Populist thinking and susceptibility to misinformation

D.J. Flynn[†] Nina Wiesehomeier[‡]

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Abstract

Populism and misinformation are two of the most extensively studied political phenomena in recent years. However, existing research has failed to consider potential causal effects of populism on citizens' susceptibility to misinformation. We develop a theory to explain how populism affects belief in fake news and responsiveness to corrective information. We test the theory with experiments that activate latent populism and randomize exposure to corrections about 30 fake news stories in four countries (Spain, Portugal, India, United States). Descriptive results indicate that populist sentiment is consistently associated with misperceptions. Experimentally activating latent populism causes strong emotional reactions; however, contrary to our preregistered hypotheses, activation does not increase belief in fake news or reduce the effectiveness of corrections. Collectively, our results suggest that strongly populist citizens are vulnerable to misinformation, but attempts to activate latent populism (e.g., through campaigns) are unlikely to make misperceptions more prevalent or resistant to correction.

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[†]Associate Professor of Political Science; School of Politics, Economics, and Global Affairs; IE University. E-mail: dflynn@faculty.ie.edu.

[‡]Associate Professor of Comparative Politics; School of Politics, Economics, and Global Affairs; IE University. E-mail: nwiesehomeier@faculty.ie.edu.

Misinformation can distort democratic debate and complicate policy efforts to address pressing crises from climate change to infectious disease. In many countries, these challenges are exacerbated by elites who make false or unsupported claims to attract voters (Nyhan 2020, 227–229). For instance, populist leaders often make conspiratorial claims about powerful elites allegedly working in secret to advance their own interests at the expense of the general public (Mudde and Rovira Kaltwasser 2017; Müller 2016). In the mass public, correlational evidence suggests that citizens with populist attitudes are more likely to hold conspiratorial worldviews (Castanho Silva, Vegetti, and Littvay 2017) and endorse certain misperceptions (Eberl, Huber, and Greussing 2021; Stecula and Pickup 2021; van Kessel, Sajuria, and Hauwaert 2021).

While populism and misinformation often co-occur (Törnberg and Chueri 2025), existing research has failed to consider the potential causal effects of populism on citizens' susceptibility to misinformation. Integrating research on populist attitudes and the psychology of misinformation, we develop a theory to explain how activating latent populism affects belief in fake news and responsiveness to corrections. Specifically, we argue that activating latent populism will increase belief in populist fake news and reduce the effectiveness of corrections — effects that we expect to be driven by respondents with high levels of latent populism. We test these predictions with preregistered survey experiments covering 30 fake news stories in four countries — two with low to moderate levels of elite populism (Spain, Portugal) and two with high levels of elite populism (India, United States) at the time of our studies.[1] Our experimental design combines pre-treatment measures of latent populism with randomized treatments that activate populism via dispositional blame attribution, an approach that has been widely validated in previous studies of populist communication (Busby et al. 2025; Busby, Gubler, and Hawkins 2019; Busby et al. 2019; Hameleers, Bos, and De Vreese 2017). We then ask respondents to evaluate a series true and false news items that were circulating at the time of data collection, and randomize exposure to corrective information. This approach provides the first causal estimates of the effect of individual-level populism on misinformation belief and persistence.

[1] These categorizations reflect political conditions at the time of our data collection. We discuss country selection in greater detail below.

Before turning to the experimental results, however, we document a robust positive relationship between latent populism and belief in fake news across topics and countries. We then report three key experimental results, which run counter to our preregistered hypotheses. First, we find that activating latent populism does not increase belief in fake news. Second, turning to the effects of corrective information, we find that respondents are inconsistently responsive to fact checks, with pooled estimates in the predicted direction in two countries (although small in magnitude) and null in two countries. Finally, we find no evidence that activating latent populism reduces the effectiveness of fact checks. In exploratory analyses, we find that activating latent populism leads to strong emotional reactions, increasing negative emotions and decreasing positive emotions. However, these strong emotional responses do not in turn increase belief in fake news or reduce the effectiveness of corrections.

These findings offer important insights for ongoing research into populism and misinformation. For populism researchers, they call into question the prevailing view of populism as a "a set of loosely articulated ideas ... that ... generally lie dormant and require activation" (Hawkins, Kaltwasser, and Andreadis 2020, 286). Rather, our data suggest that populism operates as a stable predisposition — more akin to partisan identification — which exerts influence on beliefs even in the absence of activation. Indeed, even when activated, populism increases emotional arousal, but does not fundamentally reshape how citizens view political facts. This suggests a more complicated relationship between populism and public opinion than often assumed: populist attitudes may reflect pre-existing beliefs about the state of the world, or both populism and factual beliefs may reflect broader feelings of political dissatisfaction or alienation without necessarily being causally related to each other. In either case, we argue that our results underscore the need for more comprehensive theorizing about the relationship between populism and factual beliefs.

For misinformation researchers, our results offer an important addendum to recent studies finding that fact checks consistently decrease belief in fake news (e.g., Wood and Porter 2019; Porter and Wood 2021; Porter, Velez, and Wood 2023). Examining 30 fake news claims on diverse topics across four countries, we find that corrections significantly decrease belief in one-third of cases (with mostly null effects in other cases). We also observe significant variation across countries: weak, moderate, and strongly populist respondents in one country (Portugal) consistently accept corrections, but effects are inconsistent in other countries (Spain, India, United States). These results suggest that the effectiveness of corrections is more contingent on country- and claim-specific factors than recent research suggests.

In the remainder of this article, we present a theoretical framework to understand the relationship between individual-level populism and belief in fake news, derive hypotheses, describe the experimental design and data, and present the descriptive and experimental results. We conclude with a discussion of implications for future research and normative issues surrounding factual knowledge in an era of rising populism.

Populism, corrections, and belief in fake news

Canonical theories of public opinion describe beliefs as resulting from the interaction of information and *predispositions*, understood as "stable individual-level traits that regulate the acceptance or nonacceptance of the political communications [a] person receives" (Zaller 1992, 22). Historically, much public opinion research has focused on fundamental predispositions, such as partisan identification (Campbell et al. 1960) and ideology (Converse 1964). Researchers have since turned their attention to a wider set of predispositions, including social identities (Klar 2013), values (Jacoby 2014), moral foundations (Clifford 2014), and, more recently, populism.

The study of populist predispositions — or populist attitudes — draws from the ideational approach, which conceives of populism as consisting of three distinct sets of beliefs: anti-elitism, people-centrism, and a moralized Manichean worldview (cf. Mudde and Rovira Kaltwasser 2017). Together, these sets of beliefs inform the ideas that individuals hold about the political world and its actors (Hawkins 2009; Hawkins, Riding, and Mudde 2012; Akkerman, Mudde, and Zaslove 2014).[2] Conceptualized this way, populist attitudes have been found to be common across

[2] We use the terms *populist attitudes* and *populist predispositions* interchangeably.

countries (Van Hauwaert, Schimpf, and Azevedo 2018) and may be growing in recent years (Meyer and Wagner 2020). We follow the ideational approach and define populism as an individual-level predisposition that leads people to view politics and society as a perpetual and antagonistic struggle between an evil, corrupt elite and the virtuous "common" people.

Existing literature argues that populist attitudes do not operate at the same level as consciously held opinions towards candidates or issues. Rather, populist attitudes are a latent disposition that require activation by contextual, linguistic, or emotional cues (Hawkins and Kaltwasser 2018; Hawkins, Kaltwasser, and Andreadis 2020). Once activated, populist attitudes can create a "powerful motivation for action" (Hawkins and Kaltwasser 2018, 62) and, in turn, shape beliefs and behavior. For instance, experimental research indicates that exposure to populist frames in news articles can increase feelings of resentment and boost support for populist parties (Bos, van der Brug, and de Vreese 2013). Similarly, Hameleers, Bos, and de Vreese (2018) demonstrate that populist frames blaming elites for national problems reduce support for incumbents and increase support for populist challengers. Bos et al. (2020) conduct experiments in 15 European countries and find that populist frames increase perceptions of economic insecurity and stimulate soft forms of participation, such as interest in discussing policy problems or signing a petition. Conversely, existing research argues that when populism is not activated on the supply slide (e.g., by politicians), populist attitudes may have little or no electoral effect (Hawkins, Kaltwasser, and Andreadis 2020; Medeiros 2021; Santana-Pereira and Cancela 2020).

While many past studies examine the effect of populist frames, other work demonstrates that individual-level populism can be activated by manipulating the manner in which people attribute blame for political or social problems (e.g., Busby et al. 2025; Busby, Gubler, and Hawkins 2019; Hameleers, Bos, and De Vreese 2017). When considering a policy problem, voters can attribute blame *situationally* or *dispositionally*. Situational blame attribution involves focusing on the events or circumstances that gave rise to a problem (e.g., blaming unemployment on global economic trends). By contrast, dispositional blame attribution entails placing responsibility in the hands of groups or individuals who are morally or ethically flawed (e.g., blaming unemployment on corrupt actions by policymakers). This dispositional approach closely resembles populist rhetoric, which often blames problems on the actions of corrupt or immoral elites who pursue their own interests at the expense of the general public.

Past research indicates that these two forms of blame attribution — dispositional and situational — have strikingly different effects. In particular, dispositional blame attribution has been shown to stimulate populist ways of thinking and increase support for populist candidates. In a large, four-country study, Busby et al. (2025) show that encouraging dispositional blame attribution increases expressions of populist sentiment (also see Busby, Gubler, and Hawkins 2019, study 1). Busby, Gubler, and Hawkins (2019, study 2) find that dispositional blame attribution increases support for populist candidates. By contrast, situational blame attribution has no such effects. Respondents who are encouraged to attribute blame situationally behave similarly to pure control respondents who received no blame attribution treatment at all (Busby, Gubler, and Hawkins 2019, 624–627).[3]

While dispositional blame attribution has been shown to stimulate populist thinking and increase support for populist candidates, the extent to which this process affects broader attitudes — such as factual beliefs — remains an open question. We argue that activating individual-level populism should increase belief in fake news stories, especially stories that are framed in explicitly populist terms. Past research has demonstrated that individual-level populism is correlated with conspiratorial worldviews (Castanho Silva and Wratil 2023) and certain misperceptions (van Kessel, Sajuria, and Hauwaert 2021). Individuals with differing levels of latent populism, then, start with different baseline (i.e., non-activated) propensities to believe populist fake news. The question then becomes whether these groups are similarly or differentially responsive to stimuli that activate latent populism.

Here, existing literature offers conflicting insights. Some past research finds that the effects of populism activation are limited to individuals with low to moderate levels of latent populism. For instance, Busby, Gubler, and Hawkins (2019, 619) argue, based on framing theory, that the

[3] In the experiments reported below, we take the same approach, comparing respondents who had their latent populism activated via a dispositional blame attribution task to respondents who did not.

effects of dispositional blame attribution should be limited to respondents with low levels of latent populism. They contend that individuals with high levels of latent populism are likely to adopt populist ways of thinking even in the absence of activation; by contrast, individuals with low levels of latent populism are not inclined to view the world in populism terms, but can be convinced to do so when presented with relevant frames or cues.

However, other research on populism — and the broader literature on opinion formation — suggest a contradictory possibility. For instance, Zaller's (1992) model suggests that opinions are affected by considerations that are received and accepted, where acceptance is based in part on consistency with pre-existing considerations (cf., Lodge and Taber 2013; Kunda 1990). Focusing on latent populism and belief in fake news, this logic suggests that a stimulus intended to activate latent populism (e.g., dispositional blame attribution) would not resonate with individuals who are not inclined to see the world through a populist lens — and therefore not affect related beliefs. Instead, activation should be most consequential for respondents with high levels of latent populism because such stimuli are consistent with their predispositions. And indeed, some existing research suggests that populist frames have larger effects among respondents with high levels of political cynicism (Bos, van der Brug, and de Vreese 2013) or extreme ideological positions (Hameleers et al. 2021). We expect to observe a similar dynamic when it comes to latent populism. Specifically, we expect the effects of populism activation on factual beliefs to be largest for respondents with high levels of latent populism. We therefore predict that:

> H1: Among people with populist predispositions, activating populism will increase belief in populist fake news.[4]

The same line of reasoning can help generate predictions about how people will respond to corrective information. In recent years, a large literature has developed examining the psychology of misinformation and best practices for correcting misperceptions (for overviews, see Ecker et al. 2022; Jerit and Zhao 2020).[5] In an influential early article, Nyhan and Reifler (2010)

[4] This hypothesis was numbered H2 in our preregistrations.

[5] Consistent with this literature, we use the term *misperceptions* to refer to "beliefs about factual matters are

found that corrections sometimes fail to reduce misperceptions — and may backfire among strongly directionally motivated respondents on some issues. More recent research, however, suggests that the "backfire effect" is exceedingly rare; to the contrary, corrections are effective at reducing misperceptions among most audiences on most issues (Wood and Porter 2019; Guess and Coppock 2020; Haglin 2017; Nyhan 2021). Several experimental studies have demonstrated the effectiveness of corrections across policy issues and countries. For instance, Wood and Porter (2019) conduct fact-checking experiments on 52 issues and find no instances of backfire; instead, "when presented with factual information...the average subject accedes to the correction and distances himself from the inaccurate claim" (160). Similarly, Porter and Wood (2021) conduct 28 experiments in four countries covering politics, economics, crime, and Covid–19, concluding that fact checks consistently reduce misperceptions (also see Porter, Velez, and Wood 2023). These findings are consistent with recent meta-analyses, which have concluded that fact checks are effective at reducing misperceptions (Chan et al. 2017; Walter et al. 2020). In the experiments below, we examine the effectiveness of corrections in the context of fake news, which often has broadly populist and anti-institutional overtones and may therefore be more resistant to correction. Nonetheless, given existing evidence, we expect that:

H2: Fact checks will reduce belief in fake news claims.[6]

While we expect corrections to be generally effective, past research makes clear that the magnitude of correction effects can vary across contexts and across individuals with relevant predispositions. We focus in particular on how individuals with varying levels of latent populism respond to corrections about populist fake news. In this context, we theorize that the magnitude of correction effects will vary across individuals with different levels of latent populism. Specifically, we expect individuals with high levels of latent populism who undergo activation should be strongly motivated to believe populist fake news and, correspondingly, motivated to resist

not supported by clear evidence and expert opinion — a definition that includes both false and unsubstantiated beliefs about the world" (Nyhan and Reifler 2010, 305). This definition encompasses belief in the fake news claims examined below. We use the terms *corrective information*, *corrections*, and *fact checks* interchangeably to refer to any message that seeks to reduce misperceptions by providing relevant facts or evidence.

[6] This hypothesis was numbered H1 in our preregistrations.

corrective information. While previous research has not examined the potential for populism to serve as a directional motivation in this fashion, other work suggests that the effectiveness of corrections can vary across individuals with different prior beliefs (Nyhan, Reifler, and Ubel 2013) and ideologies (Walter et al. 2020). More broadly, research on social identities has found that priming message-relevant identities can affect the persuasiveness of subsequent information. For instance, Druckman, Peterson, and Slothuus (2013) find that priming partisan identity (via a prompt that accentuates elite partisan polarization) alters the manner in which people process political arguments. Specifically, they find that when partisan polarization is accentuated, people tend to follow arguments from their preferred party regardless of the direction or strength of those arguments (also see Slothuus and de Vreese 2010).

In the context of fake news, we expect activated populism to serve as an especially strong directional motivation because it is so proximate to the message (i.e., misinformation) and counter-message (i.e., correction) at hand. Specifically, we expect that:

> H3: Among people with populist predispositions, activating populism will reduce the effectiveness of fact checks about populist fake news.

Design and data

We test these hypotheses with preregistered survey experiments in four countries: Spain ($N = 8,789$), Portugal ($N = 4,962$), India ($N = 3,003$), and the United States ($N = 3,203$).[7] We selected these four countries because they offer substantial variation in terms of both elite and mass populism — the most theoretically relevant variable in our analyses (Druckman and Kam 2011).

On the elite side, the salience and electoral success of populist parties varies significantly across

[7]We filed two preregistrations. The first was filed in February 2021 and covered the Spain and Portugal studies. After we secured additional funding, we filed a second preregistration in December 2021, which covered the India and US studies. An anonymized version of both preregistrations is included in the supplemental materials. Following the preregistrations, we recruited the maximum number of respondents possible given the study budget in all four studies.

these four countries. At the time of our experiments, Spain was (and continues to be) governed by mainstream center-left party PSOE; however, the country was experiencing a nascent surge in elite populism on both the left and right, with left-wing populists Podemos (We Can) in 2015 followed by right-wing populists Vox in 2019. Despite sharing many cultural and socioeconomic characteristics with Spain, elite populism was largely absent in Portugal (Santana-Pereira and Cancela 2020).[8] By contrast, during this period, politics in India and the United States were dominated by populists Narendra Modi and Donald Trump, respectively. While both are right-wing populists, Modi came to power on an agenda of religious (Hindu) nationalism while Trump more closely resembles many western European leaders elected in recent years on anti-immigration nationalistic platforms.

On the mass side, populism is also present in all four countries to varying degrees. This is reflected in levels of pre-treatment populism measured in the surveys analyzed below. Specifically, populist sentiment is lowest in Portugal (mean = 2.84 out of 5), slightly higher in the United States (3.00) and Spain (3.03), and significantly higher in India (3.46). The distribution of populism is roughly normal in Spain, Portugal, and the United States, and strongly right-skewed in India, suggesting higher levels of latent populism in that country.[9] These differences allow us to examine the extent to which our treatments (populism activation and corrections) have different effects across countries where populism is differentially salient. We provide more information about the distribution of pre-treatment populism in all four samples in Appendix B.

Respondents in Spain and Portugal were recruited from a commercial panel (Netquest) and resembled the national population in terms of age, education, gender, and region. Respondents in India and the United States were recruited from Amazon's Mechnical Turk (MTurk; Berinsky, Huber, and Lenz 2012). While MTurk samples are descriptively different from national populations, treatment effect estimates have been shown to generalize from MTurk to representative samples (Coppock 2019; Coppock, Leeper, and Mullinix 2018; Krupnikov, Nam, and Style 2021; Mullinix,

[8] Right-wing populist party Chega has gained representation in recent years, but was not a salient national force at the time our data were collected.

[9] All pairwise comparisons are significant at $p < .001$ using both t-tests and nonparametric Kolmogorv-Smirnov tests.

Druckman, and Freese 2015), including recent studies of fake news discernment (Pennycook and Rand 2022).[10]

The design of all four survey experiments is similar (see Appendix A for full instruments). Respondents began the survey by answering a series of demographic and background questions. Our critical pre-treatment characteristic is populist attitudes, which we measure using the standard six-item battery developed by Akkerman, Mudde, and Zaslove (2014). These questions ask respondents to agree or disagree with a series of six statements designed to capture the three subdimensions of populism: people-centrism, Manicheanism, and anti-elitism.[11] Following Wuttke, Schimpf, and Schoen (2020), we use responses to these six items to calculate an overall populism score for each respondent.[12] We use this overall score to divide our samples into terciles of pre-treatment (i.e., latent) populism. We refer to respondents in these terciles as *weak*, *moderate*, and *strong* populists, respectively. Here, we note a deviation from our preregistration, which indicates that we would restrict certain experimental analyses to respondents in the top tercile of populist sentiment.[13] Instead, we present all results on the full sample of respondents, which we break down into terciles. This approach allows us to better contextualize the results from our preregistered subsample of strong populists. As will become clear shortly, weak, moderate, and strong populists have different baseline levels of belief in fake news. Presenting treatment effects only among strong populists would therefore offer a potentially misleading picture of treatment effects, which are estimated relative to an extreme baseline. (Of course, readers who prefer to consider only preregistered results can focus exclusively on the results among strong populists,

[10] More generally, the suitability of convenience samples depends not on descriptive similarity but instead on the existence of sufficient variance on theoretically relevant moderators (Druckman and Kam 2011). In our case, the most relevant moderator is latent populism. In Appendix B we show that we have substantial variance on this variable in all four countries, which allows us to divide the samples into terciles of pre-treatment populism following the procedure described in our preregistrations.

[11] The full wording of these items is provided in Appendix B. One might worry that this pre-treatment measure could result in priming and therefore contaminate our experimental results. Fortunately, recent evidence suggests that measuring moderators pre-treatment does not bias treatment effect estimates (Clifford, Sheagley, and Piston 2021; Sheagley and Clifford 2023).

[12] Specifically, we calculate the arithmetic mean of the anti-elitism and people-centrism subscales. The resulting subscale scores, together with the third subscale, are then combined using a geometric mean to construct the overall populism score.

[13] This restriction concerns H1 and H3 in the analyses below.

which are presented below.)

After answering the populism battery, respondents were randomly assigned to two separate experimental treatments. The first is a latent populism activation task (treatment group) or no task (control group). The populism activation treatment consists of a three-item sequence that encourages dispositional blame attribution for a national problem. Treated respondents were first asked to rank a list of national problems in order of importance (respondents could also choose to specify another problem not listed). On the next screen, respondents were asked to explain in a few words which groups or individuals were most responsible for the problem they ranked as the most important, why these particular groups or individuals are responsible, and how they should be handled. As discussed above, past research has validated this approach to activate latent populism, which consistently increases expression of populist sentiment (Busby et al. 2025; Busby, Gubler, and Hawkins 2019, study 1; Hameleers, Bos, and de Vreese 2018) and support for populist candidates (Busby et al. 2019, study 2).

In the next section of the survey, respondents were presented with a series of short articles (which we call news blurbs) about politics, science, education, religion, and other topics. The first news blurb shown to all respondents was a true story discussing recent increases in extreme weather events linked to climate change.[14] Respondents were then presented with a series of randomly selected and ordered news blurbs that described recent fake news stories specific to the country context (see Appendix C for more information). For instance, in the Spanish experiment, all respondents first read the climate change blurb, and then were randomly assigned to read one blurb covering science (about genetically modified foods or vaccines), education (replacing language classes with religion or mandatory Islamic studies), political parties (about pacts by left- or right-wing coalitions in regional governments), and alleged conspiracies (by patent holders or NATO). In our preregistrations, we distinguish between fake news blurbs that are overtly populist (e.g., about conspiring politicians in Spain or corrupt Members of Parliament in India) and those that are not (e.g., about the safety of GMOs or vaccines). For ease of presentation, we report

[14] Placing the true story first in the sequence creates a few seconds of separation between the populism activation treatment and the first fake news blurb. The topic and order of subsequent blurbs was randomized.

pooled models in the main text and separate claim-specific models (which distinguish between populist and non-populist stories) in Appendix D. Our results do not change depending on whether we consider all claims or the subset of populist claims in Appendix D.

Our second experimental treatment — corrective information — was randomized at the blurb level. We created multiple versions of each news blurb: one version that included only a headline and short description of the false claim (control group), and other versions that included included a short piece of corrective information (treatment group). To maximize realism, we created multiple versions of each correction varying only the source (e.g., fact checkers, scientists, economists).[15] After reading each news blurb, respondents were asked to rate the accuracy of the central factual claim on a four-point scale ranging from "not at all accurate" to "very accurate." This item serves as our primary dependent variable in the analyses below. This approach is consistent with past research into factual beliefs (Nyhan and Reifler 2010) and the perceived accuracy of fake news stories (Guess et al. 2020; Porter and Wood 2021).

Given our studies' focus on misinformation, we took several additional steps to minimize potential harms and comply with disciplinary ethical guidelines (American Political Science Association 2020). First, to avoid the possibility of popularizing low salience claims, we selected claims that were at least moderately salient already at the time of our experiments. Second, we fully debriefed all respondents at the conclusion of the study by presenting a list of all claims and explaining which were true and false. Finally, we supplemented this standard debriefing in Studies 3 and 4, which were conducted after the outbreak of Covid–19, with a statement about the safety and efficacy of vaccines and links to national and international health authorities. Our research protocols were reviewed and approved by the IRB at [REDACTED] before data collection began.

To summarize, the experimental design used in all four studies randomizes populism activation and exposure to corrective information about a range of fake news stories. Our outcome variable is belief in the central factual claim in each fake news blurb.

[15] Following our preregistration, we maximize power by collapsing all respondents who saw corrections from any source into a single treatment group.

Results

Descriptive results

Before turning to the experimental results, we conduct a descriptive analysis of the relationship between latent populism and belief in fake news. Previous research has documented a positive relationship between populism and misperceptions on several topics, including Covid–19 (Eberl, Huber, and Greussing 2021; Stecula and Pickup 2021) and vaccines (Kennedy 2019), and conspiracy theories (van Prooijen et al. 2022). However, our data permit a more comprehensive test of this relationship across a diverse set of 30 false claims in four countries.

As described above, we divide the samples into terciles of pre-treatment populism, which we refer to as weak, moderate, and strong populists. In each country, we estimated preregistered OLS models predicting average belief in fake news (across all stories shown) based on populism tercile, demographics, left/right ideology, media consumption habits, conspiratorial thinking, and institutional trust.[16] Because we are interested in the relationship between latent populism and baseline belief in fake news, we restrict this analysis to pure control respondents — that is, respondents who did not receive a populism activation treatment and were presented with an uncorrected version of a particular fake news story. The pooled results are presented in Table 1. We report separate claim-specific models in Appendix D.

[16]These models were preregistered as RQ1.

Table 1: Latent populism and belief in fake news (OLS models)

	DV = belief in false claim (pooled)			
	Study 1 (Spain)	Study 2 (Portugal)	Study 3 (India)	Study 4 (USA)
Moderate populist (tercile 2)	0.07*	0.05	−0.10*	0.39***
	(0.03)	(0.05)	(0.04)	(0.04)
Strong populist (tercile 3)	0.18***	0.12	0.12**	0.53***
	(0.03)	(0.06)	(0.04)	(0.05)
Constant	2.11***	2.26***	2.94***	2.05***
	(0.06)	(0.29)	(0.05)	(0.06)
Strong populist − moderate populist	0.11***	0.07	0.22***	0.14***
Demographics	✓	✓	✓	✓
Conspiratorial thinking	✓	✓	✓	✓
Institutional trust	✓	✓	✓	✓
Get news from social media	✓	✓	✓	✓
Left/right ideology	✓	✓		✓
Political knowledge	✓	✓		✓
N (respondent-blurbs)	5,633	1,463	3,281	3,366

Note: Cell entries are OLS coefficients with clustered standard errors in parentheses. Dependent variable ranges from 1–4 with higher values indicating greater belief in false claims. This specification was preregistered as an exploratory research question (RQ1). Demographics include age, sex, and education. Political knowledge and left/right ideology were not measured in Study 3 (India). Samples includes pure control condition for each blurb (no populism activation, no correction). Full results in Appendix Table A4. Significance levels: *p<.05, **p<.01, ***p<.001.

Results demonstrate that latent populism is positively associated with fake news belief in three countries — Spain, India, and the United States — with estimates in the expected direction but insignificant in Portugal. While the results are somewhat mixed for moderate populists, holding strong populist predispositions is associated with greater belief in false claims in Spain, India, and the United States. Moreover, in these three countries, the coefficient on strong populists is significantly larger than the coefficient on moderate populists ($p < .001$ in all three models).

To further contextualize our results, we estimated separate claim-specific models in each country (see Appendix D). These results indicate that the relationship between strong populist attitudes and fake news belief is consistent across claims in Spain (6 out of 8 claims) and the United States (8 out of 8 claims). India presents an interesting test because of its strongly right-skewed distribution of latent populism. In this setting, strong populists are less distinct from weak and moderate populists than in countries (like Spain, Portugal, and the United States) where the distribution of populist attitudes is more normal. Nonetheless, in India, the relationship between strong latent populism and fake news belief is in the expected direction in all 9 models, but only significant in 1 model. Portugal stands out as the one country in which latent populism is not associated with fake news belief. In the claim-specific models, this relationship is significant in only 1 out of 5 claims.[17]

Overall, these results suggest that latent populism is strongly associated with fake news belief in three countries (Spain, India, United States). This relationship is null in the one country (Portugal), which lacked salient populist politics at the time of our data collection. We now turn to our preregistered analyses, which examine the causal effects of activating latent populism in all four countries.

Experimental results

The descriptive results demonstrate that strong levels of latent populism are associated with belief in fake news claims in three of our four countries. Past research indicates that latent populism can be activated by an external cue. Our interest is whether this sort of activation affects downstream outcomes, namely belief in fake news and responsiveness to corrections. In our experiments, we activate latent populism with the dispositional blame attribution treatment discussed above. H1 predicts that this treatment will increase belief in fake news among strong populists.[18] We test this hypothesis with OLS models that regress belief in false claims on a dummy variable for the populism activation treatment, pre-treatment populism tercile, and the interaction of these two terms. For all experimental analyses, we present pooled results in the

[17] The claim involves an alleged conspiracy by the holders of medical patents.

[18] This hypothesis was preregistered as H2. We reorder our hypotheses for expositional clarity.

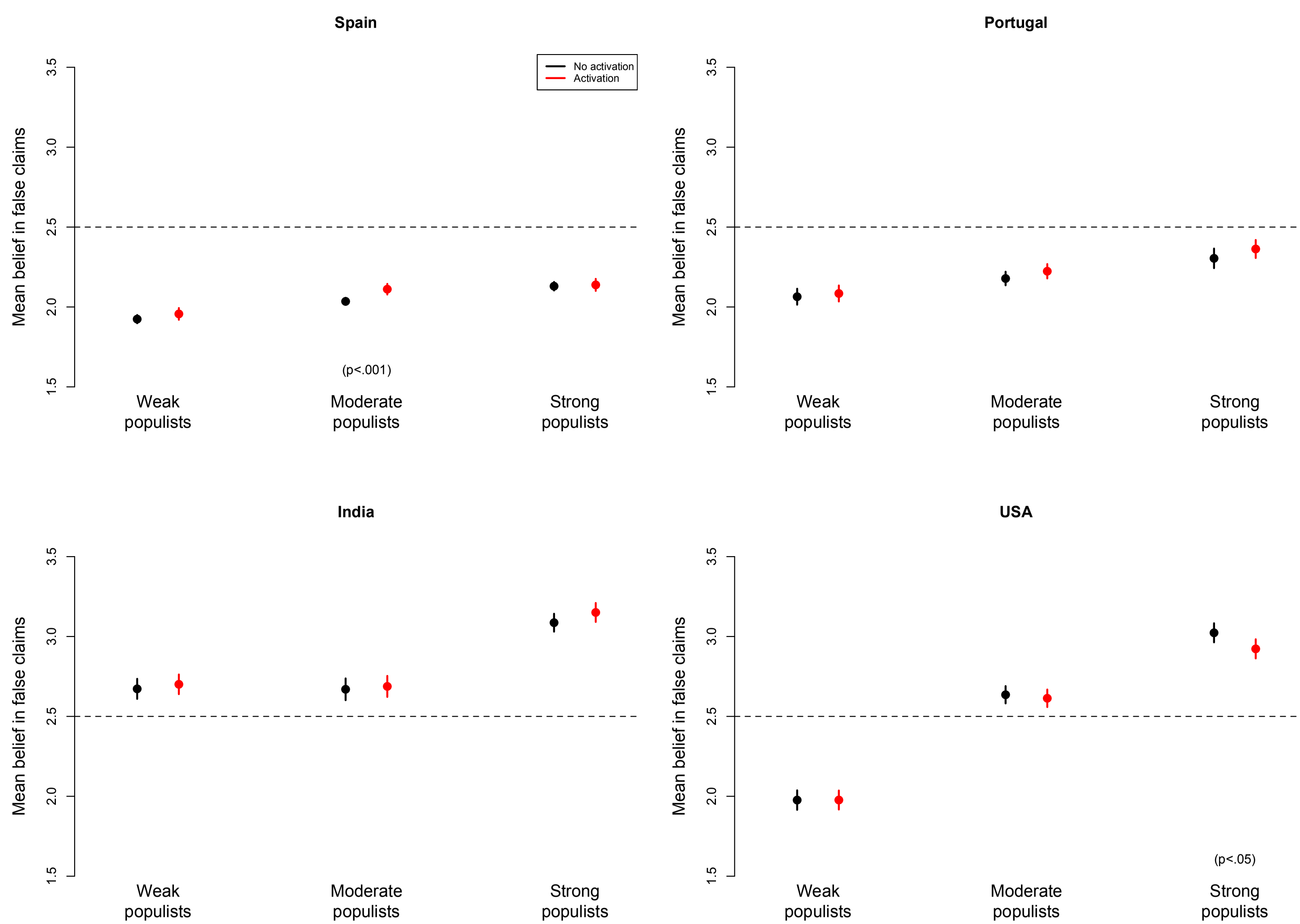
main text and claim-specific models in Appendix D.

Figure 1 illustrates the effect of populism activation on overall belief in false claims within each tercile for all countries. Specifically, the figure depicts mean levels of belief among respondents assigned to the populism activation treatment (red dots) or not (black dots) along with 95 percent confidence intervals. An initial look at the figure reveals that, consistent with the descriptive results presented above, belief in false claims increases significantly with increases in latent populism (i.e., moving from left to right in each panel of the figure).

The key test of H1, however, is whether activation increases belief in fake news among respondents with high levels of latent populism. Contrary to H1, we fail to find any evidence that activation increase belief in false claims among strong populists: the effect is null in three countries (Spain, Portugal, India) and incorrectly signed, but only marginally significant, in the fourth country (USA). Looking beyond strong populists, we similarly find that activation fails to increase belief in false claims. Weak populists are unaffected by activation in all four countries. Among moderate populists, activating latent populism increases fake news belief in one country (Spain, $p < .001$) and has no effect in three countries (Portugal, India, United States)

Results from the claim-specific models reinforce these null effects (see Appendix Tables A13–16): across four countries and 30 fake news stories, we find that activation consistently fails to increase belief in fake news. We also find scant evidence that the effect of activation is heterogeneous across respondents with different levels of pre-treatment populism. We find only two instances — both in Spain — in which the effect of activation on belief in fake news is significantly larger for respondents with moderate compared to weak levels of pre-treatment populism (see Appendix Table A13). Overall, these results suggest that although latent populism is associated with fake news belief, activating this latent populism does not increase belief in fake news. H1 is not supported.

Figure 1: Effect of activating latent populism on belief in fake news



Note: Point estimates display mean belief in fake news claims among respondents exposed to populism activation treatment (red) or not exposed (black). Means calculated from models in Appendix Table A12. Belief is measured 1–4, where higher values indicate more belief. Error bars contain 95% confidence intervals. Dotted line shows the scale midpoint.

Our next two hypotheses focus on corrections. Based on previous research discussed above, H2 predicts that corrections will reduce belief in fake news. We test this hypothesis by examining the overall effectiveness of corrections, considering all respondents and all fake news claims in each country. Table 2 presents the results of pooled models, which include respondent fixed effects and clustered standard errors. The dependent variable is again belief in fake news; negative estimates therefore correspond to successful corrections.

As shown in Table 2, the effectiveness of corrections is inconsistent across countries. The pooled estimate is negative in two countries (Portugal $p < .001$, USA $p < .05$) and null in two countries (Spain, India). Claim-specific models suggest that these pooled estimates are masking substantial heterogeneity in the effectiveness of corrections across issues (see Appendix Tables A17–20). For instance, corrections significantly reduce belief in 3 out of 8 false claims in Spain, 4 out of 5 claims in Portugal, 1 out of 9 claims in India, and 2 out of 8 claims in the United States.

Table 2: Effect of corrections on fake news belief

	DV = belief in false claims (pooled)			
	Study 1 (Spain)	Study 2 (Portugal)	Study 3 (India)	Study 4 (USA)
Correction	-0.02	-0.13^{***}	-0.004	-0.03^{*}
	(0.01)	(0.02)	(0.01)	(0.01)
Constant	3.22^{***}	2.21^{***}	2.80^{***}	2.99^{***}
	(0.02)	(0.03)	(0.02)	(0.03)
Respondent fixed effects	✓	✓	✓	✓
# fake news blurbs per respondent	4	3	5	5
# respondents	8,789	4,962	3,003	3,203
N (respondent-blurbs)	34,700	9,358	14,053	15,073

Note: Cell entries are OLS coefficients with clustered standard errors in parentheses. Dependent variable ranges from 1–4 with higher values indicating greater belief in false claims. Models include all fake news stories from all studies. Significance levels: *p<.05, **p<.01, ***p<.001.

To further explore these country differences, we turn to the two false claims that were included in all four studies: the alleged unsafety of childhood vaccines and an alleged conspiracy by the holders of medical patents. Focusing first on vaccines, we find that corrections have null effects in three countries (Portugal, India, United States) and backfire in Spain (though the effect is only marginally significant, $p < .05$). Turning to the patent holders conspiracy, we find that corrections reduce misperceptions in two countries (Portugal $p < .001$, USA $p < .05$), have null effects in one country (India), and backfire in one country (Spain $p < .05$).

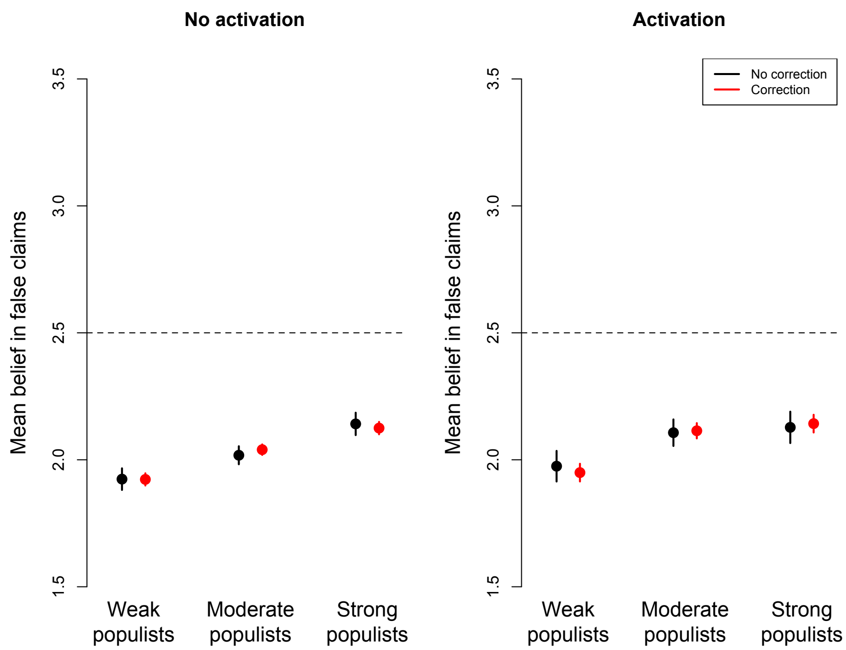
These analyses offer only partial support for H2 (in Portugal and the United States). More importantly, they suggest that the effectiveness of corrections varies significantly across claims and countries. This finding runs counter to some research work, discussed above, which finds that corrections are generally effective across claims and countries. We consider potential reasons for this disparity in the conclusion.

Our final hypothesis concerns the potential moderating effect of latent populism activation on the effectiveness of corrections. Specifically, H3 predicts that activating latent populism will reduce the effectiveness of corrections among strongly populist respondents. We test this hypothesis with models that interact exposure to a correction with pre-treatment populism, estimated separately for respondents who were assigned to the activation treatment or not.[19] We present the results graphically in Figure 2. The figure depicts the effect of a correction on belief in false claims within each tercile. We further distinguish between respondents who received the latent populism activation treatment (right panel) or not (left panel). If H3 is supported, we would expect to observe significantly larger (and negatively signed) correction effects among respondents on in the left panels compared to the right.

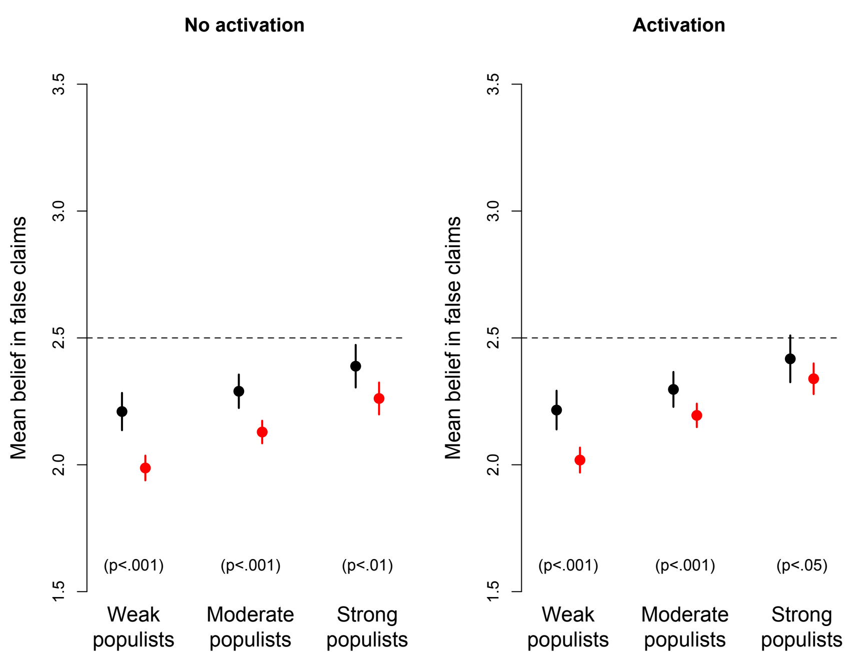
[19]Our preregistered test of this hypothesis mistakenly omits a necessary interaction between these variables and the populism activation treatment. For H3, the question of interest is whether the effect of a correction on belief varies across activated and non-activated respondents — a difference-in-differences. Our pooled models, where the unit of analysis is respondent-blurbs, are well powered to detect these difference-in-differences (see Appendix Tables A21–24).

Figure 2: Effect of corrections on belief in fake news: populism activation (treatment) vs. no activation (control) groups

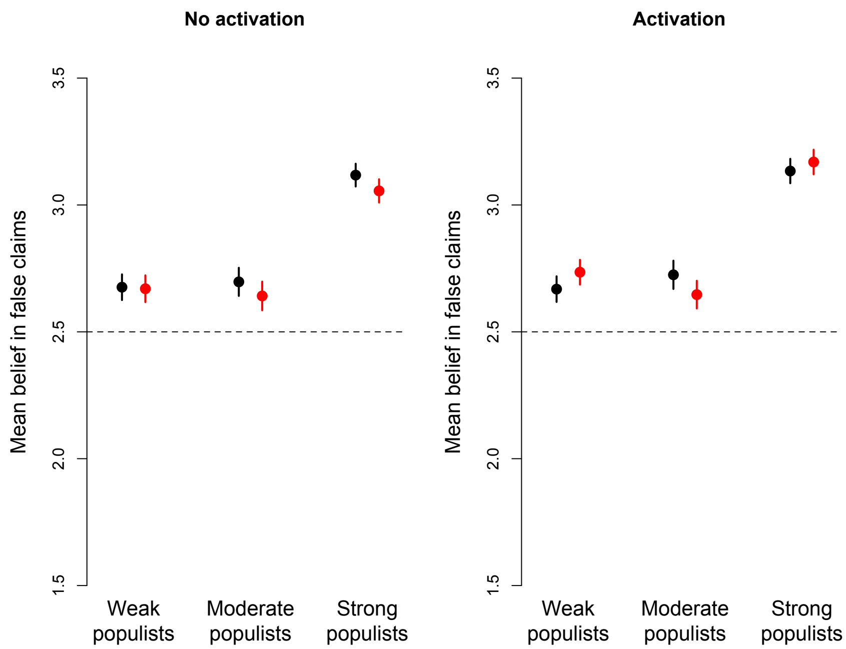
(a) Spain



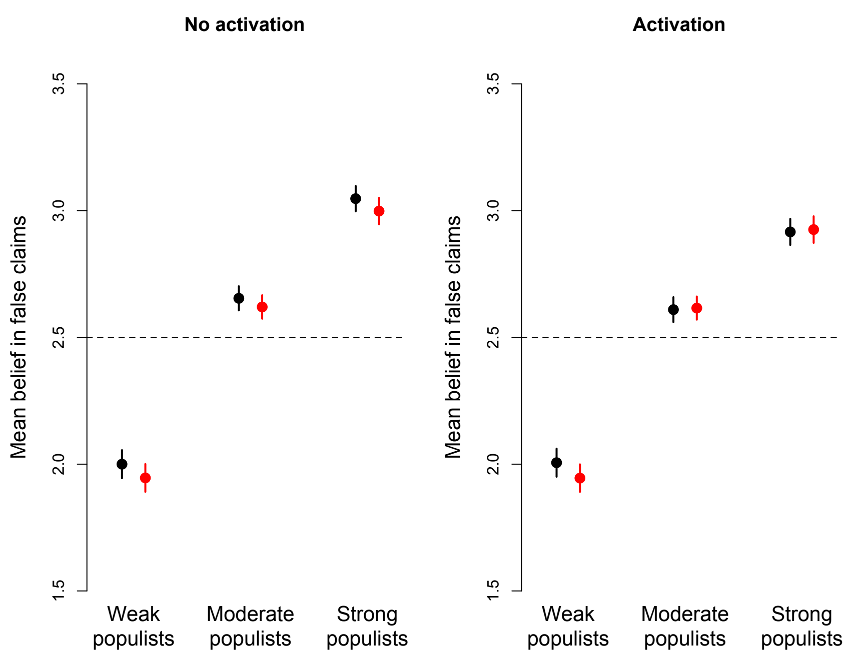
(b) Portugal



(c) India



(d) USA



Note: Point estimates show mean belief in false claims among respondents exposed to a correction (red) or not (black). Means calculated from models in Appendix Tables A21–A24. Left panels show populism activation (treatment) group; right panels show no activation (control) group. Belief is measured 1–4 (higher values indicate more belief). Error bars contain 95% confidence intervals. Dotted line shows the scale midpoint.

However, Figure 2 reveals no evidence that the effectiveness of corrections is diminished when latent populism is activated. Instead, in each country, we observe a similar pattern of results under both populism activation (right panels) and no activation (left panels). The effectiveness of corrections appears to depend on country context much more than populism activation. Consider the Portuguese results in panel (b). Here, we see that corrections consistently reduce misperceptions — both when populism is activated or not activated. In fact, in Portugal, corrections significantly reduce misperceptions across the board: among weak ($p < .001$), moderate ($p < .001$), and strong populists ($p < .01$) who were not activated, and among weak ($p < .001$), moderate ($p < .001$), and strong populists ($p < .01$) who were activated. Furthermore, there is no evidence that the magnitude of these correction effects is diminished when latent populism is activated.

The Portuguese results offer a stark contrast to the other countries — Spain, India, and the United States — where the effect of corrections on overall belief in false claims is null across all terciles.[20] In these three countries, corrections fail to reduce misperceptions even in the no activation groups (left panels). Correspondingly, we find no evidence to support our prediction that activating latent populism reduces the effectiveness of corrections in these countries. H3 is not supported.

Exploratory analysis: activation causes strong emotional responses

Why does activating latent populism fail to increase misperceptions or reduce the effectiveness of corrections? One potential explanation is that our activation treatment, which relies on a writing task that encourages dispositional blame attribution, failed. While such failure would be inconsistent with past research that use the same approach (Busby et al. 2025; Busby, Gubler, and Hawkins 2019; Hameleers, Bos, and De Vreese 2017), we nonetheless consider this possibility by examining the effect of the treatment on an outcome that is arguably more proximate than

[20]Recall from our discussion of the H2 results that the pooled correction estimate is negative and significant in the United States. However, when splitting the sample for purposes of testing H3, these pooled effects are no longer significant.

factual beliefs: emotions.

Research suggests that populist messages or cues lead to strong emotional reactions, and that emotions may be a key mechanism through which populism affects broader attitudes (e.g., Demasi, McCoy, and Littvay 2024; Jost, Maurer, and Hassler 2020; Marcus 2021; Rico 2024; Sandberg, Jacobs, and Spierings 2022; Seawright 2012). In our experiments, we would therefore expect our treatment, if successful, to cause strong emotional reactions. More precisely, we would expect the treatment to increase negative emotions (e.g., anger, disgust) and reduce positive emotions (e.g., happiness, hope).

To test these expectations, we take advantage of a battery of questions that were asked of all respondents immediately before they evaluated the fake news stories analyzed above (i.e., immediately post-treatment for respondents assigned to the activation treatment). These questions asked respondents to self-report the extent to which they felt various negative and positive emotions. Negative emotions included anger, disgust, fear/dread, and sadness, and positive emotions included enthusiasm, happiness, hope, and interest. For simplicity, we collapse negative and positive emotions into separate indices and examine how our activation treatment affects each index.[21]

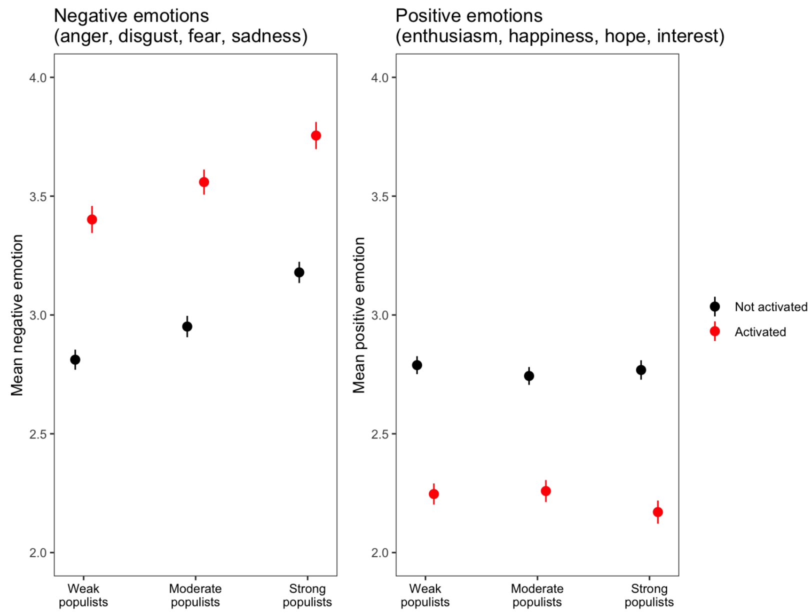
Figure 3 presents the effects of our treatments on self-reported emotions. Specifically, the figure depicts mean levels of negative emotions (left panels) and positive emotions (right panels) among respondents who received the activation treatment (red dots) or not (black dots). The lines contain 95 percent confidence intervals. Like the previous figures, we again break the samples down into terciles of pre-treatment populism on the horizontal axis.

Results demonstrate that our activation treatment led to strong emotional reactions (in the expected directions) in nearly all cases. In three countries — Spain, Portugal, and the United States — the treatment increased negative emotions and decreased positive emotions among respondents in all three terciles ($p < .001$ for all). This suggests that our treatments were successfully received and incorporated into respondents' emotional states in these three countries.

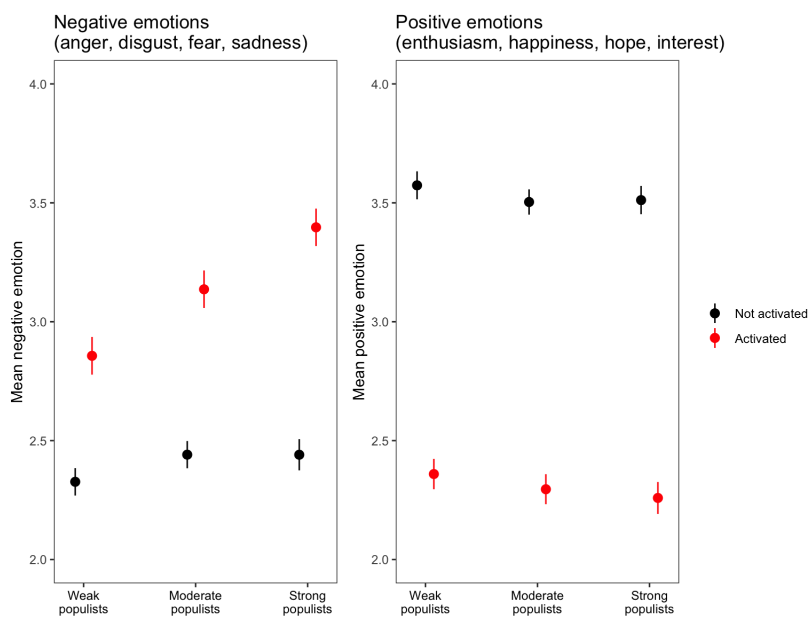
[21] Our analysis of negative emotions was preregistered (RQ5). Our analysis of positive emotions is exploratory.

Figure 3: Effect of activating latent populism on negative and positive emotions

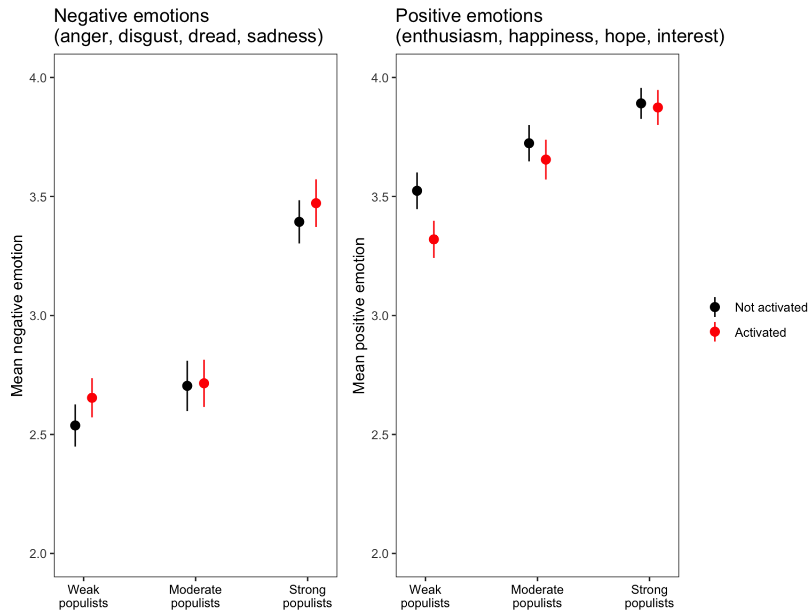
(a) Spain



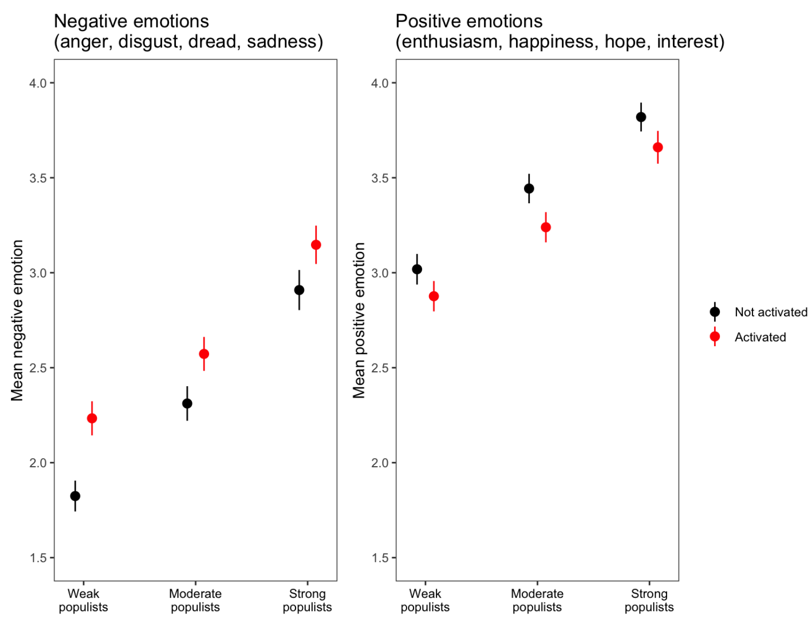
(b) Portugal



(c) India



(d) USA



Note: Point estimates show mean levels of negative emotions (left panels) and positive emotions (right panels). Red points show populism activation (treatment) group; black points show no activation (control) group. Emotions are measured 1–5 (higher values indicate more emotion). Error bars contain 95% confidence intervals.

India presents an interesting context for these analyses because of its uniquely high levels of pre-treatment populism (see Appendix B). In this setting, our treatment may potentially be received and internalized yet fail to affect downstream attitudes (e.g., emotions) due to a ceiling effect (for a similar argument, see Busby, Gubler, and Hawkins 2019). Consistent with this logic, Figure 3(c) demonstrates that in India the treatment affected negative and positive emotions in the expected directions only among weak populists ($p < .05$ and $p < .001$, respectively). By contrast, the treatment did not significantly affect negative or positive emotions among moderate and strong populists. Viewed in light of the results among weak populists in India, and all respondents in the other countries, we do not interpret these null effects as evidence of treatment failure. Rather, we argue that moderate and strong populists in India — the most populist respondents in our four studies — are pre-treated: they are likely to adopt populist ways of thinking even in the absence of activation.

More broadly, these patterns underscore the importance of understanding the pre-treatment environment in each country when interpreting the experimental results presented earlier (Druckman and Leeper 2012). We suspect that the effect of latent populism activation on broader attitudes may depend on pre-existing levels of populism and related emotional states. We return to this point in the conclusion.

Conclusion and discussion

This article examines the relationship between two of the most extensively discussed political phenomena in recent years: populism and misinformation. While previous research has established a descriptive association between populism and belief in false claims, ours is the first study to experimentally manipulate individual-level populism in order to gauge potential causal effects on misinformation belief and persistence.

Consistent with past work, our descriptive results reveal that latent populism is associated with fake news belief in three countries (Spain, India, United States), but not in Portugal —

the one included country in which populism was not a salient political force at the time of our studies. Our experimental results reveal that activating latent populism causes strong emotional reactions; however, contrary to our preregistered hypotheses, activation does not increase belief in false claims or undermine the effectiveness of corrections. Optimistically, these results suggest that attempts to activate latent populism (e.g., during campaigns) are unlikely to make misperceptions more prevalent or resistant to correction. Instead, our results suggest that misperceptions are more reflective of underlying populist attitudes, which likely interact with related attitudes (e.g., dissatisfaction with institutions) to shape how individuals interpret political reality.

These findings offer broader insights for our understanding of populism and misinformation. When it comes to populism, they raise questions about the prevailing account of populism as a latent disposition that requires activation by a rhetorical or emotional cue. In our data, respondents with varying levels of latent populism have very different baseline levels of belief in fake news, and these baselines are largely unaffected by activation. Of course, we could not control the pre-treatment environment our subjects found themselves in: respondents in our four countries were exposed to varying levels of populist rhetoric and electoral competition before receiving our activation treatment. For instance, populism was especially prevalent in elite discourse and electoral competition in India and the United States at the time of our studies, raising the possibility that respondents in these studies were pre-treated by real world events before undergoing our experimental activation. By contrast, populism was salient (arguably to a lesser degree) in Spain at the time of our studies and almost entirely absent in Portugal. Future research should consider more fully the role of country context, ideally with descriptive evidence on the salience of populism in the pre-treatment communication environment.

Turning to misinformation, our results offer an important addendum to recent multi-country studies which find that corrections are widely effective (Porter, Velez, and Wood 2023; Porter and Wood 2021; Wood and Porter 2019). By contrast, our results suggest that the effectiveness of corrections varies widely across topics and countries. Of course, past studies and our own experiments focused on different factual controversies occurring in different countries at different points in time, making cross-country comparisons challenging. One possibility for the conflicting findings concerns the universe of fake news stories considered here. As described above, we strove to identify false claims that varied in their topical focus, salience, and degree of populist overtones. The latter criterion — populist overtone — may render a subset of false claims we consider more attractive to individuals with populist attitudes, reflecting either these individuals' genuine beliefs or and/or some level of expressive responding. To investigate this possibility, future research could experimentally manipulate the degree of populist language used to describe the same factual controversy. We suspect that the effectiveness of corrections may vary across versions of the same false claim and across individuals with different levels of populist attitudes. More broadly, we believe our results highlight the need for more comprehensive theorizing about the linkages between populism activation, corrections, and beliefs — as well as how this process varies across country contexts.

Of course, the studies reported here are limited and should be expanded upon in future research. We note three issues that strike us as particularly worthy of future exploration. First, our experiments seek to activate latent populism with a single approach: dispositional blame attribution. Given the diverse forms of populist communication across countries and parties, future research should explore alternative methods for activating latent populism (e.g., through frames or multimedia treatments). Second, future work should examine the effect of populism activation on factual beliefs in other countries, ideally those that differ substantially in terms of elite populist rhetoric and electoral competition. Finally, our results are of course limited to the universe of factual claims we included in our experiments. We encourage future studies to incorporate a wider range of factual controversies, ideally those that are salient in multiple countries to facilitate comparison.

Addressing these limitations and pursuing future studies like those suggested here would improve our understanding of the conditions under which populism contributes to one of the most pressing social and political challenges of our time: the prevalence and persistence of misinformation.

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Online Appendix Table of Contents

Online Appendix A: Overview of studies

Online Appendix B: Pre-treatment populism measure

Online Appendix C: News blurbs by country

Online Appendix D: Supplemental tables and figures

Appendix A: Overview of studies

The table below provides an overview of the studies analyzed in this article. Ns include the number of respondents who reached the experimental portion of the survey. The Netquest samples (studies 1 and 2) included quotas for age, sex, education, and region. The MTurk samples (studies 3 and 4) were restricted to respondents with at least 95% prior task approval rates and who are located in India or the US, respectively.

In all studies, respondents were randomly assigned to receive a populism activation treatment or not (control group) before being presented with a series of randomly selected blurbs covering fake news stories in their country. More information about these blurbs is provided in Appendix C.

Appendix Table A1: Overview of studies

	Study 1 (Spain)	Study 2 (Portugal)	Study 3 (India)	Study 4 (USA)
Sample	Netquest (N=8,789)	Netquest (N=4,962)	MTurk (N=3,003)	MTurk (N=3,203)
Data collection	2019/20	2020/21	2021	2021
Populism activation conditions	-control -dispositional -situational*	-control -dispositional	-control -dispositional	-control -dispositional
Total fake news blurbs shown	8	5	9	8
Fake news blurbs per respondent	4	3	5	4

*Study 1 (Spain) included two populism activation treatments — situational blame attribution and dispositional blame attribution — drawn from prior research (Busby, Gubler, and Hawkins 2019). These treatments are similar in format: they ask respondents to arrange a series of national problems in order of importance; on the next screen, respondents are asked to complete a short writing task. The situational activation treatment asks which events or circumstances are responsible for the respondent's top ranked problem, while the dispositional treatment asks which groups or individuals are responsible and what should be done to them. Past research indicates that dispositional blame attribution causes individuals to express populist sentiment (Busby, Gubler, and Hawkins 2019, study 1) and makes them more likely to support populist candidates (Busby, Gubler, and Hawkins 2019, study 2). By contrast, situational attribution does not. We therefore treat the situational activation treatment in study 1 as a placebo and merge it with the pure control condition. Given the smaller samples in studies 2–4, we omit the situational attribution treatment and compare the dispositional attribution group to a pure control.

Appendix Table A2: Sample descriptives

	Study 1 (Spain)	Study 2 (Portugal)	Study 3 (India)	Study 4 (USA)
N	8,789	4,962	3,003	3,203
Median age	45	52	30	36
Percent female	51.8	49.2	29.4	44.3
Percent university grad	60.2	41.6	82.0	78.7

While MTurk samples are descriptively unrepresentative, past research indicates that treatment effects estimated on MTurk samples generalize to representative samples (Coppock 2019; Coppock, Leeper, and Mullinix 2018; Krupnikov, Nam, and Style 2021; Mullinix, Druckman, and Freese 2015). This includes recent studies focusing on fake news discernment (Pennycook and Rand 2022).

Appendix B: Pre-treatment populism measure

We measure populist predispositions with the six-item Akkerman, Mudde, and Zaslove (2014) scale. The six items are:

> Using the following scale, to what extent do you agree or disagree with the following statements? [order of statements randomized]
>
>> Politicians in [Congress/the House] need to follow the will of the people. (*People-centrism*)
>>
>> The people, and not politicians, should make our most important policy decisions. (*People-centrism*)
>>
>> The political differences between the elite and the people are large than the differences among the people. (*People-centrism*)
>>
>> What people call "compromise" in politics is really just selling out on one's principles. (*Manicheanism*)
>>
>> I would rather be represented by an ordinary citizen than an experienced politician. (*Anti-elitism*)
>>
>> Politicians talk too much and take too little action. (*Anti-elitism*)
>>
>> -Strongly agree [5]
>> -Somewhat agree [4]
>> -Neither agree nor disagree [3]
>> -Somewhat disagree [2]

-Strongly disagree [1]

As described in the main text, we follow Wuttke, Schimpf, and Schoen (2020) and aggregate the subscales of anti-elitism and people-centrism using arithmetic means and then calculate the geometric mean of the three subscales to create an overall populism score. Following our pre-registration, we use this overall score to divide our samples into terciles of pre-treatment (i.e., latent) populism, which we refer to as weak, moderate, and strong populists.

Appendix Table A3: Descriptive statistics on pre-treatment populism (all studies)

	Study 1 (Spain)	Study 2 (Portugal)	Study 3 (India)	Study 4 (USA)
Mean (SD)	3.03 (0.92)	2.84 (0.84)	3.46 (0.78)	3.00 (0.93)
Median	3.00	3.00	3.67	3.00
Tercile 1 | tercile 2 cutoff	3.00	3.08	3.72	3.00
Tercile 2 | tercile 3 cutoff	3.00	3.68	4.30	3.50

Appendix C: News blurbs by country

Working with research assistants, we identified fake news stories that were circulating in each country at the time of our experiments and reported on by professional fact-checking organizations. In each country, we aimed to identify a set of stories that varied on the following dimensions: topical focus (e.g., science, religion, education, corruption, generalized conspiracies), salience, and populist overtones. (Our preregistration identifies a subset of stories that are overtly populist in tone. We mark these stories with an asterisk in the list and tables below.) After identifying a large set of potential stories for use in our experiments, we consulted with country experts about the salience of each story and suitability for inclusion in our experiments.

The final set of news stories used in our experiments is listed below. For each story, we wrote a headline and one paragraph overview, which we call a "news blurb." The blurb resembles the length and format of a social media post or search engine result. For each news blurb, we also wrote a short paragraph that provides corrective information attributed to an expert source (e.g., fact-checkers, public health experts, etc.). To maximize realism, we randomized corrections at the blurb level and attributed corrections to different sources across stories.

Spain

- Climate change (true story about extreme weather events)

  (Order of all subsequent blurbs randomized)

- ONE of the following: Genetically modified foods unsafe; vaccine-autism link
- ONE of the following: Replace language classes with religion; mandatory Islamic studies
- ONE of the following: Left-wing (PSOE/Podemos) secret pact*; right-wing (PP/Vox) secret pact*
- ONE of the following: Patent holders; NATO secret fumigations

Portugal

- Climate change (true story about extreme weather events)

  (Order of all subsequent blurbs randomized)
- ONE of the following: Genetically modified foods unsafe; vaccine-autism link
- ONE of the following: Left-wing (PPD/PSD/CDS-PP) secret pact*; right-wing (PS/BE) secret pact*
- Patent holders

India

- Climate change (true story about extreme weather events)

  (Order of all subsequent blurbs randomized)
- TWO of the following: Vaccine-autism link; Covid–19 side effects; swabs implant devices in brain
- ONE of the following: Law easing mosque construction*; Islamic studies on civil service exam*
- ONE of the following: Patent holders restricting supply; hospital managers hoarding oxygen tanks
- ONE of the following: Cabal releasing Covid–19 variants; MPs get rent paid for*

United States

- Climate change (true story about extreme weather events)

  (Order of all subsequent blurbs randomized)
- ONE of the following: Genetically modified foods unsafe OR vaccine-autism link
- ONE of the following: Covid–19 side effects OR swabs implant devices in brain
- ONE of the following: Biden lies about voting laws*; Republicans lie about voting laws*
- BOTH of the following: Patent holders restricting supply; cabal releasing Covid–19 variants

Example stimuli

Here we provide an example news blurb (used in Studies 3 and 4) as seen by our respondents.
The control (no correction) version of the blurb appears as follows:

YOU HEARD IT HERE: LEAKED DOCXS SHOW SUPER-WEALTHY CABAL PLOTTING TO RELEASE NEW COVID-19 VARIANTS

Thursday (10:30pm EST): Newly released documents suggest a plot by universities, nonprofits, and global elites to release Covid-19 variants on a planned schedule. The website where the documents first appeared claims, “These are the PLANNED COVID-19 VARIANTS - just look at this doc with a table of 'release dates' in different major cities!!" Next to the table, the document included logos of universities and organizations including Johns Hopkins University, the World Health Organization, the World Economic Forum and the Bill and Melinda Gates Foundation.

The treatment (correction) version appears as follows:

YOU HEARD IT HERE: LEAKED DOCXS SHOW SUPER-WEALTHY CABAL PLOTTING TO RELEASE NEW COVID-19 VARIANTS

Thursday (10:30pm EST): Newly released documents suggest a plot by universities, nonprofits, and global elites to release Covid-19 variants on a planned schedule. The website where the documents first appeared claims, “These are the PLANNED COVID-19 VARIANTS - just look at this doc with a table of 'release dates' in different major cities!!" Next to the table, the document included logos of universities and organizations including Johns Hopkins University, the World Health Organization, the World Economic Forum and the Bill and Melinda Gates Foundation.

After the story went viral, fact checkers were quick to point out that table doesn’t represent the work of any of the named organizations. The World Health Organization and the Bill and Melinda Gates Foundation both responded to press queries to confirm the documents weren't genuine. The table also falsely claims the delta variant of the coronavirus emerged in June 2021. Finally, the posts ignore that variants occur in the population through random mutations and are not created by humans.

The dependent variable appeared as follows:

As far as you know, how accurate is the statement that an international group of powerful people and institutions is working together to release new Covid-19 variants?

- Totally accurate
- Very accurate
- Not very accurate
- Not at all accurate

Appendix D: Supplemental tables and figures

We present pooled results in the main text and separate claim-specific models in appendices. Our preregistrations identify a subset of news stories that are more overtly populist (e.g., about alleged electoral pacts in Spain or corrupt members of parliament in India). These claims are marked with an asterisk (*) in the tables below.

Descriptive analysis (latent populism and belief in fake news)

Table 1 in the main text reports pooled models examining the relationship between latent populism and belief in fake news (preregistered as RQ1). Here we reproduce the same table showing estimates for the covariates that are suppressed in Table 1. The estimates shown in Table 1 are shaded in the table below.

We also report separate claim-specific models using the same pre-registered specification in all four countries.

As noted in the main text, we are interested here in the relationship between latent (i.e., non-activated) populism and baseline belief in fake news. We therefore restrict these analyses to respondents in the pure control condition for each news blurb — that is, respondents who received neither populism activation nor a correction.

Appendix Table A4: Latent populism and belief in fake news

	DV = belief in false claim (pooled)			
	Study 1 (Spain)	Study 2 (Portugal)	Study 3 (India)	Study 4 (USA)
Moderate populist (tercile 2)	0.07*	0.05	−0.10*	0.39***
	(0.03)	(0.05)	(0.04)	(0.04)
Strong populist (tercile 3)	0.18***	0.12	0.12**	0.53***
	(0.03)	(0.06)	(0.04)	(0.05)
Conspiracism (tercile 2)	−0.001	0.07	0.14***	0.32***
	(0.03)	(0.05)	(0.04)	(0.04)
Conspiracism (tercile 3)	0.06	0.19***	0.44***	0.44***
	(0.03)	(0.06)	(0.05)	(0.05)
Ideology (conservative)	0.004	−0.001		0.01*
	(0.01)	(0.01)		(0.01)
University grad	−0.05	−0.16***	−0.28***	0.24***
	(0.03)	(0.05)	(0.04)	(0.04)
Frequent social media news	0.02	−0.02	−0.11***	0.02
	(0.02)	(0.05)	(0.03)	(0.03)
Age 29–44	−0.02	−0.15**	−0.15***	−0.19***
	(0.04)	(0.07)	(0.03)	(0.04)
Age 45–59	−0.11**	−0.06	−0.49***	−0.26***
	(0.04)	(0.07)	(0.08)	(0.05)
Age 60+	−0.12***	−0.16**	−0.51***	−0.33***
	(0.04)	(0.08)	(0.18)	(0.07)
Female	0.06**	0.06	−0.04	−0.05
	(0.03)	(0.05)	(0.03)	(0.03)
Institutional trust (tercile 2)	−0.05	−0.02	0.05	0.04
	(0.03)	(0.06)	(0.04)	(0.04)
Institutional trust (tercile 3)	−0.15***	−0.03	0.10**	0.29***
	(0.03)	(0.06)	(0.05)	(0.05)
Political knowledge (tercile 2)	−0.07*	0.14		−0.11**
	(0.03)	(0.28)		(0.04)
Political knowledge (tercile 3)	−0.14**	0.08		−0.36***
	(0.03)	(0.28)		(0.04)
Constant	2.11***	2.26***	2.94***	2.05***
	(0.06)	(0.29)	(0.05)	(0.06)
Strong populist − moderate populist	0.11***	0.07	0.22***	0.14***
N	5,633	1,463	3,281	3,366

Note: Cell entries are OLS coefficients with clustered standard errors in parentheses. Dependent variable ranges from 1–4 with higher values indicating greater belief in false claims. This specification was preregistered as an exploratory research question (RQ1). Political knowledge and left/right ideology were not measured in Study 3 (India). Samples include respondents in pure control condition for each blurb (no populism activation, no correction). Significance levels: *p<.05, **p<.01, ***p<.001.

Appendix Table A5: Claim-specific models (Spain, 1 of 2)

	DV: belief in false claim			
	GMOs unsafe	Vaccines unsafe	Religion in school	Islamic studies
Moderate populist (tercile 2)	0.06	0.02	0.17**	0.01
	(0.08)	(0.08)	(0.07)	(0.07)
Strong populist (tercile 3)	0.26***	0.15*	0.15**	0.11
	(0.09)	(0.08)	(0.07)	(0.07)
Conspiracism (tercile 2)	0.17**	−0.07	−0.18***	−0.02
	(0.08)	(0.08)	(0.07)	(0.07)
Conspiracism (tercile 3)	0.33***	−0.16*	−0.09	−0.09
	(0.09)	(0.09)	(0.07)	(0.07)
Ideology (conservative)	−0.01	−0.003	−0.003	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
University grad	−0.07	−0.06	−0.03	−0.003
	(0.07)	(0.07)	(0.06)	(0.06)
Frequent social media news	0.11*	0.06	0.09*	0.02
	(0.07)	(0.06)	(0.05)	(0.06)
Age 29–44	0.02	0.09	−0.08	−0.02
	(0.10)	(0.10)	(0.08)	(0.08)
Age 45–59	−0.06	−0.09	−0.26***	−0.19**
	(0.10)	(0.10)	(0.08)	(0.09)
Age 60+	−0.09	−0.24**	−0.26***	−0.11
	(0.12)	(0.12)	(0.10)	(0.10)
Female	0.16**	−0.01	0.08	0.01
	(0.07)	(0.07)	(0.05)	(0.06)
Institutional trust (tercile 2)	−0.02	−0.11	−0.04	−0.10
	(0.08)	(0.08)	(0.07)	(0.07)
Institutional trust (tercile 3)	−0.11	−0.06	−0.10	−0.19***
	(0.09)	(0.08)	(0.07)	(0.07)
Political knowledge (tercile 2)	−0.12	−0.11	−0.11	−0.03
	(0.09)	(0.09)	(0.07)	(0.08)
Political knowledge (tercile 3)	−0.16*	−0.10	−0.17**	−0.03
	(0.09)	(0.09)	(0.07)	(0.08)
Constant	2.46***	2.00***	1.88***	1.68***
	(0.17)	(0.16)	(0.13)	(0.15)
N	685	675	883	927

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable ranges from 1–4 with higher values indicating greater belief in false claims. This specification was preregistered as an exploratory research question (RQ1). Sample includes respondents in pure control condition for each blurb (no populism activation, no correction). Significance levels: *p<.05, **p<.01, ***p<.001.

Appendix Table A6: Claim-specific models (Spain, 2 of 2)

	DV: belief in false claim			
	Left-wing* pact	Right-wing* pact	Patent holders	NATO fumigations
Moderate populist (tercile 2)	0.05	0.21***	0.09	−0.08
	(0.07)	(0.08)	(0.08)	(0.10)
Strong populist (tercile 3)	0.08	0.35***	0.18**	0.23**
	(0.08)	(0.08)	(0.09)	(0.11)
Conspiracism (tercile 2)	−0.04	−0.02	0.07	0.23**
	(0.07)	(0.08)	(0.08)	(0.10)
Conspiracism (tercile 3)	0.04	0.07	0.31***	0.29**
	(0.08)	(0.09)	(0.09)	(0.12)
Ideology (conservative)	0.05***	−0.06***	0.01	−0.001
	(0.01)	(0.01)	(0.01)	(0.02)
University grad	−0.14**	0.02	0.002	−0.20**
	(0.07)	(0.07)	(0.07)	(0.09)
Frequent social media news	0.15**	−0.04	−0.0002	−0.04
	(0.06)	(0.06)	(0.07)	(0.08)
Age 29–44	−0.14	−0.05	0.23**	−0.14
	(0.09)	(0.10)	(0.10)	(0.13)
Age 45–59	−0.15	−0.19*	0.29***	−0.29**
	(0.10)	(0.10)	(0.10)	(0.14)
Age 60+	−0.31***	−0.26**	0.42***	−0.36**
	(0.11)	(0.11)	(0.12)	(0.15)
Female	0.06	−0.08	0.02	0.28***
	(0.06)	(0.07)	(0.07)	(0.09)
Institutional trust (tercile 2)	0.10	−0.01	−0.18**	−0.01
	(0.07)	(0.08)	(0.08)	(0.10)
Institutional trust (tercile 3)	−0.10	−0.13	−0.28***	−0.02
	(0.08)	(0.08)	(0.09)	(0.11)
Political knowledge (tercile 2)	−0.12	−0.03	0.01	−0.04
	(0.08)	(0.09)	(0.09)	(0.12)
Political knowledge (tercile 3)	−0.06	−0.10	−0.08	−0.14
	(0.08)	(0.09)	(0.09)	(0.12)
Constant	1.98***	2.50***	2.25***	1.96***
	(0.15)	(0.16)	(0.17)	(0.22)
N	654	691	709	409

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable ranges from 1–4 with higher values indicating greater belief in false claims. This specification was preregistered as an exploratory research question (RQ1). Sample includes respondents in pure control condition for each blurb (no populism activation, no correction). Significance levels: *p<.05, **p<.01, ***p<.001.

Appendix Table A7: Claim-specific models (Portugal)

	DV: belief in false claim				
	GMOs unsafe	Vaccines unsafe	Left-wing* pact	Right-wing* pact	Patent holders
Moderate populist (tercile 2)	0.06	−0.05	−0.20*	0.15	0.13
	(0.12)	(0.12)	(0.11)	(0.13)	(0.09)
Strong populist (tercile 3)	0.04	0.17	−0.05	0.07	0.22**
	(0.15)	(0.15)	(0.14)	(0.15)	(0.11)
Conspiracism (tercile 2)	0.16	−0.06	0.12	−0.11	0.14
	(0.12)	(0.12)	(0.12)	(0.13)	(0.09)
Conspiracism (tercile 3)	0.28**	0.01	0.41***	−0.04	0.30***
	(0.14)	(0.13)	(0.13)	(0.14)	(0.11)
Ideology (conservative)	−0.05**	0.01	−0.03	0.08***	−0.003
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
University grad	−0.24**	−0.38***	0.11	0.06	−0.21**
	(0.10)	(0.11)	(0.10)	(0.11)	(0.08)
Frequent social media news	−0.11	−0.06	−0.05	0.06	−0.02
	(0.10)	(0.10)	(0.10)	(0.11)	(0.08)
Age 29–44	−0.15	−0.01	−0.33**	−0.47**	−0.05
	(0.17)	(0.15)	(0.15)	(0.20)	(0.13)
Age 45–59	−0.001	−0.05	−0.21	−0.61***	0.11
	(0.16)	(0.15)	(0.14)	(0.19)	(0.13)
Age 60+	−0.02	−0.15	−0.16	−0.90***	0.02
	(0.18)	(0.17)	(0.16)	(0.21)	(0.14)
Female	0.37***	−0.10	0.16	−0.18	−0.02
	(0.10)	(0.10)	(0.10)	(0.12)	(0.08)
Institutional trust (tercile 2)	0.03	−0.004	0.07	−0.04	−0.13
	(0.12)	(0.12)	(0.12)	(0.14)	(0.10)
Institutional trust (tercile 3)	0.04	−0.07	−0.02	−0.15	−0.07
	(0.13)	(0.13)	(0.13)	(0.14)	(0.10)
Political knowledge (tercile 2)	−0.58	0.33	−0.42	−0.06	−0.06
	(0.80)	(0.41)	(0.57)	(0.51)	(0.51)
Political knowledge (tercile 3)	−0.60	0.25	−0.51	0.02	−0.12
	(0.79)	(0.41)	(0.57)	(0.12)	(0.50)
Constant	3.25***	1.76***	2.88***	2.43***	2.55***
	(0.84)	(0.41)	(0.60)	(0.32)	(0.51)
N	246	242	261	247	467

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable ranges from 1–4 with higher values indicating greater belief in false claims. This specification was preregistered as an exploratory research question (RQ1). Sample includes respondents in pure control condition for each blurb (no populism activation, no correction). Significance levels: *p<.05, **p<.01, ***p<.001.

Appendix Table A8: Claim-specific models (India, 1 of 2)

	DV: belief in false claim				
	Vaccines unsafe	Covid vax side effx	Nasal swabs	Mosque* construction	Islamic* studies
Moderate populist (tercile 2)	-0.04	-0.20^{*}	-0.26^{**}	-0.05	-0.38^{***}
	(0.11)	(0.11)	(0.12)	(0.13)	(0.13)
Strong populist (tercile 3)	0.18	0.13	0.06	0.14	-0.16
	(0.12)	(0.12)	(0.14)	(0.15)	(0.15)
Conspiracism (tercile 2)	0.26^{**}	0.19^{*}	0.03	-0.08	0.16
	(0.11)	(0.11)	(0.13)	(0.13)	(0.14)
Conspiracism (tercile 3)	0.32^{**}	0.34^{**}	0.55^{***}	0.34^{**}	0.57^{***}
	(0.14)	(0.13)	(0.15)	(0.16)	(0.17)
University grad	-0.25^{**}	-0.39^{***}	-0.36^{**}	-0.45^{***}	-0.12
	(0.11)	(0.11)	(0.14)	(0.12)	(0.14)
Frequent social media news	-0.13	-0.01	-0.08	-0.12	-0.21^{*}
	(0.09)	(0.09)	(0.10)	(0.10)	(0.11)
Age 29–44	-0.09	-0.23^{***}	-0.18^{*}	-0.13	-0.15
	(0.09)	(0.09)	(0.10)	(0.10)	(0.11)
Age 45–59	-0.65^{***}	-0.62^{**}	-0.95^{***}	-0.30	-0.23
	(0.23)	(0.25)	(0.28)	(0.27)	(0.28)
Age 60+	0.71	-1.17^{**}	-0.69	-0.62	-0.005
	(0.44)	(0.51)	(0.55)	(0.53)	(0.65)
Female	-0.01	-0.05	-0.04	-0.14	0.08
	(0.09)	(0.09)	(0.10)	(0.11)	(0.11)
Institutional trust (tercile 2)	0.15	0.05	0.30^{**}	0.29^{**}	0.12
	(0.11)	(0.10)	(0.12)	(0.13)	(0.13)
Institutional trust (tercile 3)	0.22^{*}	0.14	0.28^{*}	0.34^{**}	0.23
	(0.13)	(0.13)	(0.15)	(0.16)	(0.17)
Constant	2.73^{***}	3.02^{***}	2.75^{***}	2.95^{***}	2.91^{***}
	(0.15)	(0.15)	(0.19)	(0.17)	(0.19)
N	428	460	393	347	305

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable ranges from 1–4 with higher values indicating greater belief in false claims. This specification was preregistered as an exploratory research question (RQ1). Sample includes respondents in pure control condition for each blurb (no populism activation, no correction). Significance levels: *p<.05, **p<.01, ***p<.001.

Appendix Table A9: Claim-specific models (India, 2 of 2)

	DV: belief in false claim			
	Patent holders	CO2 tanks	Covid vaccines	MPs'* rent
Moderate populist (tercile 2)	0.02	0.06	0.05	−0.02
	(0.11)	(0.11)	(0.13)	(0.11)
Strong populist (tercile 3)	0.15	0.29**	0.08	0.11
	(0.11)	(0.12)	(0.13)	(0.13)
Conspiracism (tercile 2)	0.05	0.16	0.35***	0.22*
	(0.11)	(0.11)	(0.12)	(0.12)
Conspiracism (tercile 3)	0.34***	0.39***	0.69***	0.55***
	(0.13)	(0.14)	(0.16)	(0.14)
University grad	−0.28***	−0.13	−0.10	−0.29**
	(0.11)	(0.12)	(0.13)	(0.11)
Frequent social media news	−0.11	−0.03	−0.23**	−0.15
	(0.09)	(0.09)	(0.10)	(0.09)
Age 29–44	−0.11	−0.03	−0.17*	−0.16*
	(0.08)	(0.09)	(0.10)	(0.09)
Age 45–59	−0.11	−0.44*	−0.59**	−0.10
	(0.23)	(0.23)	(0.26)	(0.27)
Age 60+	−1.89***	−1.01	−0.14	−0.51
	(0.53)	(0.77)	(0.59)	(0.48)
Female	−0.11	−0.07	−0.03	−0.03
	(0.09)	(0.09)	(0.10)	(0.10)
Institutional trust (tercile 2)	0.03	−0.12	−0.20	−0.25**
	(0.10)	(0.11)	(0.12)	(0.11)
Institutional trust (tercile 3)	0.08	−0.30**	−0.10	−0.10
	(0.12)	(0.13)	(0.15)	(0.15)
Constant	3.07***	3.00***	2.81***	3.15***
	(0.14)	(0.15)	(0.17)	(0.16)
N	350	345	311	342

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable ranges from 1–4 with higher values indicating greater belief in false claims. This specification was preregistered as an exploratory research question (RQ1). Sample includes respondents in pure control condition for each blurb (no populism activation, no correction). Significance levels: *p<.05, **p<.01, ***p<.001.

Appendix Table A10: Claim-specific models (USA, 1 of 2)

	DV: belief in false claim			
	GMOs unsafe	Vaccines unsafe	Covid vax side effx	Nasal swabs
Moderate populist (tercile 2)	0.45***	0.31***	0.47***	0.60***
	(0.11)	(0.12)	(0.14)	(0.13)
Strong populist (tercile 3)	0.49***	0.30**	0.46***	0.75***
	(0.14)	(0.15)	(0.16)	(0.16)
Conspiracism (tercile 2)	0.34***	0.51***	0.48***	0.33**
	(0.11)	(0.12)	(0.14)	(0.13)
Conspiracism (tercile 3)	0.53***	0.56***	0.62***	0.38**
	(0.14)	(0.14)	(0.16)	(0.15)
Ideology (conservative)	0.01	0.05**	0.04	0.002
	(0.02)	(0.02)	(0.03)	(0.03)
University grad	0.26**	0.25**	−0.02	0.57***
	(0.10)	(0.13)	(0.13)	(0.13)
Frequent social media news	0.08	0.16*	0.13	−0.04
	(0.08)	(0.09)	(0.11)	(0.10)
Age 29–44	−0.20*	−0.19*	−0.08	−0.09
	(0.11)	(0.11)	(0.13)	(0.12)
Age 45–59	−0.25*	0.06	−0.16	−0.47***
	(0.13)	(0.14)	(0.16)	(0.15)
Age 60+	−0.12	−0.29	0.004	−0.42**
	(0.21)	(0.20)	(0.22)	(0.19)
Female	0.18**	−0.07	−0.09	−0.08
	(0.08)	(0.09)	(0.10)	(0.10)
Institutional trust (tercile 2)	−0.01	0.12	−0.17	0.27**
	(0.11)	(0.11)	(0.12)	(0.13)
Institutional trust (tercile 3)	0.20	0.48***	0.21	0.55***
	(0.12)	(0.14)	(0.15)	(0.15)
Political knowledge (tercile 2)	−0.07	−0.12	−0.04	−0.02
	(0.11)	(0.13)	(0.15)	(0.15)
Political knowledge (tercile 3)	−0.31***	−0.46***	−0.29**	−0.14
	(0.10)	(0.11)	(0.13)	(0.13)
Constant	2.03***	1.70***	1.99***	1.11***
	(0.17)	(0.19)	(0.21)	(0.21)
N	351	370	329	353

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable ranges from 1–4 with higher values indicating greater belief in false claims. This specification was preregistered as an exploratory research question (RQ1). Sample includes respondents in pure control condition for each blurb (no populism activation, no correction). Significance levels: *p<.05, **p<.01, ***p<.001.

Appendix Table A11: Claim-specific models (USA, 2 of 2)

	DV: belief in false claim			
	Dems* lie	GOP* lies	Patent holders	Covid variants
Moderate populist (tercile 2)	0.16	0.31***	0.15*	0.53***
	(0.12)	(0.11)	(0.08)	(0.08)
Strong populist (tercile 3)	0.33**	0.57***	0.21**	0.79***
	(0.14)	(0.13)	(0.09)	(0.10)
Conspiracism (tercile 2)	0.14	0.45***	0.28***	0.31***
	(0.12)	(0.11)	(0.08)	(0.08)
Conspiracism (tercile 3)	0.26*	0.62***	0.45***	0.35***
	(0.14)	(0.12)	(0.09)	(0.10)
Ideology (conservative)	−0.07***	0.06**	−0.01	0.05***
	(0.02)	(0.02)	(0.01)	(0.02)
University grad	0.14	0.41***	0.01	0.29***
	(0.11)	(0.11)	(0.08)	(0.08)
Frequent social media news	−0.08	−0.01	0.03	0.02
	(0.09)	(0.08)	(0.06)	(0.07)
Age 29–44	−0.35***	−0.13	−0.19**	−0.22***
	(0.11)	(0.11)	(0.07)	(0.08)
Age 45–59	−0.47***	−0.36***	−0.13	−0.30***
	(0.13)	(0.13)	(0.09)	(0.10)
Age 60+	−0.63***	−0.002	−0.31**	−0.32**
	(0.23)	(0.18)	(0.13)	(0.14)
Female	−0.08	−0.11	0.01	−0.14**
	(0.09)	(0.09)	(0.06)	(0.06)
Institutional trust (tercile 2)	0.33***	−0.33***	0.02	0.06
	(0.11)	(0.10)	(0.07)	(0.08)
Institutional trust (tercile 3)	0.60***	−0.24*	0.24***	0.44***
	(0.14)	(0.12)	(0.09)	(0.10)
Political knowledge (tercile 2)	−0.07	−0.13	−0.17**	−0.18**
	(0.13)	(0.12)	(0.08)	(0.09)
Political knowledge (tercile 3)	−0.12	−0.41***	−0.33***	−0.56***
	(0.11)	(0.11)	(0.07)	(0.08)
Constant	2.76***	2.04***	2.68***	1.68***
	(0.18)	(0.17)	(0.13)	(0.13)
N	379	388	769	756

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable ranges from 1–4 with higher values indicating greater belief in false claims. This specification was preregistered as an exploratory research question (RQ1). Sample includes respondents in pure control condition for each blurb (no populism activation, no correction). Significance levels: *p<.05, **p<.01, ***p<.001.

H1 (effect of activation on belief)

Figure 1 in the main text presents the effect of activation on belief in fake news across terciles on pre-treatment populism. Following our preregistration, we estimate a pooled model and separate claim-specific models in each country. As described in the main text, in estimating the pooled model, we deviate from our preregistration by including all respondents rather than restricting the analysis to the top tercile of populist sentiment. This approach allows us to better contextualize the results among our preregistered subsample, where effects are relative to an extreme baseline of high belief in fake news. Our pooled models interact populism terciles with a dummy variable for the activation treatment:

$$Y_i = \beta_0 + \beta_1 \text{activation}_i + \beta_2 \text{tercile}_i + \beta_3 \text{activation} \times \text{tercile} + \epsilon_i,$$

where Y_i is respondent i's average belief across all fake news stories they were shown, activation is a dummy variable for treatment, tercile is a categorical variable for level of pre-treatment populism, and ϵ is random error.[1]

The pooled results in each country are presented in the table below.

[1]Our preregistration mistakenly indicates that we will include respondent fixed effects in the pooled model. Such a model cannot be estimated because the activation dummy and respondent fixed effect are perfectly collinear.

Appendix Table A12: Effect of populism activation on fake news belief

	DV: average belief in false claims			
	Spain	Portugal	India	USA
Populism activation	0.03	0.02	0.03	0.00
	(0.02)	(0.04)	(0.04)	(0.04)
Moderate populist (tercile 2)	0.10^{***}	0.11^{***}	-0.003	0.66^{***}
	(0.02)	(0.03)	(0.05)	(0.04)
Strong populist (tercile 3)	0.23^{***}	0.24^{***}	0.41^{***}	1.05^{***}
	(0.03)	(0.04)	(0.04)	(0.04)
Activation $\times$ moderate	0.04	0.03	-0.01	-0.02
	(0.03)	(0.05)	(0.06)	(0.06)
Activation $\times$ strong	-0.05	0.04	0.04	-0.10
	(0.03)	(0.05)	(0.06)	(0.06)
Constant	1.89^{***}	2.06	2.67	1.98
	(0.02)	(0.02)	(0.03)	(0.03)
Effect of populism activation:				
Weak populists (tercile 1)	0.03	0.02	0.03	0.00
Moderate populists (tercile 2)	0.08^{***}	0.05	0.02	-0.02
Strong populists (tercile 3)	0.01	0.06	0.06	-0.10^{*}
Respondent fixed effects	✓	✓	✓	✓
N	8,697	3,201	2,817	3,024

Note: Cell entries are OLS coefficients with clustered standard errors in parentheses. Dependent variable is the average belief in all false claims respondent was randomly displayed, which ranges from 1–4 with higher values indicating greater belief. Models include all fake news stories from all studies. Significance levels: *p<.05, **p<.01, ***p<.001.

Claim-specific models for each country are presented in the tables below. As explained in the main text, our preregistrations indicated that we would limit our experimental analyses to the subset of fake news stories that are overtly populist. In the analyses, we find no systematic differences across populist and non-populist framed stories; we therefore opt to present pooled models, which reflect results across all stories, in the main text and separate claim-specific models below. The stories that were preregistered as populist-valenced are marked with an asterisk below. Readers who prefer to focus exclusively on preregistered analyses can focus only on these results.

Appendix Table A13: Effect of populism activation on fake news belief (Spain)

	DV: belief in false claim							
	GMOs unsafe	Vaccines unsafe	Religion in school	Islamic studies	Left-wing* pact	Right-wing* pact	Patent holders	NATO fumigations
Populism activation	0.02	0.08	−0.004	−0.07	0.08	0.10*	0.03	0.03
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Moderate populist (tercile 2)	0.12***	0.10***	0.12***	0.03	0.14***	0.10**	0.14***	0.15***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Strong populist (tercile 3)	0.26***	0.15***	0.14***	0.05	0.19***	0.24***	0.33***	0.31***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Activation × moderate	0.01	−0.11	0.10*	0.14**	0.02	−0.01	0.07	0.12*
	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)
Activation × strong	−0.05	−0.07	0.02	0.04	0.01	−0.16**	−0.01	−0.05
	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Constant	2.40***	1.72***	1.52***	1.72***	1.92***	2.00***	2.40***	1.70***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
N	4,355	4,312	4,419	4,240	4,293	4,354	4,395	4,262

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable is belief in the false claim (measured 1–4 where higher values indicate greater belief). Significance levels: *p<.05, **p<.01, ***p<.001.

Appendix Table A14: Effect of populism activation on fake news belief (Portugal)

	DV: belief in false claim				
	GMOs unsafe	Vax unsafe	Left-wing* pact	Right-wing* pact	Patent holders
Populism activation	−0.04	−0.08	0.03	0.02	0.10
	(0.07)	(0.06)	(0.06)	(0.07)	(0.05)
Moderate populist (tercile 2)	0.04	0.10	0.001	0.14^{*}	0.23^{**}
	(0.07)	(0.06)	(0.06)	(0.07)	(0.05)
Strong populist (tercile 3)	0.17^{*}	0.17^{*}	0.14	0.21^{**}	0.37^{**}
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)
Activation × moderate	0.11	0.10	−0.02	0.02	−0.03
	(0.09)	(0.09)	(0.09)	(0.10)	(0.07)
Activation × strong	−0.01	0.05	−0.03	0.05	0.09
	(0.10)	(0.10)	(0.10)	(0.10)	(0.08)
Constant	2.39^{***}	1.57^{***}	2.09^{***}	1.99^{***}	2.20^{***}
	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)
N	1,569	1,628	1,639	1,549	2,946

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable is belief in the false claim (measured 1–4 where higher values indicate greater belief). Significance levels: *p<.05, **p<.01, ***p<.001.

Appendix Table A15: Effect of populism activation on fake news belief (India)

	DV: belief in false claim								
	Vaccines unsafe	Covid vax side effx	Nasal swabs	Mosque* construction	Islamic* studies	Patent holders	CO2 tanks	Covid variants	MPs'* rent
Populism activation	0.06	0.02	0.05	0.05	−0.02	0.06	−0.04	0.03	0.04
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)
Moderate populist (tercile 2)	0.03	−0.03	−0.02	0.07	−0.14*	0.03	0.01	0.03	−0.01
	(0.07)	(0.07)	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)
Strong populist (tercile 3)	0.48***	0.41***	0.50***	0.42***	0.37***	0.36***	0.31***	0.41***	0.41***
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)
Activation × moderate	0.004	−0.14	0.04	−0.14	0.14	0.001	0.03	0.07	−0.08
	(0.10)	(0.10)	(0.11)	(0.12)	(0.12)	(0.11)	(0.11)	(0.12)	(0.11)
Activation × strong	−0.02	0.11	−0.02	0.06	0.03	0.07	0.08	0.02	0.01
	(0.10)	(0.10)	(0.11)	(0.12)	(0.12)	(0.10)	(0.10)	(0.11)	(0.11)
Constant	2.63***	2.70***	2.53***	2.57***	2.72***	2.75***	2.83***	2.66***	2.73***
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)
N	1,872	1,883	1,861	1,460	1,352	1,420	1,391	1,378	1,436

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable is belief in the false claim (measured 1–4 where higher values indicate greater belief). Significance levels: *p<.05, **p<.01, ***p<.001.

Appendix Table A16: Effect of populism activation on fake news belief (USA)

	DV: belief in false claim							
	GMOs unsafe	Vaccines unsafe	Covid vax side effx	Nasal swabs	Dems* lie	GOP* lies	Patent holders	Covid variants
Populism activation	0.005	−0.03	0.09	−0.03	0.02	0.02	0.004	−0.04
	(0.07)	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.05)	(0.06)
Moderate populist (tercile 2)	0.60^{***}	0.70^{***}	0.69^{***}	0.90^{***}	0.44^{***}	0.62^{***}	0.45^{***}	0.89^{***}
	(0.07)	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.05)	(0.06)
Strong populist (tercile 3)	0.91^{***}	1.13^{***}	0.92^{***}	1.45^{***}	0.87^{***}	1.06^{***}	0.76^{***}	1.32^{***}
	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)	(0.09)	(0.05)	(0.06)
Activation × moderate	−0.06	−0.07	−0.14	0.04	−0.07	0.10	−0.02	−0.001
	(0.10)	(0.11)	(0.11)	(0.12)	(0.11)	(0.11)	(0.07)	(0.08)
Activation × strong	−0.13	−0.08	−0.11	−0.10	−0.17	−0.19	−0.07	−0.05
	(0.11)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)	(0.08)	(0.09)
Constant	2.18^{***}	1.93^{***}	2.06^{***}	1.43^{***}	2.23^{***}	2.00^{***}	2.31^{***}	1.63^{***}
	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.04)	(0.04)
N	1,497	1,482	1,516	1,535	1,486	1,532	3,007	3,013

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable is belief in the false claim (measured 1–4 where higher values indicate greater belief). Significance levels: *p<.05, **p<.01, ***p<.001.

H2 (effect of corrections on belief)

Table 2 in the main text presents the results of pooled models estimating the effect of corrections on fake news belief. Here we report claim-specific models for each country.

Appendix Table A17: Effect of corrections on fake news belief (Spain)

	DV: belief in false claim							
	GMOs unsafe	Vaccines unsafe	Religion in school	Islamic studies	Left-wing* pact	Right-wing* pact	Patent holders	NATO fumigations
Correction	-0.10^{***}	0.06^{*}	-0.02	0.06^{*}	-0.03	-0.06^{*}	-0.06^{*}	-0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Constant	2.61^{***}	1.77^{***}	1.64^{***}	1.70^{***}	2.09^{***}	2.17^{***}	2.62^{***}	1.91^{***}
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
N	4,362	4,322	4,422	4,254	4,303	4,362	4,403	4,272

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable is belief in false claim (measured 1–4, where higher values indicate more belief). Significance levels: *$p<.05$, **$p<.01$, ***$p<.001$.

Appendix Table A18: Effect of corrections on fake news belief (Portugal)

	DV: belief in false claim				
	GMOs unsafe	Vaccines unsafe	Left-wing* pact	Right-wing* pact	Patent holders
Correction	-0.21^{***}	-0.05	-0.22^{***}	-0.14^{***}	-0.14^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
Constant	2.59^{***}	1.67^{***}	2.28^{***}	2.21^{***}	2.53^{***}
	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)
N	1,573	1,633	1,644	1,553	2,955

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable is belief in false claim (measured 1–4, where higher values indicate more belief). Significance levels: *$p<.05$, **$p<.01$, ***$p<.001$.

Appendix Table A19: Effect of corrections on fake news belief (India)

	DV: belief in false claim								
	Vaccines unsafe	Covid vax side effx	Nasal swabs	Mosque* construction	Islamic* studies	Patent holders	CO2 tanks	Covid variants	MPs'* rent
Correction	−0.04	0.03	0.05	0.003	−0.06	0.001	-0.10^{*}	0.02	−0.07
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)	(0.05)
Constant	2.86^{***}	2.82^{***}	2.70^{***}	2.75^{***}	2.86^{***}	2.93^{***}	2.99^{***}	2.83^{***}	2.92^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
N	1,872	1,883	1,861	1,460	1,352	1,420	1,391	1,378	1,436

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable is belief in false claim (measured 1–4, where higher values indicate more belief). Significance levels: *$p<.05$, **$p<.01$, ***$p<.001$.

Appendix Table A20: Effect of corrections on fake news belief (USA)

	DV: belief in false claim							
	GMOs unsafe	Vaccines unsafe	Covid side effx	Nasal swabs	Dems* lie	GOP* lies	Patent holders	Covid variants
Correction	−0.05	0.02	0.06	0.02	-0.19^{**}	−0.03	-0.10^{*}	0.07
	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.03)	(0.04)
Constant	2.67^{***}	2.49^{***}	2.58^{***}	2.18^{***}	2.71^{***}	2.58^{***}	2.75^{***}	2.31^{***}
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.02)	(0.03)
N	1,497	1,483	1,517	1,535	1,487	1,532	3,008	3,014

Note: Cell entries are OLS coefficients with standard errors in parentheses. Dependent variable is belief in false claim (measured 1–4, where higher values indicate more belief). Significance levels: *$p<.05$, **$p<.01$, ***$p<.001$.

H3 (moderating effect of populism activation on corrections)

Figure 2 in the main text presents the effect of corrections on fake news belief across terciles of pre-treatment populism, comparing respondents who received the populism activation treatment (right panels) or not (left panels). Here we report the result of pooled models for each country.

Appendix Table A21: Effect of corrections on fake news belief (Spain)

	DV: belief in false claim	
	No activation	Activation
Correction	−0.001	−0.03
	(0.03)	(0.04)
Moderate populist (tercile 2)	0.09**	0.13**
	(0.03)	(0.04)
Strong populist (tercile 3)	0.22***	0.15**
	(0.03)	(0.03)
Correction × moderate	0.02	0.03
	(0.03)	(0.05)
Correction × strong	−0.02	0.04
	(0.04)	(0.05)
Constant	1.92***	1.97***
	(0.02)	(0.03)
Effect of correction by tercile:		
Weak populists	−0.001	−0.03
Moderate populists	0.02	0.01
Strong populists	−0.02	0.01
N (respondent-blurbs)	23,070	11,560

Note: Cell entries are OLS coefficients with clustered standard errors in parentheses. Dependent variable is belief in false claim (measured 1–4, where higher values indicate more belief). Significance levels: *p<.05, **p<.01, ***p<.001.

Appendix Table A22: Effect of corrections on fake news belief (Portugal)

	DV: belief in false claim	
	No activation	Activation
Correction	-0.22^{***}	-0.20^{***}
	(0.05)	(0.05)
Moderate populist (tercile 2)	0.08	0.08
	(0.05)	(0.05)
Strong populist (tercile 3)	0.18^{**}	0.20^{**}
	(0.06)	(0.06)
Correction × moderate	0.06	0.10
	(0.0.06)	(0.06)
Correction × strong	0.10	0.12
	(0.07)	(0.07)
Constant	2.21^{***}	2.22^{***}
	(0.04)	(0.04)
Effect of correction by tercile:		
Weak populists	-0.22^{***}	-0.20^{***}
Moderate populists	-0.16^{***}	-0.10^{*}
Strong populists	-0.13^{*}	-0.08
N (respondent-blurbs)	4,682	4,649

Note: Cell entries are OLS coefficients with clustered standard errors in parentheses. Dependent variable is belief in false claim (measured 1–4, where higher values indicate more belief). Significance levels: *p<.05, **p<.01, ***p<.001.

Appendix Table A23: Effect of corrections on fake news belief (India)

	DV: belief in false claim	
	No activation	Activation
Correction	-0.01	0.07
	(0.04)	(0.04)
Moderate populist (tercile 2)	0.02	0.06
	(0.05)	(0.05)
Strong populist (tercile 3)	0.44^{***}	0.47^{***}
	(0.05)	(0.05)
Correction × moderate	-0.05	-0.14^{**}
	(0.06)	(0.05)
Correction × strong	-0.06	-0.03
	(0.05)	(0.05)
Constant	2.68^{***}	2.67^{***}
	(0.04)	(0.04)
Effect of correction by tercile:		
Weak populists	-0.01	0.07
Moderate populists	-0.06	-0.08^{*}
Strong populists	-0.06	0.04
N (respondent-blurbs)	7,199	6,854

Note: Cell entries are OLS coefficients with clustered standard errors in parentheses. Dependent variable is belief in false claim (measured 1–4, where higher values indicate more belief). Significance levels: *p<.05, **p<.01, ***p<.001.

Appendix Table A24: Effect of corrections on fake news belief (USA)

	DV: belief in false claim	
	No activation	Activation
Correction	−0.05	−0.06
	(0.04)	(0.04)
Moderate populist (tercile 2)	0.65***	0.60***
	(0.05)	(0.05)
Strong populist (tercile 3)	1.05***	0.91***
	(0.05)	(0.05)
Correction × moderate	0.02	0.07
	(0.05)	(0.05)
Correction × strong	0.01	0.07
	(0.0.06)	(0.06)
Constant	2.00***	2.01***
	(0.04)	(0.04)
Effect of correction by tercile:		
Weak populists	−0.05	−0.06
Moderate populists	−0.04	0.01
Strong populists	−0.05	0.01
N (respondent-blurbs)	7,455	7,613

Note: Cell entries are OLS coefficients with clustered standard errors in parentheses. Dependent variable is belief in false claim (measured 1–4, where higher values indicate more belief). Significance levels: *p<.05, **p<.01, ***p<.001.

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