misinformation (IU) are 0.70, 0.26, and 0.13, respectively. Thus, again for Studies 2 and 3, we fail to reject the null that covariates do not predict treatment, suggesting randomization was successful and balance was achieved. Also note that the respondents are generally representative of the US population along gender, race, age, and region, as per Lucid's recruitment approach.

A.7 Regression Tables for Figures and Tables in Paper

SI A.7 presents regression tables corresponding to Figures 2, 3, 4, and 5, as well as Tables 1 and 2, in the main paper. The tables display the relevant (standardized) average treatment effects associated with our treatments, as well as the (unstandardized) coefficients associated with covariates in the models. We use two-sided p-values and robust standard errors and report results for a variety of models (e.g., text only sample, video only sample, etc.). Notes regarding the sample for each model specification are included in the last row of each table. The general covariate profile of the reference group is Moderate, Male, White, Gen Z, High School Education or Less, Medium Income, and Northeast.

The pooled estimates for the treatment effects in Table A5 are precision-weighted averages of separate treatment effects from each study using fixed effects specifications. Results for specifications

	Politician Support Index					
	(1)	(2)	(3)	(4)	(5)	(6)
Allegation	0.074**		0.159***		−0.009	
	(0.037)		(0.052)		(0.053)	
Info. Uncertain		0.087**		0.178***		0.012
		(0.042)		(0.059)		(0.060)
Opp. Rally		0.061		0.142**		−0.032
		(0.043)		(0.059)		(0.063)
Strong Democrat	0.022	0.021	−0.012	−0.013	0.041	0.043
	(0.059)	(0.059)	(0.080)	(0.080)	(0.089)	(0.088)
Democrat	0.050	0.050	−0.036	−0.037	0.136*	0.136*
	(0.052)	(0.052)	(0.075)	(0.075)	(0.074)	(0.074)
Lean Democrat	−0.096	−0.096	−0.169**	−0.168**	−0.024	−0.024
	(0.060)	(0.060)	(0.079)	(0.079)	(0.091)	(0.091)
Lean Republican	0.093	0.093	0.036	0.034	0.129	0.131
	(0.057)	(0.057)	(0.076)	(0.076)	(0.086)	(0.086)
Republican	0.270***	0.271***	0.093	0.093	0.444***	0.447***
	(0.062)	(0.062)	(0.084)	(0.084)	(0.090)	(0.090)
Strong Republican	0.246***	0.245***	0.167*	0.166	0.312***	0.311***
	(0.069)	(0.069)	(0.101)	(0.101)	(0.095)	(0.095)
Female	−0.098***	−0.098***	−0.106**	−0.106**	−0.103**	−0.105**
	(0.036)	(0.036)	(0.049)	(0.049)	(0.052)	(0.052)
Black	0.155**	0.155**	0.065	0.065	0.236***	0.237***
	(0.061)	(0.061)	(0.085)	(0.086)	(0.088)	(0.088)
Hispanic	0.061	0.061	0.029	0.028	0.099	0.099
	(0.065)	(0.065)	(0.089)	(0.089)	(0.092)	(0.092)
Asian	−0.126*	−0.124*	−0.127	−0.127	−0.135	−0.133
	(0.067)	(0.067)	(0.100)	(0.100)	(0.092)	(0.092)
Other Race	0.176*	0.175*	0.099	0.094	0.249*	0.251*
	(0.095)	(0.095)	(0.132)	(0.132)	(0.139)	(0.140)
Millennial	0.217***	0.218***	0.182**	0.184**	0.242***	0.241***
	(0.059)	(0.059)	(0.084)	(0.085)	(0.084)	(0.085)
Gen X	0.195***	0.195***	0.097	0.098	0.290***	0.289***
	(0.062)	(0.062)	(0.088)	(0.088)	(0.089)	(0.089)
Boomer	0.054	0.054	−0.021	−0.021	0.127	0.127
	(0.064)	(0.065)	(0.091)	(0.091)	(0.094)	(0.094)
Silent Gen.	0.093	0.094	−0.084	−0.083	0.305*	0.307*
	(0.114)	(0.114)	(0.154)	(0.154)	(0.170)	(0.170)
Some College	−0.078*	−0.078*	−0.059	−0.058	−0.115*	−0.116*
	(0.046)	(0.046)	(0.063)	(0.063)	(0.067)	(0.067)
Bachelor's Degree	−0.050	−0.050	−0.070	−0.070	−0.050	−0.049
	(0.054)	(0.054)	(0.076)	(0.076)	(0.076)	(0.077)
Graduate Degree	0.230***	0.230***	0.235***	0.234***	0.212**	0.213**
	(0.063)	(0.064)	(0.086)	(0.086)	(0.092)	(0.092)
Low Income	0.044	0.043	−0.045	−0.046	0.146**	0.145**
	(0.043)	(0.043)	(0.060)	(0.060)	(0.061)	(0.061)
High Income	0.058	0.058	−0.013	−0.012	0.131**	0.128**
	(0.045)	(0.045)	(0.061)	(0.061)	(0.065)	(0.065)
Midwest	0.008	0.009	0.026	0.025	0.005	0.009
	(0.055)	(0.055)	(0.077)	(0.077)	(0.078)	(0.078)
South	−0.026	−0.027	0.008	0.008	−0.070	−0.071
	(0.048)	(0.048)	(0.066)	(0.066)	(0.069)	(0.070)
West	−0.022	−0.022	−0.077	−0.077	0.036	0.038
	(0.053)	(0.053)	(0.076)	(0.076)	(0.075)	(0.075)
Media Literacy	−0.154***	−0.154***	−0.157***	−0.157***	−0.148***	−0.148***
	(0.019)	(0.019)	(0.025)	(0.025)	(0.028)	(0.028)
Digital Literacy	0.077***	0.077***	0.075***	0.075***	0.090***	0.090***
	(0.015)	(0.015)	(0.021)	(0.021)	(0.021)	(0.021)
Constant	−0.285***	−0.284***	−0.109	−0.108	−0.471***	−0.470***
	(0.089)	(0.089)	(0.129)	(0.129)	(0.125)	(0.125)
N	2,503	2,503	1,249	1,249	1,254	1,254
R^2	0.096	0.097	0.106	0.106	0.110	0.111
Sample	Full	Full	Text Only	Text Only	Video Only	Video Only

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

Table A4: Figure 2 Regression Results

using random effects are nearly identical. Results are also largely the same if we combine samples and perform a single regression as opposed to combining separate studies' estimates through precision weighting.

For Table A8, the table shows results for Denial vs. IU and Apology vs. IU, whereas Figure 5 presents the results of IU vs. Denial and IU vs. Apology to help depict the treatment effects associated with IU. As such, the coefficients at the top of A8 are flipped in sign.

A.8 Alternative Specifications of Main Analyses

Figures A1 and A2 reproduce the main figures of results, Figure 2 and Figure 3, but using covariate-unadjusted regressions. Figure A3 and Figure A4 reproduce the main results, but with the inclusion of politician fixed effects. Results for these alternative specifications are largely consistent with main results in the paper. Note that these figures also include additional information about the belief outcome measure not reported in the main paper. Figure A5 presents results from Study 1 with the support outcome measure disaggregated into its four constituent outcome measures.

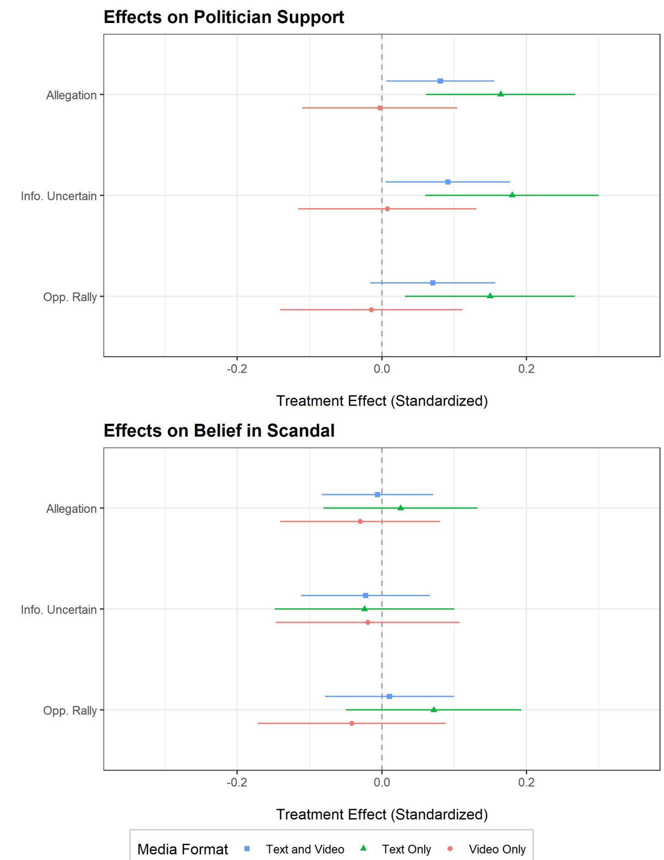

Figure A1: Study 1: Without Covariate Adjustment

A.9 Exploratory Pre-Registered Analyses

In this section, we present results based on our pre-registered exploratory hypotheses.

	Politician Support Index		
	(1)	(2)	(3)
Info. Uncertain	0.178***		
	(0.059)		
Opp. Rally	0.142**		
	(0.059)		
Info. Uncertain		0.072*	
		(0.042)	
Opp. Rally			0.164***
			(0.034)
Strong Democrat	−0.013	0.258***	0.252***
	(0.080)	(0.058)	(0.059)
Democrat	−0.037	0.134**	0.087*
	(0.075)	(0.052)	(0.052)
Lean Democrat	−0.168**	−0.065	−0.067
	(0.079)	(0.053)	(0.057)
Lean Republican	0.034	0.153***	0.089
	(0.076)	(0.056)	(0.056)
Republican	0.093	0.271***	0.115*
	(0.084)	(0.058)	(0.060)
Strong Republican	0.166	0.270***	0.222***
	(0.101)	(0.072)	(0.072)
Female	−0.106**	−0.129***	−0.147***
	(0.049)	(0.035)	(0.035)
Black	0.065	0.071	0.150**
	(0.086)	(0.058)	(0.059)
Hispanic	0.028	−0.037	−0.183***
	(0.089)	(0.072)	(0.071)
Asian	−0.127	0.008	0.012
	(0.100)	(0.070)	(0.073)
Other Race	0.094	−0.160	0.077
	(0.132)	(0.112)	(0.106)
Millennial	0.184**	0.099*	0.061
	(0.085)	(0.057)	(0.058)
Gen X	0.098	0.099*	0.089
	(0.088)	(0.060)	(0.061)
Boomer	−0.021	−0.052	−0.072
	(0.091)	(0.060)	(0.061)
Silent Gen.	−0.083	−0.188*	−0.047
	(0.154)	(0.098)	(0.103)
Some College	−0.058	−0.083*	0.029
	(0.063)	(0.045)	(0.045)
Bachelor's Degree	−0.070	−0.072	−0.021
	(0.076)	(0.051)	(0.052)
Graduate Degree	0.234***	0.247***	0.246***
	(0.086)	(0.058)	(0.059)
Low Income	−0.046	0.062	0.007
	(0.060)	(0.043)	(0.043)
High Income	−0.012	0.105**	0.070
	(0.061)	(0.044)	(0.045)
Midwest	0.025	−0.030	0.070
	(0.077)	(0.054)	(0.055)
South	0.008	0.014	0.023
	(0.066)	(0.046)	(0.046)
West	−0.077	−0.001	0.020
	(0.076)	(0.052)	(0.052)
Media Literacy	−0.157***	−0.186***	−0.183***
	(0.025)	(0.019)	(0.019)
Digital Literacy	0.075***	0.071***	0.096***
	(0.021)	(0.015)	(0.015)
Constant	−0.108	−0.204**	−0.333***
	(0.129)	(0.089)	(0.089)
N	1,249	2,518	2,518
R^2	0.106	0.137	0.135
Sample	Study 1 Text Only	Study 2	Study 2

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

Table A5: Figure 3 Regression Results

	Politician Support Index	
	(1)	(2)
Info. Uncertain	0.132***	
	(0.044)	
Opp. Rally		0.141***
		(0.038)
Anti-partisan	−0.108*	−0.112**
	(0.062)	(0.054)
Co-partisan	0.434***	0.344***
	(0.059)	(0.053)
Wave	−0.041	−0.054
	(0.036)	(0.033)
Female	−0.112***	−0.139***
	(0.034)	(0.030)
Black	−0.030	0.140***
	(0.057)	(0.050)
Hispanic	−0.033	−0.159***
	(0.071)	(0.059)
Asian	−0.025	−0.037
	(0.065)	(0.061)
Other Race	−0.058	0.055
	(0.105)	(0.092)
Millennial	0.084	0.117**
	(0.058)	(0.050)
Gen X	0.052	0.115**
	(0.060)	(0.052)
Boomer	−0.047	−0.019
	(0.060)	(0.053)
Silent Gen.	−0.154*	−0.040
	(0.094)	(0.089)
Some College	−0.064	−0.011
	(0.044)	(0.038)
Bachelor's Degree	−0.106**	−0.074*
	(0.049)	(0.044)
Graduate Degree	0.233***	0.215***
	(0.058)	(0.051)
Low Income	−0.024	−0.004
	(0.042)	(0.036)
High Income	0.094**	0.051
	(0.042)	(0.037)
Midwest	0.017	0.067
	(0.053)	(0.046)
South	0.025	0.028
	(0.045)	(0.039)
West	−0.021	0.019
	(0.050)	(0.044)
Media Literacy	−0.193***	−0.176***
	(0.018)	(0.016)
Digital Literacy	0.075***	0.087***
	(0.014)	(0.013)
Info. Uncertain x Anti-partisan	−0.070	
	(0.084)	
Info. Uncertain x Co-partisan	−0.036	
	(0.079)	
Opp. Rally x Anti-partisan		−0.035
		(0.073)
Opp. Rally x Co-partisan		0.113
		(0.069)
Constant	−0.058	−0.175*
	(0.103)	(0.094)
N	2,497	3,364
R^2	0.162	0.162
Sample	Studies 1 & 2	Studies 1 & 2

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

Table A6: Figure 4 Regression Results

	Politician Support Index	
	(1)	(2)
Allegation	−0.044	
	(0.052)	
Info. Uncertain		−0.072*
		(0.041)
Strong Democrat	0.718***	0.855***
	(0.079)	(0.055)
Democrat	0.492***	0.512***
	(0.079)	(0.053)
Lean Democrat	0.234***	0.397***
	(0.089)	(0.058)
Lean Republican	−0.239***	−0.092
	(0.085)	(0.062)
Republican	−0.374***	−0.105
	(0.095)	(0.065)
Strong Republican	−0.525***	−0.411***
	(0.100)	(0.067)
Female	−0.055	−0.112***
	(0.050)	(0.034)
Black	0.137*	0.096
	(0.081)	(0.059)
Hispanic	0.035	−0.070
	(0.091)	(0.074)
Asian	0.137	0.106
	(0.096)	(0.077)
Other Race	−0.238	−0.121
	(0.188)	(0.099)
Millennial	−0.034	0.168***
	(0.084)	(0.058)
Gen X	0.050	0.173***
	(0.086)	(0.061)
Boomer	0.017	0.121*
	(0.093)	(0.062)
Silent Gen.	0.042	0.043
	(0.164)	(0.095)
Some College	0.025	−0.099**
	(0.064)	(0.044)
Bachelor's Degree	0.096	0.010
	(0.076)	(0.051)
Graduate Degree	0.311***	0.349***
	(0.087)	(0.059)
Low Income	0.104*	0.066
	(0.061)	(0.042)
High Income	0.111*	0.071*
	(0.061)	(0.043)
Midwest	0.079	0.014
	(0.077)	(0.053)
South	−0.018	−0.044
	(0.067)	(0.046)
West	−0.019	−0.044
	(0.075)	(0.052)
Media Literacy	−0.047*	−0.057***
	(0.026)	(0.019)
Digital Literacy	0.036*	0.036**
	(0.021)	(0.014)
Constant	−0.266**	−0.368***
	(0.128)	(0.092)
N	1,249	2,518
R^2	0.239	0.265
Sample	Study 1 Text Only	Study 2

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

Table A7: Table 1 Full Regression Results

	Politician Support Index
Denial vs. IU	−0.062
	(0.039)
Apology vs. IU	−0.101**
	(0.040)
Strong Democrat	0.155***
	(0.057)
Democrat	0.125**
	(0.051)
Lean Democrat	−0.069
	(0.051)
Lean Republican	0.105*
	(0.055)
Republican	0.275***
	(0.059)
Strong Republican	0.237***
	(0.067)
Female	−0.057*
	(0.034)
Black	0.145***
	(0.056)
Hispanic	−0.046
	(0.061)
Asian	0.023
	(0.072)
Other Race	−0.078
	(0.114)
Millennial	0.286***
	(0.058)
Gen X	0.165***
	(0.061)
Boomer	0.110*
	(0.062)
Silent Gen.	0.148
	(0.098)
Some College	0.011
	(0.043)
Bachelor's Degree	0.022
	(0.050)
Graduate Degree	0.097
	(0.063)
Low Income	0.076*
	(0.040)
High Income	0.116***
	(0.043)
Midwest	−0.035
	(0.053)
South	−0.009
	(0.046)
West	−0.011
	(0.050)
Media Literacy	−0.164***
	(0.018)
Digital Literacy	0.080***
	(0.014)
Constant	−0.317***
	(0.086)
N	2,994
R^2	0.084
Sample	Study 3

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

Table A8: Figure 5 Regression Results

	Support Index	Belief Index	Trust Index
	(1)	(2)	(3)
Info. Uncertain	0.103**	−0.311***	−0.120***
	(0.040)	(0.041)	(0.038)
Strong Democrat	0.112	0.184**	0.687***
	(0.071)	(0.076)	(0.066)
Democrat	0.124**	0.326***	0.495***
	(0.061)	(0.059)	(0.060)
Lean Democrat	−0.084	0.108	0.282***
	(0.061)	(0.068)	(0.064)
Lean Republican	0.119*	0.057	−0.246***
	(0.067)	(0.070)	(0.066)
Republican	0.232***	0.114	−0.220***
	(0.076)	(0.075)	(0.076)
Strong Republican	0.192**	0.031	−0.408***
	(0.084)	(0.079)	(0.078)
Female	−0.049	−0.086**	−0.061
	(0.041)	(0.042)	(0.039)
Black	0.135**	−0.129*	−0.023
	(0.068)	(0.070)	(0.064)
Hispanic	0.033	−0.254***	−0.063
	(0.079)	(0.088)	(0.077)
Asian	0.036	−0.038	0.032
	(0.092)	(0.086)	(0.092)
Other Race	−0.125	−0.312*	−0.226
	(0.149)	(0.171)	(0.153)
Millennial	0.284***	0.048	0.200***
	(0.070)	(0.071)	(0.071)
Gen X	0.117	−0.100	0.122*
	(0.074)	(0.075)	(0.074)
Boomer	0.103	−0.106	0.048
	(0.074)	(0.076)	(0.076)
Silent Gen.	0.112	−0.202*	0.026
	(0.123)	(0.120)	(0.111)
Some College	−0.006	0.057	−0.087*
	(0.054)	(0.054)	(0.051)
Bachelor's Degree	0.023	0.059	0.150**
	(0.063)	(0.065)	(0.061)
Graduate Degree	0.141*	0.080	0.179**
	(0.077)	(0.080)	(0.075)
Low Income	0.085*	−0.027	0.144***
	(0.050)	(0.051)	(0.048)
High Income	0.106**	0.004	0.062
	(0.052)	(0.053)	(0.048)
Midwest	−0.040	−0.007	−0.127**
	(0.064)	(0.065)	(0.060)
South	0.024	−0.028	−0.108**
	(0.057)	(0.058)	(0.054)
West	−0.029	−0.109*	−0.093
	(0.061)	(0.063)	(0.059)
Media Literacy	−0.161***	0.015	−0.075***
	(0.022)	(0.023)	(0.020)
Digital Literacy	0.069***	0.075***	0.068***
	(0.017)	(0.018)	(0.017)
Constant	−0.374***	−0.022	−0.250**
	(0.107)	(0.105)	(0.105)
N	1,994	1,994	1,994
R^2	0.082	0.081	0.223
F Statistic (df = 26; 1967)	6.728***	6.650***	21.688***
Sample	Study 3	Study 3	Study 3

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

Table A9: Table 2 Full Regression Results

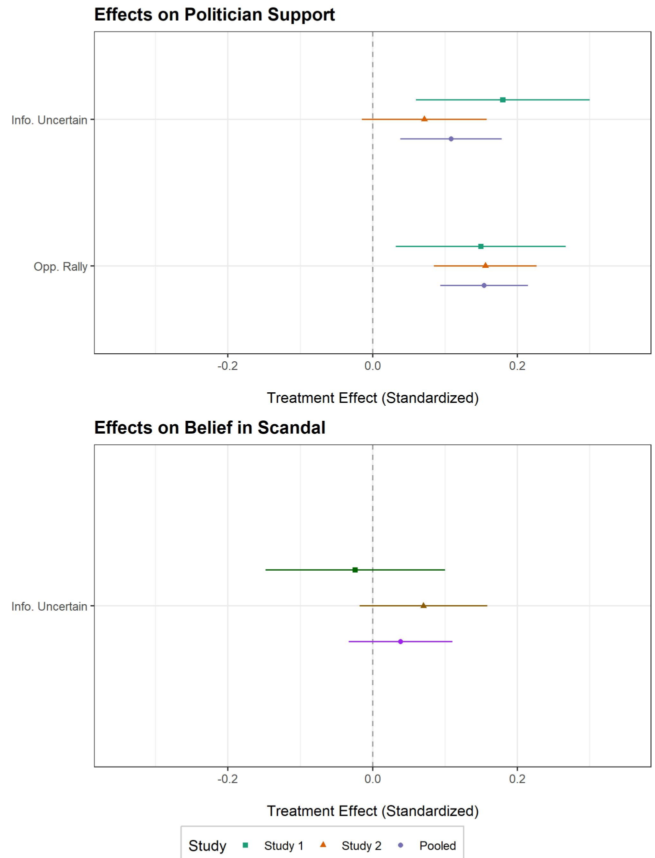

Figure A2: Study 2: Without Covariate Adjustment

A.9.1 Study 1

We first interact each treatment allegation with attentiveness and media literacy, separately, to assess heterogeneous treatment effects for the Study one survey. We use the interaction with attentiveness to explore whether treatment effects are stronger amongst surveytakers that are more engaged, and as a robustness check given the possibility of surveytaker satisficing behavior. Figure A6 shows results for both theoretical channels, stratified by participant level of attentiveness (0-2). In line with expectations, the magnitude of effect sizes is larger for attentive survey participants, though the coefficient on the interactive term in the associated regression model is not significant (nominal p-values are 0.23 and 0.16, and adjusted p-values are 0.25 and 0.25 for informational uncertainty and oppositional rallying, respectively). Our main results are likely to be conservative given that they do not exclude the inattentive participants. Indeed, Figure A7 reproduces our main results for Study 1, but subsetted to participants who passed both screeners, and the impacts of informational uncertainty and oppositional rallying on support are both larger in magnitude, reaching as high as 0.25 standard deviations.

Similarly, Figure A8 shows results for both theoretical channels, stratified by participant media literacy (0-3). Against expectations, the magnitude of effect sizes is larger for survey participants with higher levels of media literacy, though the coefficient on the interactive term in the associated regression model is not significant (nominal p-values are 0.25 and 0.20, and adjusted p-values are 0.25 and 0.25 for informational uncertainty and oppositional rallying, respectively). This result

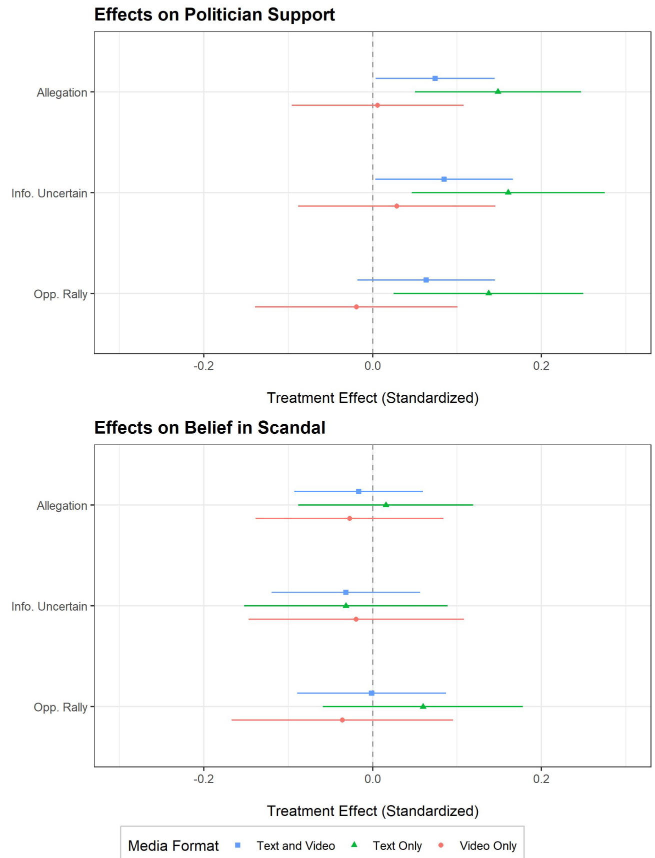

Figure A3: Study 1: With Politician Fixed Effects

suggests that more media literate individuals are actually more susceptible to the liar's dividend, whereas we had hypothesized media literacy would be a mitigating factor, in line with substantial literature and policy discourse urging media literacy education. Note, however, that these results cannot be interpreted causally, and may reflect heterogeneous effects associated with demographic characteristics such as education and partisanship that may be correlated with media literacy.

Next, Table A10 presents nominal and BH-adjusted p-values for three exploratory analyses related to informational uncertainty and the belief outcome, using Study 1 results. First, we consider whether informational uncertainty has stronger effects on belief for moderates; the effects are larger but are not statistically distinguishable. Second, we evaluate whether the informational uncertainty treatment increased the overall variance of the belief measure, as a reflection of uncertainty, compared to control. Contrary to our expectations, it does not. Indeed, there is some evidence to suggest that partisans with strong prior views actually moderated those views, leading to *less* variance for informational uncertainty (var = .79) compared to control (var = .95). That is, increased individual uncertainty may have translated to *decreased* population-level variance, such that our original hypotheses committed a compositional fallacy. Finally, we evaluate whether the coefficients on the informational uncertainty and oppositional rallying treatments are statistically distinct for belief. We find that they are not.

Table A11 presents nominal and BH-adjusted p-values for two exploratory analyses related to op-

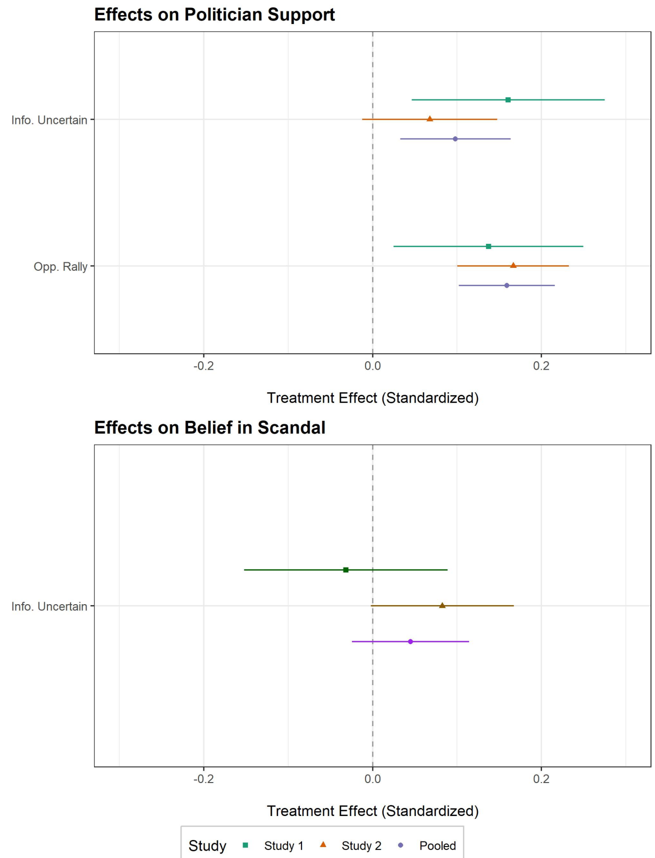

Figure A4: Study 2: With Politician Fixed Effects

	Nominal p-value	Corrected p-value
IU*Moderates (ATE for Belief)	0.19	0.42
IU vs. Control (Belief Distributions)	0.39	0.42
IU vs. OR (ATE for Belief)	0.42	0.42

Table A10: Exploratory Analyses for Informational Uncertainty

positional rallying and the support outcome, again using Study 1 results only. First, we consider whether oppositional rallying has stronger effects on support for (strong) co-partisans; the effects are larger but are not statistically distinguishable. Note, this analysis collapses moderates and anti-partisans into a single category whereas Figure **??** in the main paper separates them. The former analysis fails to support our hypothesis, though the latter analysis may be more illuminating. Second, we evaluate whether the coefficients on the informational uncertainty and oppositional rallying treatments are statistically distinct for support. We find that they are not.

A.9.2 Study 2

In Study 2, to consider factors that may mitigate the harms of the liar's dividend, we also introduced a new experimental component: fact-checking statements designed to counteract the politicians' false allegations of misinformation. We designed the fact-checking treatment based on practices considered to be most impactful according to a recent meta-analysis by Walter et al. (2020), which

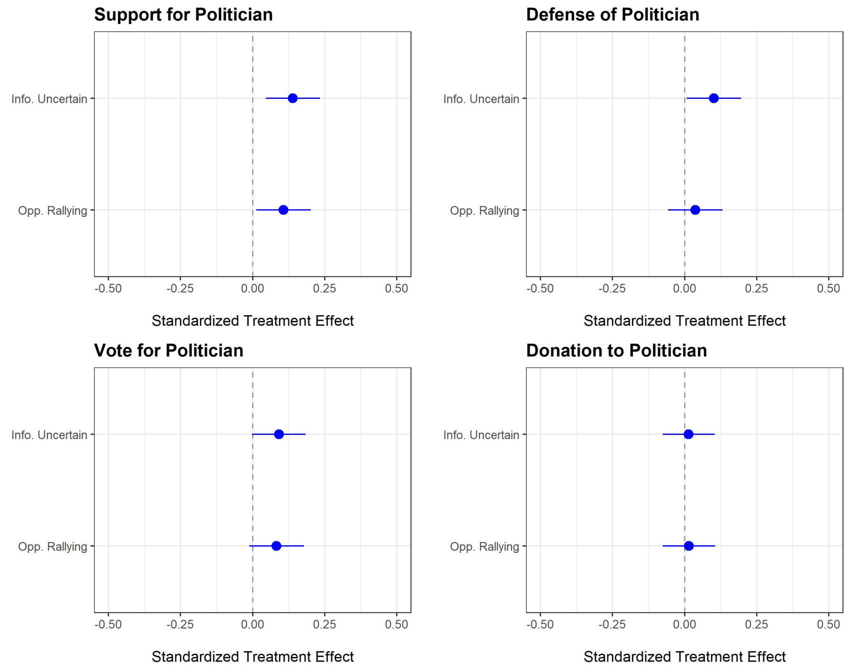

Figure A5: Study 1: Support Outcome Disaggregated

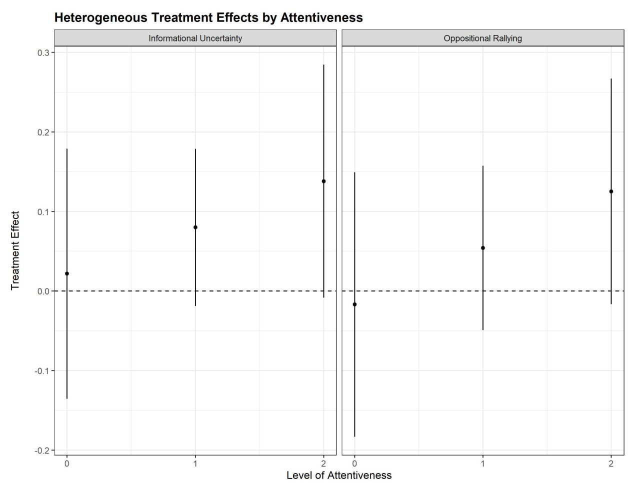

Figure A6: Heterogeneous Treatment Effects by Attentiveness

finds that complex statements and graphical elements are less effective, while length is not important. Our statements are inspired by typical language used by two prominent fact checking organizations, FactCheck.org and PolitiFact, are not overly complex or long, and omit graphics or visual elements. The fact-checking statement, reportedly from a non-partisan fact-checking organization, informs participants that "[Politician Name] was recently accused of making offensive comments but disputes the truthfulness of the story. We find evidence that [Politician Name] did make the comments as originally reported."

Following the analyses in Studies 1 and 2, we regress politician support on the informational uncertainty allegation and the allegation followed by fact-checking (the reference group received no

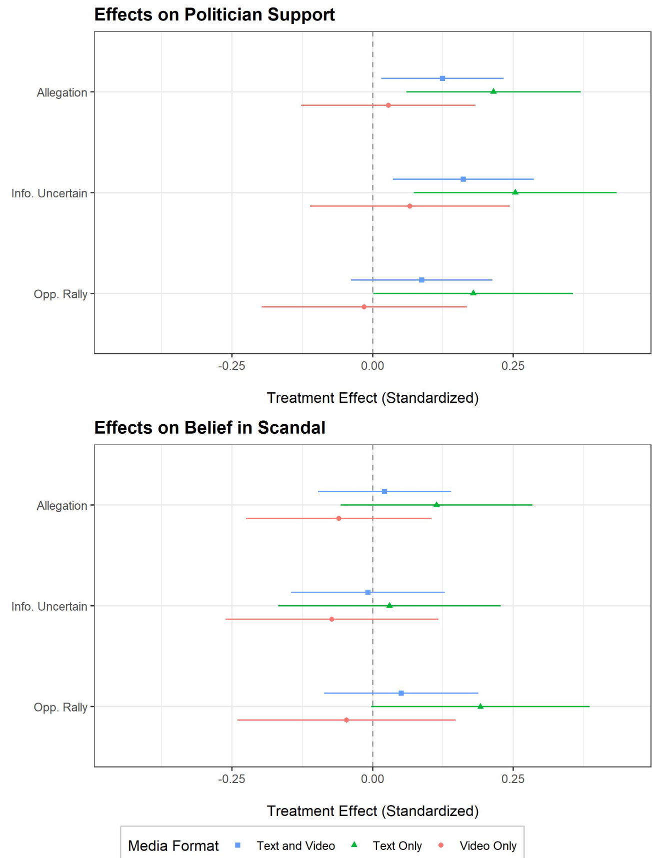

Figure A7: The Liar's Dividend: Study 1 Results for Attentive Respondents

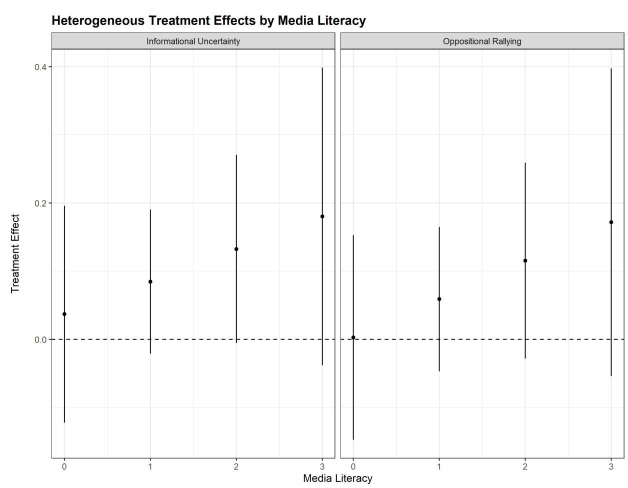

Figure A8: Heterogeneous Treatment Effects by Media Literacy

allegation), and a set of pre-registered covariates. Fortunately, Table A12 suggests that fact-checking can eliminate the liar's dividend. While the informational uncertainty treatment increased politician support, a statement rebutting the politician allegation and confirming the original scandal wipes away any politician support gains.

	Nominal p-value	Corrected p-value
OR*Co-Partisans (ATE for Support)	0.27	0.53
IU vs. OR (ATE for Support)	0.53	0.53

Table A11: Exploratory Analyses for Oppositional Rallying

	Dependent variable:
	Support
Info. Uncertain	0.072*
	(0.042)
IU + Fact Check	−0.011
	(0.042)
Observations	2,518
R^2	0.137
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A12: The Impact of Fact-Checking on the Liar's Dividend

It is reassuring that even a single fact check might counteract misinformation about misinformation, particularly as the literature on fact-checking cautions that individuals may be reluctant to accept fact checks that run counter to their political identity and beliefs. Yet, the fact-checking statements in our study are presented in the context of issues that may not be highly salient to individuals' current political priorities, with statements coming from politicians who are no longer prominent. Furthermore, in practice, fact-checking organizations may not always get the last word and politicians are likely to counter-argue and drown out fact-checkers. This may be especially problematic, as individuals may have a low propensity to seek out fact-checking information. Indeed, in this study, participants were uninterested in learning more about fact-checking, as less than 2% of respondents clicked on additional resources in the debrief for spotting fake news and deepfakes. We believe that analyzing the dynamics between politicians who falsely allege misinformation and the organizations that attempt to fact check them is a fruitful area for further research.

Also in Study 2, we incorporated new exploratory outcome and covariate questions including questions related to informational uncertainty. These questions were designed to assess whether informational uncertainty indeed works through inducing uncertainty or changing belief as originally hypothesized, or through other mechanisms. For example, we explicitly asked respondents exposed to the informational uncertainty treatment whether they believed the *politician allegation* that the original story was false. Note that this differs from our key outcome measuring respondent belief in the scandalous story. Based on our theory of informational uncertainty, we expected that individuals who reported believing the politician allegation would also be more likely to agree with the statement that "it's hard to know what's true these days," a measure of uncertainty that directly mirrors the language invoked by politician allegation. Logically, we expected this uncertainty to then translate into relative gains in politician support via the liar's dividend through affecting belief in the underlying scandal.

Believe Allegation	Hard to Know What's True	Alleg. Affects Support
No	74%	8%
Yes	81%	42%
p-value of difference	0.02	0.00

Table A13: Exploring Informational Uncertainty

Table A13 shows that, among those exposed to the informational uncertainty prime, individuals who believe the allegation are also more likely to agree with the statement that "it's hard to know what it's true these days."[3] The difference is statistically significant ($p = 0.02$) and suggests that the informational uncertainty channel works as intended for some individuals, at least in terms of its most immediate effects. Moreover, believing the politician allegation and agreement with the statement that "it's hard to know what it's true these days" are both correlated with increased politician support ($r = 0.38$ and $r = 0.22$, respectively). Consistent with this finding, when we ask participants explicitly whether the politician allegation affected their support, 42% of those who believed the allegation responded affirmatively, compared to only 8% of those who did not believe the allegation (p-value of difference = 0.00).

However, for members of this treatment group, believing the politician allegation is oddly not correlated with belief in the scandal itself ($r = -0.003$). Overall, these results are puzzling. Despite some descriptive evidence that informational uncertainty works as intended through elevating considerations of uncertainty, in combination with the experimental evidence, there appear to be substantial inconsistencies in the ways in which individuals process their beliefs. This may be evidence of a belief-support disconnect, expressive reporting, or something else. Differences within the informational uncertainty treatment group also point to heterogeneous responses to politician allegations, which are washed out when we consider the treatment group as a whole.

We also considered whether attitudes towards forgiveness, accountability, and cancel culture might influence the proclivity of participants to buy into politician allegations of misinformation and support or punish politicians as a result. We asked participants directly if hearing the politician allegation increased their support. Table A14 displays the results from an analysis which divides respondents into those who said allegations of misinformation increase their support of politicians, and those who did not increase their support. For each covariate, we present average values for each group and indicate whether the differences are statistically significant.

Amongst those who did increase their support, they are statistically significantly more likely to favor second chances over accountability, to be more concerned about fake news, to feel confident in their ability to detect fake news (perhaps an indicator of gullibility), to be co-partisans with the politician in the story, to be Democrats, and to be in favor of political correctness. While some of these differences may be informative for understanding how informational uncertainty in the liar's dividend operate, not all of them are clear or point in the same direction. As such, further work is needed to understand how individuals update their evaluations of politicians in light of allegations that invoke uncertainty.

[3]We classify those who believed the politician allegation as those who strongly agreed or agreed with the politician's allegation that the news story is false.

Covariate	No Support Increase	Support Increase	p-value of Diff.
Prefer Accountability	0.64	0.43	0.00
Cancel Culture is Problem	2.89	3.00	0.16
Concerned about Fake News	2.95	3.29	0.00
Can Detect Fake News	2.51	2.93	0.00
Find Story Offensive	3.46	3.60	0.19
Co-partisan	-0.04	0.10	0.04
Republican	3.71	3.23	0.01
Favor Political Correctness	3.50	3.78	0.00

Table A14: Factors Related to Susceptibility to Informational Uncertainty

A.10 Design Choices Based on a Pilot Study

We administered a pilot study in August 2020 to 916 American adult Amazon Mechanical Turk workers. The purpose of the study was to test a set of candidate videos for inclusion in the main study, to evaluate potential wordings of the politician response treatments, and to perform basic manipulation checks (i.e., whether respondents could see and hear the videos and whether they could correctly recall the stated political party of the politician). Table A15 summarizes how the results of the pilot study informed the design of our main study.

Question	**Pilot Result**	**Design Decision**
Are informational uncertainty and oppositional rallying mechanisms distinct enough to use as separate treatments?	IU and OR appear to have distinct impacts on outcome measures: IU has large, negative impact on belief measure; OR has large, positive impact on support measure	We will use IU and OR as distinct politician response treatments.
What is the best way to measure informational uncertainty?	Use of a bi-directional uncertainty measure was confusing and did not give us additional information beyond the distribution of the belief measure.	We will use distribution of the belief measure to evaluate uncertainty. Belief measure scale and all outcome measures will be unidirectional to be clearer for participants.
Does use of the term "fake news" carry partisan connotation?	Yes, "fake news" has a statistically significant association with Republican party, and is visibly a polarizing term in open-ended responses.	We will use alternative term "false and misleading" to describe stories in the politician response treatments.
Which video treatments from candidate set of 6 are best to use?	All videos were generally perceived as moderately embarrassing and plausibly faked, which makes them comparable and usable in a study of the liar's dividend. We found respondents were more familiar with two of the politicians/events depicted.	We will use four videos (2 Democrat, 2 Republican). Two are more familiar to respondents and thus serve as a harder test for our theory, given that we expect respondents' beliefs and support to change. The second two videos are less familiar.
Are respondents able to see/hear videos?	98% reported no difficulties.	We include subtitles in videos in case some respondents have trouble hearing them.
Can respondents correctly identify politician party that was provided to them from video description?	Between 77% and 88% correctly identify politician party.	We will mention politician party multiple times in the video/text description and title.
What sample size is necessary for the main study?	A MDE of 0.16 is possible with a sample size of 2,500.	Our study should have at least 2,500 respondents.

Table A15: Pilot Study Results that Inform Study Design

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