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Research Note

Research note: Lies and presidential debates: How political misinformation spread across media streams during the 2020 election

When U.S. presidential candidates misrepresent the facts, their claims get discussed across media streams, creating a lasting public impression. We show this through a public performance: the 2020 presidential debates. For every five newspaper articles related to the presidential candidates, President Donald J. Trump and Joseph R. Biden Jr., there was one mention of a misinformation-related topic advanced during the debates. Personal attacks on Biden and election integrity were the most prevalent topics across social media, newspapers, and TV. These two topics also surfaced regularly in voters' recollections of the candidates, suggesting their impression lasted through the presidential election.

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Research questions

- What false and misleading statements mentioned during either debate gained traction during the campaign season?
- How was misinformation from the debates reflected across modes of communication? On what media streams did discussion of these claims grow?
- What topics from the debates made an impression on the public? What key features distinguished these from topics that did not become salient?

Essay summary

- We studied how the 2020 U.S. presidential debates reinforced misinformation themes, which spread through multiple media streams: social media, newspapers, and cable TV.
- We analyzed 14 misinformation-related topics advanced by the presidential nominees during the September 29 and October 22 debates, comparing how these topics were discussed across media

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and were recalled by the general public in open-ended surveys.
- The misinformation-related topics that garnered the most media attention and had highest levels of recall by ordinary Americans were personal attacks on Joe Biden and election integrity. Newspapers and TV were the most highly correlated sources in terms of misinformation-related coverage.
- Following the first debate, Twitter conversations about the candidates focused on personal attacks on the Biden family. Election integrity was discussed more consistently but also grew across media around the debates.
- Misinformation-related topics mentioned in the debates that received moderate media attention, such as taxes, climate, and racism, were recalled far less often by ordinary Americans. This suggests that both political mentions and media attention are necessary but insufficient conditions for misinformation-related topics to "stick" in public memory.
- We suggest that discussion of false claims in the media—whether supporting or refuting them—facilitates the diffusion and acceptance of misinformation, enabling political elites to distort the truth for partisan gain.

Implications

While political figures misrepresenting facts is hardly novel, the role of media coverage in repeating candidates' claims has become hotly contested in a time of political polarization and media fractionation some have called the "post-truth era" (Lewandowsky et al., 2017). Indeed, evidence that moderate numbers of Americans share misperceptions about political issues (Pasek et al., 2015) and candidates (Budak, 2019) raises important questions about how misinformation propagates through society and what role various media play in that process. We contribute to this line of inquiry by studying how misinformation pushed by presidential candidates reverberates through the media and is later recalled by the public. We use the term "misinformation" broadly to refer to factually inaccurate but genuine understandings (Kuklinski et al., 2000, p. 792; Maurer & Reinemann, 2006, pp. 492–493), regardless of their origins or pathways through the complex information ecosystem (Scheufele & Krause, 2019).

To date, researchers have shown the power of media to echo partisan attacks and leaders' misleading claims (Jerit & Barabas, 2006; Shapiro & Bloch-Elkon, 2008), the virality of myths in online communities (Barthel et al., 2016; Vosoughi et al., 2018), and the importance of social media platform policies for mitigating the reach of misinformation (e.g., Allcott et al., 2019; Bode & Vraga, 2015).[2] Despite such advances, little is known about the role political and communicative contexts play in shaping the misinformation ecosystem (Jerit & Zhao, 2020; Lazer et al., 2018). Our study responds to this need for research by tracing false claims from presidential candidates across communication domains to the recollections of individual citizens. By tracking a broad range of misinformation-related topics over time and media and determining which ones "go viral" and then "stick" in working memory, we provide a blueprint for comparing claims that are more versus less successful in penetrating public discourse.

To study how elite rhetoric[3] spreads through the media and draws the attention of ordinary citizens, our study leverages the public performance of televised presidential debates. Debates offer an exceptional opportunity for identifying false claims likely to attract partisan attention and spread through popular discourse. The learning effects of televised debates are well-known (Benoit & Hansen, 2004;

[2] The role of media in spreading misinformation is all the more important given a number of indicators of public susceptibility to these claims, such as generally low levels of accurate political knowledge (Graham, 2020; Neuman, 1986), an inability to recognize misinformation (McGrew et al., 2018), and evidence that misinformation can distort political behavior among the "active misinformed" (Hochschild & Einstein, 2015).

[3] The terms "elite" and "elites" in this paper refer to those with significant direct influence over the messaging of a dominant political party.

Lemert, 1993), and viewers tend to actively process debate content to help inform their voting decisions (Ampofo et al., 2011; Chaffee, 1978; Eveland, 2001). For these reasons, false claims by presidential candidates during debates—especially by a sitting president—are likely to be recalled by the general public, even when more accurate information is available. As such, we expect that misinformation mentioned by political leaders during debates that evokes more discussion in the media will be more salient to the public.[4]

In our increasingly polarized political era, debates between party leaders are likely to trigger motivated reasoning (Festinger, 1957; Kunda, 1990; Lodge & Taber, 2013) and biased assessments of source credibility (Guillory & Geraci, 2013; Stecula & Pickup, 2021), leading individuals to accept and hold onto (Johnson & Seifert, 1994; Nyhan & Reifler, 2010) inaccurate claims that reflect preexisting biases.[5] By connecting debate lies with media discourses and what people recall about the candidates, we show which false claims set the media agenda (e.g., Vargo & Guo, 2017; Vargo et al., 2018)—and, among these, which kinds get filtered out and which leave a lasting impression on ordinary Americans. We specifically contribute fine-grained comparisons of how misinformation is advanced by political candidates (Biden vs. Trump), is reproduced across media formats (TV vs. newspapers vs. social media),[6] and becomes consequential for public awareness. By positioning political leaders as key drivers and various media sources as carriers of misinformation, we bridge studies of elite influence and misinformation (which typically do not use real-time media data; e.g., Maurer & Reinemann, 2006; van Duyn & Collier, 2019) and analyses of media factionalization (which typically do not capture power dynamics; e.g., Iyengar & Hahn, 2009; Stroud, 2010). We echo calls for accountability across domains: for elites who push false narratives, for media that normalize politicians' lies and distort scientific facts (e.g., Boykoff & Boykoff, 2004; Clarke, 2008), and for social media that play a role in facilitating partisan attacks and broadening the reach of misinformation (e.g., Chen et al., 2021; Stecula et al., 2020).

We argue that by providing the public with an information environment saturated with misinformation propagated by political elites, both traditional media and social media contribute to the diffusion and widespread acceptance of these false narratives. In other words, media attention has lasting consequences not only for what people encounter, but also for what they remember. A considerable body of research shows that repeatedly hearing a statement—such as a partisan-affiliated sound bite (Hallin, 1992)—makes it appear believable and trustworthy, increasing the chance that one will recall and use that information in future decision-making (Allport & Lepkin, 1945; Hasher et al., 1977; Schwarz et al., 2007). The media's uncritical repetition of how elites frame the issues may settle into false perceptions of social consensus (e.g., Gershkoff & Kushner, 2005; Weaver et al., 2007) or heightened partisanship (e.g., Page & Shapiro, 1992; Zaller, 1992), but either way, a likely outcome is a misinformed public.

Even when media sources explicitly challenge false or misleading claims—as in the fact-check columns run by reputable news outlets—such correction attempts can reinforce the familiarity and normalcy of the myths they seek to debunk (Ecker et al., 2011; Lewandowsky et al., 2012). We use phrase matching to capture the normalizing influence of media coverage of misinformation, whether it promotes the lies or attempts to counter them. In other words, we study media contestation over false claims, capturing both the factual and false aspects of misinformation discussion.[7] Indeed, media engagement—regardless of

[4] However, despite the repetition of debate sound bites across time and media, the influence of televised debate content on public memory likely declines over time, replaced by more enduring forms of campaign messaging such as advertisements.

[5] Research has generally found corrections of misperceptions to be effective (Chan et al., 2017; Walter & Murphy, 2018) and backfire effects to be rare—that is, false beliefs usually don't further entrench after correction attempts (Swire-Thompson et al., 2020; Wood & Porter, 2019). However, exposure to factual corrections affects political attitudes much less than it does specific factual beliefs (Nyhan et al., 2020), and in some cases, corrections can push those who share misinformation to do so more in the future (Mosleh et al., 2021).

[6] In supplemental analyses (see Appendix D), we also compare the spread of misinformation discussion across conventional media organizations: left-leaning vs. right-leaning TV channels and newspapers, and those in purple states vs. others.

[7] We generally used phrases reflecting explicit false claims, but in cases where these were entangled with factual ones, we instead

stance toward candidates or issues—compounds the influence of political elites and allows them to set the terms of the debate, enhancing the power of presidential candidates (for instance) to distort the truth, undermine alternative views (Maurer and Reinemann 2006), and dispense narratives made memorable merely by their shock value, given that new information "sticks" (Morley & Walker, 1987). Although best practices for combating misinformation in the media remain poorly understood (Vosoughi et al., 2018; Yang et al., 2021), we show that discussion of misinformation clearly ebbs and flows in response to elites' false claims. By connecting misleading political frames to both media coverage and public cognitions, our study shows how the ability of political elites to shape media narratives threatens both the media's function as "gatekeepers" of verifiable information (Shoemaker & Vos, 2009; Soroka, 2012) and the core democratic value of a rational and informed citizenry (Bartels, 1996; Lipset, 1960). This study thus provides some of the clearest evidence to date that shifts in attention to misinformation-related topics across media streams encourage public awareness of those false claims.

Findings

Finding 1: Personal attacks on Biden and election integrity were the predominant misinformation-related topics across media streams after the 2020 U.S. presidential debates.

Based on fact-checking sites that tracked the presidential debates, we identified terms related to statements containing misinformation mentioned by the candidates and grouped them into 14 misinformation-related topics. Across media sources, the most common of these concerned *Biden personal attacks* and *election integrity*, as Figure 1 summarizes. The *Biden personal attacks* topic focused on Joe Biden and his family and was dominated by myths about his son Hunter Biden, partly driven by increased news coverage in September and October of Hunter Biden and the Republican inquiry into his behavior (e.g., his job at a Ukrainian energy company; Fandos, 2020). This topic was especially prevalent on Twitter, capturing over 56% of the misinformation-related mentions identified; in fact, "Hunter Biden" was the number one misinformation-related term on Twitter for four of the six weeks between the first debate and election day. *Election integrity* was related to false claims that the election was "rigged," and many mail-in ballots were "fake." These top two myth categories were followed at some distance by *taxes* and *climate*.

sought to capture the full, contested discussion. More precisely identifying media content making false claims would require custom machine learning classifiers for each myth for each stream; creating such models is beyond the scope of this paper. Our goal is not to disentangle the conversation, but rather to track how its full volume (attention given to each misinformation-related topic) changes through time on different information streams.

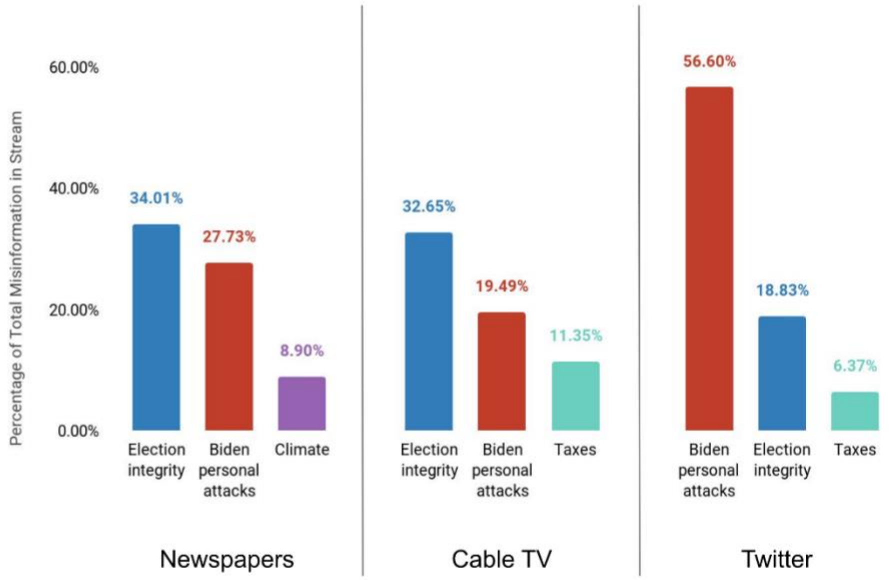

Figure 1. Top topics for misinformation mentions across media streams. *Collected between August 1, 2020 and November 3, 2020, our data consist of 186,551 newspaper articles, transcripts from 1,246 cable TV channels, and 169,753,552 tweets.*

Finding 2: Discussion of myths mentioned during the debate increased from pre-debate levels.

Table 1 shows how misinformation mentions and proportions changed across streams over time. This growth was especially marked for tweets mentioning Biden, in which the misinformation proportion nearly quadrupled between the pre-debate and post-debate periods (from 2.61% to 10.1%). While the salience of misinformation-related topics increased more than sixfold in surveys about Biden (from 1.22% to 7.48%), the prevalence of these topics in surveys about Trump actually decreased from a pre-debate peak of 4.42% to 3.38%. The growth in misinformation associated with Biden but not Trump reflects an asymmetry in the candidates' debate performances: While fact checkers identified 50 false assertions by Trump during the debates, Biden was flagged for only two (see Appendix A for counts and specific claims). In other words, while Trump succeeded (in terms of what people recalled) in redirecting attention during the debates to misinformation-related topics—many of which targeted Biden—his rival made little effort to do so.

***Table 1**. Misinformation mentions and proportions[8] by stream over time.*

Time period	Newspapers	Television	Trump Twitter	Biden Twitter	Trump surveys	Biden surveys
Pre-debate (August 1–September 28)[9]	18,070 (17.4%)	48,524 (1.85%)	951,181 (1.36%)	916,114 (2.61%)	289 (4.42%)	75 (1.22%)
Post-debate 1 (September 29–October 21)	15,373 (28.7%)	32,861 (3.44%)	157,190 (1.88%)	739,968 (9.24%)	37 (1.41%)	133 (5.47%)
Post-debate 2 (October 22–November 3)	8,399 (28.9%)	21,211 (3.84%)	264,755 (1.85%)	973,464 (10.1%)	84 (3.38%)	185 (7.48%)
Overall	41,842 (22.4%)	102,596 (2.49%)	1,373,126 (1.48%)	2,629,546 (4.99%)	410 (3.52%)	393 (3.55%)

Finding 3: Misinformation-related topics that received debate and/or media attention were recalled more by the public.

Figure 2 shows a heatmap aggregating mentions into the pre-debate, post-debate 1, and post-debate 2-time frames during 2020. There is a clear connection between debate attention (vertical order), media attention (square color), and survey prominence (square size): Greater debate attention tends to pair with more media attention and stronger recollections. However, this is a loose correlation, as more debate attention does not guarantee more media attention or public recollection. For instance, misinformation about *COVID-19* and *climate* are not discussed as much with respect to Trump and Biden as are *Biden personal attacks* or *election integrity*.[10] Nonetheless, misinformation-related topics that receive little debate and media attention (those at the bottom of the figure in lighter colors) have little chance of being remembered, suggesting that debate and media attention may be necessary but not sufficient conditions for public awareness.[11]

[8] The proportions in parentheses in Table 1 indicate the ratio of misinformation to information—that is, the number of mentions of misinformation divided by the number of units of information (articles, segments, tweets, or surveys about the candidates). Mentions are aggregated by misinformation-related topic rather than by article, so a given article may contribute to multiple topics and thus be counted more than once.

[9] Note that the pre-debate period is longer than either post-debate period and thus has greater totals. All dates refer to 2020.

[10] Indeed, even misinformation-related topics with low debate attention can get media attention (as *taxes* does), and misinformation-related topics with low to moderate debate and media attention can receive some public awareness (e.g., *law enforcement).*

[11] While we study debates as a visible platform for political expression, elites may also draw attention to misinformation-related topics through campaign advertisements, speeches, and the like. We postulate that political attention is necessary for false claims to "go viral," but debate attention may be replaced or supplemented by other forms of political expression.

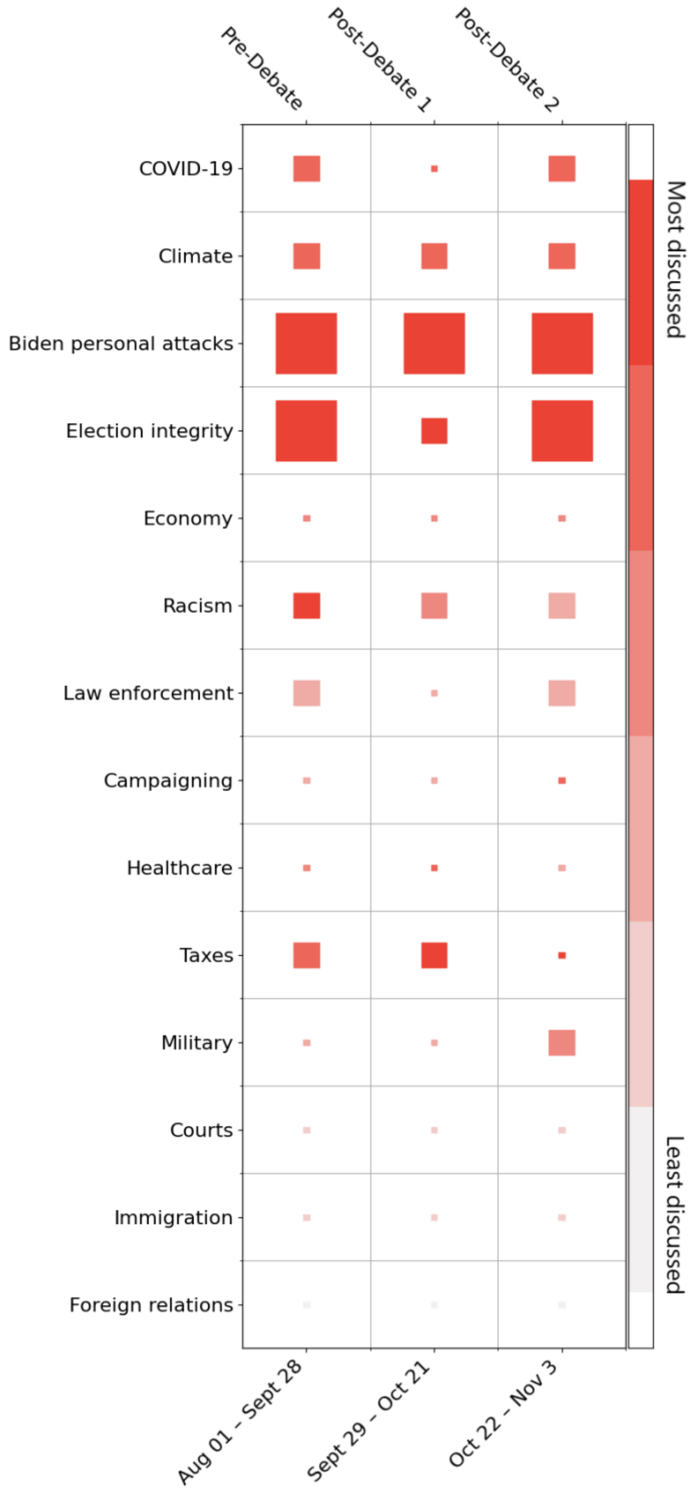

Figure 2. Heatmap showing debate and media attention and public awareness. *Each cell in this heatmap represents a topic at a particular point in time during 2020. Vertical order indicates the number of myths within the topic mentioned during the debates: Topics farther up garnered more false claims than those at the bottom. Square color reflects media attention: Topics with darker shades were mentioned more. The color legend in the far-right column shows the shades ranging from the most-discussed topics (red) to the least-discussed topics (light gray). Finally, square size indicates prominence in surveys: large size for the most prevalent topics, medium size for medium prevalence, small size for low prevalence.*

The imperfect correlation of public awareness with debate and media attention suggests that debates may be less significant platforms for spreading discussion of misinformation that has already been highlighted in the media. For instance, the prominence of discussions concerning *taxes* prior to and around the first debate is associated with the appearance of a *New York Times* report on September 27, 2020, stating that Trump paid only $750 in taxes in 2016 and 2017 (Buettner et al., 2020); one day after the release of this report, discussions related to the myth that Trump paid millions in taxes in these same years surged on Trump Twitter (see Figure 5). Indeed, political leaders may use a debate platform both to push their own agenda or narrative (such as asserting nepotistic business relations within the Biden family) and to intervene in existing public dialogue or controversies (for instance, by making false claims about Trump's tax payments in response to the highly visible *New York Times* report).

Finding 4: Most misinformation-related topics in newspapers were short-lived following each debate.

The time-series plot in Figure 3 shows three prominent spikes in misinformation-related coverage in newspapers. The largest peaks are for the two debates on September 29, 2020, and October 22, 2020, and the third-largest, around October 14, 2020, follows an unsubstantiated *New York Post* report claiming that Hunter Biden introduced his father to a Ukrainian energy executive (there is no evidence of this; Morris & Fonrouge, 2020). The *New York Post* report is linked to an increase in *Biden personal attacks*, while the debates are associated with a broader range of misinformation-related topics.

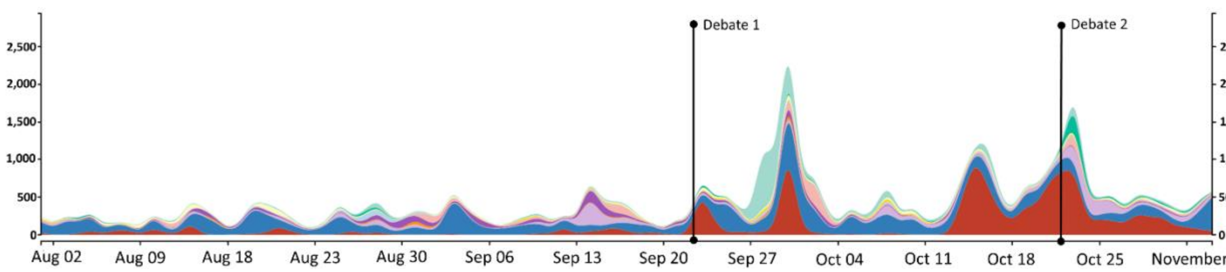

Figure 3. Mentions over time of misinformation-related topics in newspapers. *The key topics depicted are Biden personal attacks (red), election integrity (blue), taxes (light green), climate (light purple), campaigning (purple), and COVID-19 (pink). For an interactive version, click here.*

Most topics received the greatest newspaper attention on the day or two following each debate—except for *Biden personal attacks* and *election integrity*, which saw consistently high levels over time. Illustrating the typical pattern, discussions of *COVID-19* misinformation surged around the first debate, while *climate* and *racism* ascended briefly following the second debate. In contrast, *Biden personal attacks* grew most from before to after the first debate (see Table 2). In newspapers, this topic hit a high of 42.5% of all misinformation[12] mentioned after the second debate, compared to 12.7% before the debates; *election integrity* dropped over that period from 42.2% before the debates to 22.3% thereafter.

[12] These percentages indicate the proportion of all misinformation in a given time period contributed by a given misinformation-related topic. This contrasts both with the percentages in Table 1—which show the proportion of misinformation mentions across topics to the number of units of information—and with the raw topic mentions visualized in the time-series plots.

***Table 2.** Mentions (and proportions) for top misinformation-related topics before and after debates across media streams and surveys.*[13]

Misinformation-related topic and date range	News-papers	Television	Trump Twitter	Biden Twitter	Trump surveys	Biden surveys
Biden personal attacks						
Pre-debate[14]	2,288 (12.7%)	4,196 (8.6%)	88,863 (9.3%)	569,084 (62.1%)	19 (6.6%)	38 (50.7%)
Post-debate 1	5,743 (37.4%)	9,736 (29.6%)	57,929 (36.9%)	639,625 (86.4%)	11 (29.7%)	124 (93.2%)
Post-debate 2	3,570 (42.5%)	6,064 (28.6%)	107,595 (40.6%)	802,328 (82.4%)	24 (28.6%)	161 (87.0%)
Election integrity						
Pre-debate	7,619 (42.2%)	21,499 (44.3%)	463,058 (48.7%)	91,031 (9.9%)	250 (86.5%)	9 (12.0%)
Post-debate 1	4,741 (30.8%)	8,232 (25.1%)	33,204 (21.1%)	34,894 (4.7%)	13 (35.1%)	0 (0%)
Post-debate 2	1,869 (22.3%)	3,769 (17.8%)	52,679 (19.9%)	79,012 (8.1%)	51 (60.7%)	14 (7.6%)

Finding 5: Misinformation trends in newspapers and on cable TV were highly correlated.

The same trends applied to newspaper and television media streams, as Figure 4 shows (for proportions, see Table 2). As for newspapers, the *COVID-19* and *taxes* topics surged on television around the first debate: the latter peaked at 14.5% after debate 1, while coverage of *climate* and *racism* misinformation-related topics increased after the second debate (see Appendix B, Table 2). In fact, newspapers and TV were the most highly correlated pair of sources we studied, ranging from 0.17 for the *healthcare* topic to 0.98 for *racism.*[15] This suggests that these two more traditional (i.e., non-social media) streams may track the same stories, share sources and reporters, and/or seek to appeal to similar slices of the news-consuming U.S. public.

[13] The full table showing all the misinformation-related topics in these time frames can be found in Appendix B, Table 2.
[14] As in Figure 2, "pre-debate" here captures conversation before either debate took place (August 1, 2020–September 28, 2020), "post-debate 1" focuses on media content during and after debate 1 (September 29, 2020–October 21, 2020), and "post-debate 2" is limited to debate 2 and its aftermath (October 22, 2020–November 3, 2020; all these dates inclusive). Note that the pre-debate period is longer and thus has greater totals than either post-debate period.
[15] The correlations between newspaper and TV coverage were 0.54 for *COVID-19*, 0.60 for *election integrity*, and 0.88 for *Biden personal attacks*; all Pearson correlation coefficients significant at $p < 0.001$. As the time-series plots hint, trends in the *racism* topic were highly correlated across streams—the highest of all topics we tracked—ranging from 0.46 between Trump- and Biden-related Twitter to 0.98 between newspapers and TV (both Pearson correlation coefficients significant at $p < 0.001$). See Appendix E for the complete correlation analysis between sources across topics.

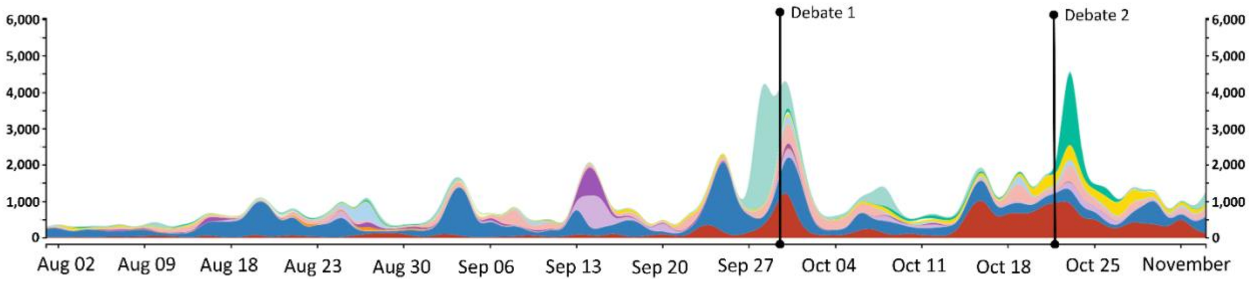

Figure 4. Mentions over time for misinformation-related topics in television. *The key topics depicted are Biden personal attacks (red), election integrity (darker blue), climate (light purple), campaigning (purple), COVID-19 (pink), taxes (light green), racism (green), and healthcare (yellow). For an interactive version, click here.*

Finding 6: Twitter misinformation centered on election integrity when mentioning Trump and on personal attacks when mentioning Biden.

Trump-related misinformation discussion on Twitter[16] was heavily concentrated in the *election integrity* topic (at 40.0%), followed by *Biden personal attacks* (18.5%) and *taxes* (16.5%; see Appendix B, Table 2 for detail). The first two switched places in tweets about Biden: A heavy concentration mentioned the *Biden personal attacks* topic (76.5%), followed distantly by *election integrity* (7.8%) and *military* (4.2%).[17] Figures 5 and 6 show how these numbers changed over time. As in other streams, after the first debate, *Biden personal attacks* grew to 36.9% and 86.4% of misinformation in Trump- and Biden-related conversation, respectively (compared to 9.3% and 62.1% before the debates; see Table 2), while *election integrity* shrunk to 21.1% and 4.7%, respectively (compared to 48.7% and 9.9%).[18] The more frequent, less coordinated spikes in Figures 5 and 6 relative to those in newspapers and TV suggest a freer spread of misinformation on social media—and an apparently less coherent influence of political debates in this media stream.

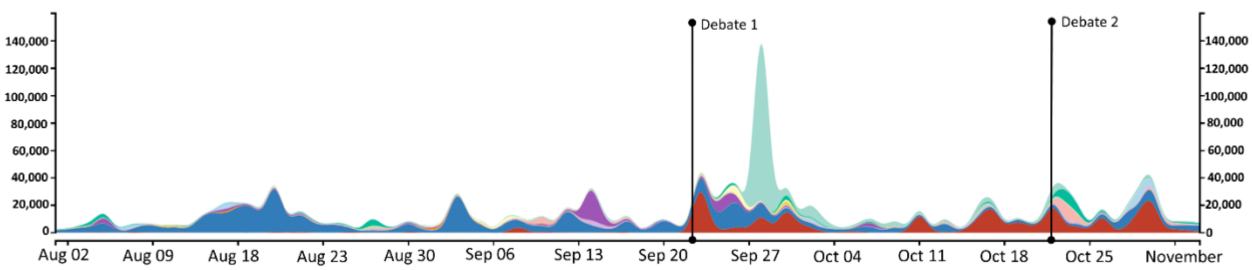

Figure 5. Mentions over time of misinformation-related topics in Trump tweets. *The key topics depicted are Biden personal attacks (red), election integrity (blue), campaigning (purple), COVID-19 (pink), and taxes (light green). For an interactive version, click here.*

[16] Due to the short-text nature of social media, the candidate the tweeter is focusing on can easily be identified through keyword matching. We analyzed tweets and surveys separately for each candidate to avoid loss of precision (see Methods section).

[17] The Trump and Biden Twitter streams were the least correlated pair of media sources we analyzed, ranging from a low of 0.01 for *election integrity* ($p > 0.10$) to a high of 0.46 for *racism* ($p < 0.001$). Correlations for *Biden personal attacks* were significantly higher when mentions in the Biden stream were set to lag behind mentions in the Trump stream by one day (0.60 for a one-day lag vs. 0.45 for same-day mentions, $p < 0.001$). A similar pattern was observed for other issues, suggesting that some misinformation may have emerged in Trump-related conversations on Twitter before diffusing to Biden-related Twitter.

[18] The influence of the debates on Twitter discourse was less pronounced for other topics. As Figure 5 shows, the *taxes* topic surged before the first debate for Trump Twitter (growing from 18.1% to 23.6% and then declining; see Table 2) and much less so for Biden Twitter (see Figure 6), while Biden Twitter saw a crest for the *military* topic before and after the first debate and for *climate* in early October.

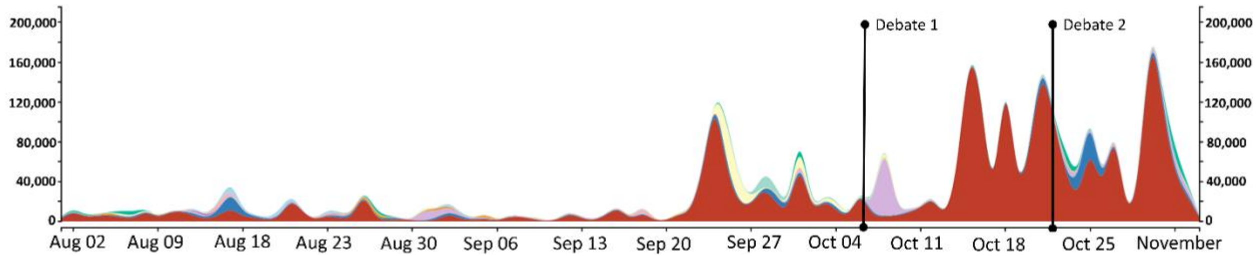

Figure 6. Mentions over time of misinformation-related topics in Biden Twitter. *The key topics depicted are Biden personal attacks (red), election integrity (blue), climate (light purple), military (light yellow), and taxes (light green). For an interactive version, click here.*

Finding 7: Public recollections about the candidates reflected misinformation dominant in the media.

Election integrity dominated survey respondents' recollections of Trump but not Biden (accounting for 76.6% of misinformation-related topics and 2.70% of respondents for Trump, vs. 5.85% and 0.21%, respectively, for Biden), while *Biden personal attacks* crowded out any other memorable misinformation-related topics for Biden but not Trump (at 82.2% of misinformation and 2.92% of respondents for Biden, vs. 13.2% and 0.46%, respectively, for Trump; see Appendix B, Table 1 for complete numbers).[19] Figures 7 and 8 show how these trends varied over time. While *Biden personal attacks* topped out during the week of the second debate (mentioned by over 10% of respondents) and then slowly declined, *election integrity* peaked in mid-August[20] (mentioned by over 9% of respondents) and surged just before the election. This suggests that political leaders (e.g., Trump) may push misinformation to secure partisan votes when the electoral outcome is uncertain—a strategic appeal similar to emphasizing divisive issues like abortion (Glaeser et al., 2005).

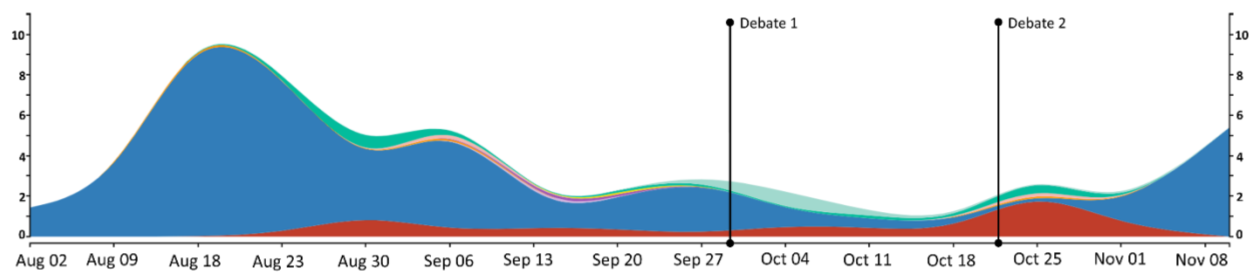

Figure 7. Mentions over time of misinformation-related topics in Trump surveys. *The key topics depicted are Biden personal attacks (red), election integrity (blue), taxes (light green), and racism (green). The y-axis represents the percentage of responses related to a given topic. For an interactive version, click here.*

A similar pattern is observed for *Biden personal attacks* (comparing the sky-blue curves in Figures 7 and 8). This topic was the most correlated topic for surveys, ranging from 0.54 for the correlation of Biden surveys and Trump surveys *(*$p < 0.05$*)* to 0.92 for that of surveys and newspapers *(*$p < 0.001$*)*.[21] Moreover, similar to the media streams, misinformation in both sets of survey results shifted toward *Biden personal*

[19] Other common misinformation-related topics also resurfaced in surveys: *taxes* and *racism* grew among Trump recollections around the first and second debates, respectively (reaching 1.02% and 0.61% of respondents), while *military* and *racism* crested in Biden recollections around the first and second debates, respectively (reaching 0.27% and 0.25% of respondents).

[20] Misinformation related to *election integrity* was likely brought to prominence relatively early due to then-President Trump's tweets. Testing this hypothesis is beyond the scope of this paper and will be the focus of future work.

[21] For *Biden personal attacks*, correlations show that surveys led Twitter by a week to the same extent as on the same day: their contemporaneous correlation is 0.78, while their one-week lead is 0.75 and their one-week lag is 0.31 ($p < 0.001$ for all but the lag). In the same way but on a somewhat smaller scale, Biden surveys led Trump surveys for this topic (0.54 vs 0.55 vs. 0.34 for contemporaneous vs. one-week lead vs. one-week lag; $p < 0.05$ for all but the lag).

attacks after the first debate, growing to 28.9% in Trump surveys and 89.9% in Biden surveys. This suggests that multiple media streams echoed this line of attack and may have allowed the debates to reinforce this impression later in the campaign. Moreover, while both top topics showed staying power or "continuing influence" (Johnson & Seifert, 1994; Lewandowsky et al., 2012), the later climax of *Biden personal attacks*—a relatively new storyline when it emerged during the first debate to gain a wide audience—suggests that novel information can carry extra weight (Morley & Walker, 1987) for both the media engaging with misinformation and the public remembering it.[22]

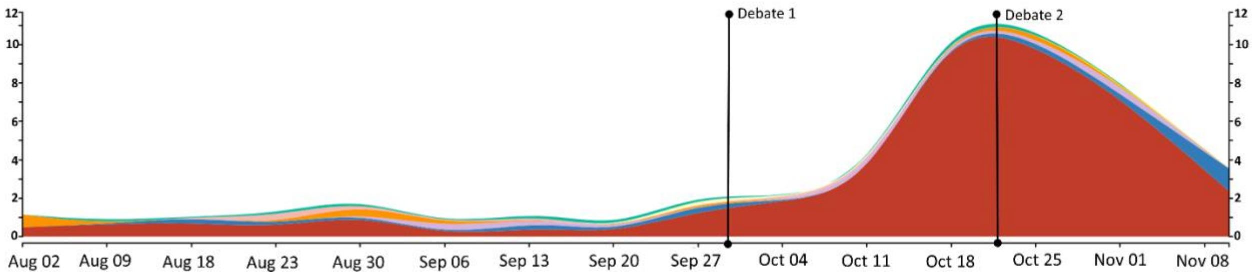

Figure 8. Mentions over time of misinformation-related topics in Biden surveys. *The key topics depicted are Biden personal attacks (red), election integrity (blue), law enforcement (orange), and racism (green). The y-axis represents the percentage of responses related to a given topic. For an interactive version, click here.*

Methods

We examined the relationships between political influence, media coverage, and misinformation by studying which misleading statements by presidential candidates during debates gained traction during the campaign season. To understand the presence of false claims across modes of communication, we compared the prevalence of misinformation-related content across six streams of data between August 1 and November 3, a period spanning both debates in the 2020 U.S. presidential election cycle. These streams included traditional television and newspaper media, tweets mentioning each of the candidates' names, and open-ended survey data asking Americans what they had recently read, seen, or heard about each of the candidates. We also asked which misinformation-related topics made an impression on the public and what distinguished these from topics that did not become salient.

Across all streams, we tracked terms related to misleading or fallacious claims candidates made during at least one of the two debates and categorized them into 14 topics. We identified false and misleading statements by either candidate during the presidential debates using several reputable fact checkers: Snopes (snopes.com), PolitiFact (politifact.com), and *The Washington Post* (washingtonpost.com/news/fact-checker). We then traced the spread of these false and misleading statements from August 1 to November 3, 2020, using Twitter, newspapers, and television. A strength of our analysis is the scale and diversity of the media streams studied.

We used the coverage of the three fact checkers to create an initial list of misleading or false statements made by the candidates during the debates (excluding partially true statements), amounting to 35 statements from the first debate and 17 statements from the second. We placed these statements into categories or topics, developed phrase lists specific to each misleading statement,[23] and used these

[22] In comparison, the influence of Trump's debate claims about *election integrity* myths may have been limited by their familiarity. The struggle for public attention may have motivated more coordinated messaging by the Trump campaign, possibly explaining the growth in recollection of this misinformation-related topic in the week before the election.

[23] To create a phrase list, we mixed distinctive words and synonyms within each phrase to capture the main topic of a given misleading statement while minimizing overlap with similar but unrelated statements. For instance, to capture the myth that "the California forest fires were caused by forest mismanagement," we included phrases such as "forest management," "forest floor," and "clean your floors." While some phrases have broader connotations than the specific myth at hand, their contextual meaning

phrases to identify relevant discussion from August 1 to November 3, 2020. Appendix A describes our misinformation themes and shows example phrases. We used the number of mentions to track misinformation-related topics in our streams at the unit level: articles, TV segments, Twitter posts, or surveys. The first three were measured daily while surveys were collected weekly.

Although our phrases target specific false claims—allowing for high precision in identifying mentions of the claims—our topics are intended to capture misinformation conversation more broadly, including both statements that promote and statements that refute a false claim.[24] Our validation, described in Appendix F, suggests that our dictionary-based method does indeed capture myths for our most and least common misinformation-related topics, with minimal contamination by factual dialogue using similar language (e.g., discussion of California forest fires in the context of climate change).[25]

We also performed correlation analysis (lagging, contemporaneous, and leading) to describe how tightly connected streams were to one another. Our results thus include the following measures for a given topic and point in time: the number of mentions in a given media stream, the proportion of misinformation contributed to a given media stream, and the correlations between a given pair of media streams. We used each of these measures in our analysis.[26] These analytical steps and our supplemental analyses[27] provided a precise signal of misinformation presence across media streams and allowed us to differentiate topics by their success in gaining public salience.

We did not combine Trump- and Biden-related tweets or surveys to prevent loss of measurement precision. Specifically, while newspaper and television streams often focus on both candidates in the same article or segment, tweets and surveys were contributed for specific candidates (through hashtags or interview questions). In other words, analyzing Trump tweets and surveys separately from Biden tweets and surveys avoids distorting candidate-specific patterns and provides a more nuanced analysis. Below we describe our sampling and data collection approach for each of our data sources.

Newspapers

We collected 186,551 articles containing the keywords "Biden" or "Trump" from 308 newspapers around the country using the EventRegistry API. We initially manually identified a total of 750 local, national, and national newspapers, ensuring we had at least two newspapers from every state (with more papers for larger states). The API gave us access to 308 newspapers from our initial sample.

was rarely off-topic because we selected only posts or articles that also included a candidate's name. We demonstrate this precision with a dictionary validation study in Appendix F.

[24] Misinformation discussion contains both false and factual claims, one often motivating and providing context for the other. We focused on explicit false claims where possible; for the *taxes* topic, however, conflation of facts with lies motivated us to instead capture the full, contested discussion. The *New York Times* report that broke the news about Trump paying $750 in taxes in 2016 and 2017 also included a Trump organization lawyer's false claim that Trump had paid millions in taxes (Buettner et al., 2020). To capture the competition between these positions often concealed by the short format of social media, we sought to capture both the factual and false aspects of their interchange by using phrases such as "750 in taxes" together with phrases like "paid millions in taxes." Moreover, each topic has a different balance of factual and false claims, and these may vary by media stream. For instance, our phrases similar to "750 in taxes" account for about 99% of Trump Twitter content related to *taxes*. However, the less frequent (and less diverse) phrases similar to "Trump paid millions of dollars in taxes" followed the same pattern as above (see Figure 5), surging on September 28, 2020—from zero to 1,134 mentions—and persisting at low–moderate levels until the election. The correlation between these phrases and the overall *taxes* topic is very high at 0.959 ($p < 0.001$). This supports our expectation that, within our contested topics, dueling factual and false claims rise and fall together in similar proportions.

[25] We validated our dictionary-based method using three of the most common misinformation-related topics (*climate change*, *Biden personal attacks*, and *election integrity*) and three of the least common ones (*healthcare*, *taxes*, and *military*) on social media. The results thus support the validity of our approach both for our most central, enduring topics and for those that were short-lived (see Appendix F).

[26] For the full list of frequencies (number of mentions) proportions contributed by a given topic to a given stream, see Appendix B, Table 2. For our full results on correlations between streams, see Appendix E.

[27] See Appendix C for analysis of topics' spread using the proportion of sources (newspapers and TV channels), rather than mentions, that discuss a given misinformation-related topic. See Appendix D for breakdowns of media organizations by partisan leaning and selected regions.

Television
We obtained 24/7 closed caption transcripts from 1,246 television channels with news programming from TVEyes. The data is broken down into 5- to 10-minute segments determined by advertising. We identified segments that referred to the U.S. presidential election or their candidates using the words “election,” “Trump,” and “Biden,” allowing us to look at the daily frequency of the misinformation-related topics.

Twitter
We used the Twitter API to collect tweets containing either the “Biden” or “Trump” keyword, yielding 62,343,263 and 107,410,289 tweets, respectively.[28] We shortened some phrases in our dictionary (e.g., “Hunter” instead of “Hunter Biden”) to count mentions of myths in the context of tweets that specifically referenced candidate names. Our minimal preprocessing removed punctuation and capitalization and expanded contractions.[29]

Surveys
We collected 17,800 telephone surveys from July 1, 2020, to November 10, 2020, among a nationwide, random sample of approximately 1,000 adults per week via the SSRS Omnibus survey. The surveys used were part of The Breakthrough. Surveys were conducted over a six-day period each week, typically between Tuesday and Sunday, in English and Spanish. Roughly 70% of surveys each week were completed with respondents reached via cellphone. Each respondent was asked, “What, if anything, have you heard, read, or seen in the past few days about Donald Trump?” and “What, if anything, have you heard, read, or seen in the past few days about Joe Biden?” The order in which the two questions were asked was randomized so that some respondents were asked about Trump first and others were asked about Biden first. Exact responses to these questions were transcribed by interviewers. As with Twitter, we used a modified misinformation dictionary (with shorter phrases more typical of spoken language) to count how many survey respondents freely recalled our misinformation-related topics.[30]

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[28] Tweets that contain both “Biden” and “Trump” are in both individual sets.
[29] Because we relied on manually derived keywords and phrases to identify misinformation in a social media environment rife with informal language (e.g., abbreviations and slang), our analysis likely fails to capture many variations on our misinformation themes of interest. As such, the findings above likely underrepresent the extent of false and misleading conversation on Twitter.
[30] The full list of additional phrases we used to track misleading statements on surveys is available on our project repository. See the file “Additional Survey Phrases.xlsx.”

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Competing interests
None.

Ethics
Our Twitter data is subject to an IRB exemption at Georgetown University (study number STUDY00000579). Our newspaper and TV data did not involve human subjects and therefore were not subject to IRB approval. Misinformation was labeled by team members. We did not use Mechanical Turk or other paid data labeling services for this study.

Data availability
To generate structured variables—including work frequencies, topics, and sentiment—based on the raw data analyzed here, we invite researchers to request permission through the Georgetown Massive Data Institute Analytic portal (https://portals.mdi.georgetown.edu/). Information to assist in reproducing our analysis is available in our GitHub repository (https://github.com/GU-DataLab/misinformation-2020_presidential_debates). However, we are not allowed to give access to raw Twitter data, television transcripts, newspaper data, or surveys given the terms of usage.

Appendix A: Misinformation-related topics, claims, and phrases

Table 1 describes our misinformation-related topics and the number of false or misleading statements each candidate made during the two debates within each category. Table 2 shows the candidates' specific false claims and their associated topics.

***Table 1**. Misleading and false claims by candidates during 2020 presidential debates.*

Category of misinformation	What most of the false claims in this category are about	Source of claims	Number of claims by Trump (debate 1, debate 2)	Number of claims by Biden (debate 1, debate 2)
Biden personal attacks	Biden and his family, especially his son Hunter	Trump	(4, 2)	(0, 0)
Campaigning	Trump rallies, other miscellaneous claims	Trump	(3, 1)	(0, 0)
Climate	Fracking and clean energy	Trump	(3, 4)	(0, 0)
Courts	Obama left judge seats to fill	Trump	(1, 0)	(0, 0)
COVID-19	What Trump did and did not do about the pandemic, H1N1	Trump	(5, 2)	(0, 0)
Economy	State of economy under Trump or Obama, China deficit	Both candidates	(4, 0)	(1,0)
Election integrity	Selling or stealing votes, election rigging, mail ballots	Trump	(3, 2)	(0, 0)
Foreign relations	Kim Jong Un did not like Obama	Trump	(0, 1)	(0, 0)
Healthcare	Biden supporting an end to private insurance	Trump	(2, 1)	(0, 0)
Immigration	Immigrants do not show up to their court hearings	Trump	(0, 1)	(0, 0)
Law enforcement	Protests, endorsements, defunding the police	Both candidates	(3, 0)	(1, 0)
Military	What Biden has said about service members, Trump rebuilding the military	Trump	(2, 0)	(0, 0)
Racism	Biden's statements, Trump's record	Trump	(1, 3)	(0, 0)
Taxes	Trump's tax payments	Trump	(2, 0)	(0, 0)

Table 2. *Misinformation categories, specific claims, and example phrases.*[31]

Misinformation-related topic	Specific claim	Example phrase 1	Example phrase 2	Example phrase 3	Example phrase 4	Example phrase 5
Biden personal attacks	Hunter Biden controversies	hunter biden	dishonorably discharged	use cocaine	using cocaine	tested positive for cocaine
	Hunter Biden received $3.5M from Moscow mayor's wife	hunter biden	elena baturina	baturina	wife of moscow mayor	russia's only female billionaire
	Biden forgot where he went to college	biden went to delaware state	delaware state	forgot name of college	biden college attend	start at delaware state
	Biden graduated either the lowest or almost lowest in his class	finish last in class	last in his class	last in college class	last in his college class	nothing smart about joe
	Biden isn't from Scranton	biden doesn't come from scranton	biden left scranton at five	he isn't from scranton	he left scranton at age nine	biden's not from scranton
Campaign-ing	Kellyanne Conway did not say violence and anarchy were politically advantageous for Trump	riots and chaos	violence helps his cause	kellyanne conway	trump more chaos and anarchy	trump vandalism and violence
	Trump has not held indoor rallies	henderson, nv	henderson nevada	hendersen nevada	no indoor rally	indoor rally
	Obama Administration spied on Trump campaign	crossfire hurricane	operation crossfire hurricane	robert litt	russian interference obama spying	carter page
	Nancy Pelosi was dancing on the streets in San Francisco	dancing in the streets	dancing in chinatown	pelosi was dancing	bring your infection with you	pelosi danced
Climate	Biden supports the Green New Deal	support green new deal	support climate plan	support green deal	in favor of green	wants green new deal
	Cause of forest fires = forest mismanagement	forest management	federal government manages forests	cleaning forest	cleaned forests	forests were cleaned
	Green New Deal will cost $100T	alexandria ocasio-cortez's green new deal	100 percent clean energy	$100 trillion green new deal	aoc green deal cost	green new deal cost
	Biden wants to end fracking	end fracking	ban all fracking	ban fracking	eliminate fracking	ban on fracking
	Windmills generate harmful fumes, are worse than natural gas, etc.	windmills kill all the birds	i know more about wind than you do	wind extremely expensive	wind turbines are extremely expensive	windmills are extremely expensive
	The U.S. is energy independent	us is energy independent	makes us energy independent	keeps us energy independent	we are energy independent	we're energy independent

[31] Our full list of associated phrases for these misleading statements is available on our project repository. See the file "Misinformation Topics and Phrases.xlsx."

Courts	Obama left 128 judge seats to fill	128 vacancies	128 judge vacancies	left 128 openings	obama left 128 openings	obama left 128 vacancies
COVID-19	Biden wants to "shut down" U.S. to address coronavirus	wants to shut down the country	wants to shut down our country	wants to shut down the economy	wants to shut down our economy	shut down country if scientists
	Trump brought back BIG10 football	brought back big10	brought back big 10	brought back big ten	brought big10 football back	brought big 10 football back
	Serious people do say masks are not important - Fauci said it	fauci said masks	mask stance was taken out of context	fauci said the opposite	fauci pushes back on trump	fauci's mask stance
	Trump took bold action to stop the spread of coronavirus	china ban	biden called it xenophobic	called trump xenophobic	called him xenophobic	europe ban
	Obama administration did not handle H1N1 effectively	12000 dead	12,000 deaths	infected 60 million	obama did nothing	2009 h1n1
	Trump’s corona efforts have saved 2 million lives	saved 2 million lives	saving 2.2m lives	2 million people would have died	2.2 million people would have died	biden would have killed 2 million
	U.S. is rounding the corner on coronavirus	we are rounding the corner	rounding the corner beautifully	vaccine on the horizon	should have a vaccine in weeks	will have a vaccine soon
Economy	Trade deficit with China has increased under Trump	trade deficit with china is up	higher trade deficit with china	art of the steal	trade deficit with china	trade deficit with china shrank
	Obama-era recovery was weakest economic recovery since 1929	worst economic recovery	slowest economic recovery	weakest economic recovery	obama-era recovery	obama's recovery
	Trump is only POTUS since WWII to host decline in jobs	overall decline in jobs	worst jobs president	trump's job losses	jobs loser	leave office having fewer jobs
	Before coronavirus	we had the greatest economy in the history of the country	greatest economy in history	greatest economy in the history of the world	greatest economy in the history of our country	greatest economy in the history
	Trump created 700,000 manufacturing jobs	700k manufacturing jobs	700,000 manufacturing jobs	237,000 manufacturing jobs	brought back half a million	230,000 manufacturing jobs
Election integrity	Poll watchers were improperly barred from observing early voting in Philadelphia	philadelphia poll watchers	philly poll watchers	poll watchers blocked	poll watchers barred	satellite election offices
	WV mailmen sold ballots	wv mailman sold ballots	wv mailmen sold ballots	west virginia mailman sold ballots	west virginia mailmen sold ballots	thomas cooper
	The election was rigged	voter fraud	mail balloting	9 ballots	nine ballots	9 military ballots
	The Mueller Report found no collusion	collusion	report witch hunt	mueller find	mueller's finding	found absolutely nothing wrong
Foreign relations	Kim Jong Un did not like Obama	kim jong un didn't like obama	obama begged for a meeting	kim wouldn't meet with obama	north korea disliked obama	obama couldn't get a meeting
Healthcare	Trump guaranteed preexisting conditions via Executive Order	executive order preexisting	executive order health care	everyone receives healthcare	everyone receive healthcare	does not guarantee coverage

	Prices of insulin and other prescription drugs are falling	insulin so cheap	insulin like water	lowered drug prices	lowered price of insulin	insulin prices
	Biden wants to end private health insurance	biden wants socialized medicine	joe wants socialized medicine	joe's plan would end private insurance	he will end private insurance	his healthcare plan threatens private insurance
	No one with private insurance lost their insurance with obamacare	no one lost insurance	obamacare canceled plan	plans were not up to standard	find new insurance plan	lost health coverage
Immigration	Less than 1 percent of people released into the country show up to their court hearings	never returned for court hearings	don't return for court hearings	didn't show up for catch-and-release court hearings	1% show up to immigration	didn’t appear at immigration court hearings
Law enforce-ment	Trump has all law enforcement endorsements; Biden has none	law endorsements	police endorsemen ts	police all endorsed trump	no police like biden	sheriff endorsement
	Trump brought back law and order to Seattle and Minneapolis	seattle law and order	minneapolis law and order	law and order back	brought back law and order	returned law and order
	Biden wants to defund the police	defunding the police	defund the police	biden wants to defund	biden will defund	biden said he wants to defund
	Violent crime has increased under Trump	violent crime increased	violent crime went up	trump increased violent crime	crime increased under trump	violence increased under trump
Military	Biden called military members "stupid bastards"	karen johnson	stupid bastards	appointed johnson to the academy	finest generation of warriors	troops at al dhafra air base
	Trump administration has rebuilt the military	military rebuild	invested $2 trillion	military was a joke	military was depleted	rebuilt the military
	Trump ended military diversity training because it was "racist"	ended military diversity training	military racist	anti-diversity training	diversity training	racist training
Racism	Biden called African-Americans superpredators	super predators	superpredat ors	1993 speech	predators on our streets	beyond the pale
	Trump is "the least racist person in this room"	trump not racist	trump is not a racist	trump does not discriminate	he is not racist	he is not a racist
	Trump has done more for Black community than every President except MAYBE Lincoln—especially re: HBCU funding	done more for black	done more for blacks	helped black people more	nobody's done more	nobody done more
Taxes	Trump has paid millions of dollars vs. $750 in federal income tax (in 2016/2017)	$750 taxes	$400 million in debt	trump paid no taxes	he paid less taxes than a teacher	many millions of dollars in taxes
	Trump's depressed tax burden was possible due to Obama-era legislation	obama-era tax laws	trump paid no federal income tax	trump losses	obama tax cuts 2009	obama tax cuts 2010

Appendix B: Misinformation-related topic mentions in detail

Table 1. *Misinformation-related topic mentions (and proportions) at the mention level across media streams and surveys.*

Misinformation-related topic	Newspapers	Television	Trump Twitter	Biden Twitter	Trump surveys	Biden surveys
Biden personal attacks	11,601 (27.7%)	19,996 (19.5%)	254,387 (18.5%)	2,011,037 (76.5%)	54 (13.2%)	323 (82.2%)
Campaigning	2,334 (5.6%)	3,544 (3.5%)	93,141 (6.8%)	9,839 (0.4%)	2 (0.5%)	0 (0%)
Climate	3,725 (8.9%)	5,840 (5.7%)	21,423 (1.6%)	89,580 (3.4%)	1 (0.2%)	14 (3.6%)
Courts	8 (0%)	0 (0%)	130 (0%)	3 (0%)	0 (0%)	0 (0%)
COVID-19	2,340 (5.6%)	11,619 (11.3%)	63,049 (4.6%)	44,260 (1.7%)	4 (1%)	7 (1.8%)
Economy	742 (1.8%)	3,709 (3.6%)	51,145 (3.7%)	39,544 (1.5%)	0 (0%)	0 (0%)
Election integrity	14,229 (34%)	33,500 (32.7%)	548,941 (40%)	204,937 (7.8%)	314 (76.6%)	23 (5.9%)
Foreign relations	0 (0%)	0 (0%)	2 (0%)	0 (0%)	0 (0%)	0 (0%)
Healthcare	587 (1.4%)	6,159 (6%)	11,211 (0.8%)	4,444 (0.2%)	1 (0.2%)	1 (0.3%)
Immigration	0 (0%)	0 (0%)	30 (0%)	5 (0%)	0 (0%)	0 (0%)
Law enforcement	372 (0.9%)	703 (0.7%)	11,201 (0.8%)	22,694 (0.9%)	3 (0.7%)	13 (3.3%)
Military	1,529 (3.7%)	745 (0.7%)	28,590 (2.1%)	110,035 (4.2%)	0 (0%)	3 (0.8%)
Racism	1,015 (2.4%)	5,140 (5%)	63,082 (4.6%)	65,024 (2.5%)	18 (4.4%)	9 (2.3%)
Taxes	3,360 (8%)	11,641 (11.3%)	226,794 (16.5%)	28,144 (1.1%)	13 (3.2%)	0 (0%)
Number of misinformation mentions[32]	41,842 (100%)	102,596 (100%)	1,373,126 (100%)	2,629,546 (100%)	410 (100%)	393 (100%)
Number of units	186,551	4,126,137	92,593,686	52,715,854	11,638	11,055
Misinformation mentions/unit[33]	22.4%	2.49%	1.37%	4.99%	3.52%	3.55%

[32] While "Number of misinformation mentions" refers to all mentions of any misinformation-related topic in a given stream, "Number of units" indicates the overall number of articles, segments, tweets, or surveys in that stream (i.e., all information, not just misinformation).
[33] This indicates the ratio of misinformation to information—that is, the number of mentions of misinformation divided by the number of units of information (articles, segments, tweets, or surveys). Mentions are aggregated by topic rather than by article, so a given article may contribute to multiple topics and thus be counted more than once.

Table 2. *Mentions (and proportions) for all misinformation-related topics before and after debates across media streams and surveys.*

Misinformation-related topic and date range	**Newspapers**	**Television**	**Trump Twitter**	**Biden Twitter**	**Trump surveys**	**Biden surveys**
Biden personal attacks						
Pre-debate[34]	2,288 (12.7%)	4,196 (8.6%)	88,863 (9.3%)	569,084 (62.1%)	19 (6.6%)	38 (50.7%)
Post-debate 1	5,743 (37.4%)	9,736 (29.6%)	57,929 (36.9%)	639,625 (86.4%)	11 (29.7%)	124 (93.2%)
Post-debate 2	3,570 (42.5%)	6,064 (28.6%)	107,595 (40.6%)	802,328 (82.4%)	24 (28.6%)	161 (87.0%)
Campaigning						
Pre-debate	1,723 (9.5%)	2,983 (6.1%)	89,341 (9.4%)	8,155 (0.9%)	2 (0.7%)	0 (0%)
Post-debate 1	470 (3.1%)	477 (1.5%)	2,131 (1.4%)	1,057 (0.1%)	0 (0%)	0 (0%)
Post-debate 2	141 (1.7%)	84 (0.4%)	1,669 (0.6%)	627 (0.1%)	0 (0%)	0 (0%)
Climate						
Pre-debate	1,744 (9.7%)	3,532 (7.3%)	15,161 (1.6%)	46,268 (5.1%)	1 (0.3%)	5 (6.7%)
Post-debate 1	800 (5.2%)	1,182 (3.6%)	1,762 (1.1%)	6,600 (0.9%)	0 (0%)	4 (3%)
Post-debate 2	1,181 (14.1%)	1,126 (5.3%)	4,500 (1.7%)	36,712 (3.8%)	0 (0%)	5 (2.7%)
Courts						
Pre-debate	0 (0%)	0 (0%)	12 (0%)	0 (0%)	0 (0%)	0 (0%)
Post-debate 1	8 (0.1%)	0 (0%)	115 (0.1%)	1 (0%)	0 (0%)	0 (0%)
Post-debate 2	0 (0%)	0 (0%)	3 (0%)	2 (0%)	0 (0%)	0 (0%)
COVID-19						
Pre-debate	1,057 (5.8%)	5,026 (10.4%)	26,901 (2.8%)	26,764 (2.9%)	2 (0.7%)	5 (6.7%)
Post-debate 1	912 (5.9%)	4,391 (13.4%)	5,486 (3.5%)	7,759 (1%)	0 (0%)	2 (1.5%)
Post-debate 2	371 (4.4%)	2,202 (10.4%)	30,662 (11.6%)	9,737 (1%)	2 (2.4%)	0 (0%)
Economy						
Pre-debate	471 (2.6%)	2,014 (4.2%)	24,865 (2.6%)	32,592 (3.6%)	0 (0%)	0 (0%)

[34] As in Figure 2, "pre-debate" here captures conversation before either debate took place (August 1–September 28), "post-debate 1" focuses on media content during and after debate 1 (September 29–October 21), and "post-debate 2" is limited to debate 2 and its aftermath (October 22–November 3; all these dates inclusive).

Post-debate 1	191 (1.2%)	991 (3%)	6,325 (4%)	2,709 (0.4%)	0 (0%)	0 (0%)
Post-debate 2	80 (1%)	704 (3.3%)	19,955 (7.5%)	4,243 (0.4%)	0 (0%)	0 (0%)
Election integrity						
Pre-debate	7,619 (42.2%)	21,499 (44.3%)	24,865 (2.6%)	91,031 (9.9%)	250 (86.5%)	9 (12%)
Post-debate 1	4,741 (30.8%)	8,232 (25.1%)	6,325 (4%)	34,894 (4.7%)	13 (35.1%)	0 (0%)
Post-debate 2	1,869 (22.3%)	3,769 (17.8%)	19,955 (7.5%)	79,012 (8.1%)	51 (60.7%)	14 (7.6%)
Foreign relations						
Pre-debate	0 (0%)	0 (0%)	2 (0%)	0 (0%)	0 (0%)	0 (0%)
Post-debate 1	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Post-debate 2	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Healthcare						
Pre-debate	309 (1.7%)	1,544 (3.2%)	6,827 (0.7%)	2,687 (0.3%)	1 (0.3%)	0 (0%)
Post-debate 1	204 (1.3%)	1,790 (5.4%)	3,090 (2%)	192 (0%)	0 (0%)	0 (0%)
Post-debate 2	74 (0.9%)	2,825 (13.3%)	1,294 (0.5%)	1,565 (0.2%)	0 (0%)	1 (0.5%)
Immigration						
Pre-debate	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Post-debate 1	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Post-debate 2	0 (0%)	0 (0%)	30 (0%)	5 (0%)	0 (0%)	0 (0%)
Law enforcement						
Pre-debate	258 (1.4%)	595 (1.2%)	10,612 (1.1%)	21,332 (2.3%)	2 (0.7%)	10 (13.3%)
Post-debate 1	102 (0.7%)	105 (0.3%)	321 (0.2%)	926 (0.1%)	0 (0%)	0 (0%)
Post-debate 2	12 (0.1%)	3 (0%)	268 (0.1%)	436 (0%)	1 (1.2%)	3 (1.6%)
Military						
Pre-debate	909 (5%)	436 (0.9%)	23,188 (2.4%)	80,798 (8.8%)	0 (0%)	2 (2.7%)
Post-debate 1	429 (2.8%)	227 (0.7%)	2,387 (1.5%)	25,270 (3.4%)	0 (0%)	1 (0.8%)
Post-debate 2	191 (2.3%)	82 (0.4%)	3,015 (1.1%)	3,967 (0.4%)	0 (0%)	0 (0%)
Racism						
Pre-debate	314 (1.7%)	541 (1.1%)	30,566 (3.2%)	22,747 (2.5%)	11 (3.8%)	6 (8%)
Post-debate 1	149 (1%)	962 (2.9%)	7,308 (4.6%)	9,436 (1.3%)	2 (5.4%)	2 (1.5%)

Post-debate 2	552 (6.6%)	3,637 (17.1%)	25,208 (9.5%)	32,841 (3.4%)	5 (6%)	1 (0.5%)
Taxes						
Pre-debate	1,378 (7.6%)	6,158 (12.7%)	171,785 (18.1%)	14,656 (1.6%)	1 (0.3%)	0 (0%)
Post-debate 1	1,624 (10.6%)	4,768 (14.5%)	37,132 (23.6%)	11,499 (1.6%)	11 (29.7%)	0 (0%)
Post-debate 2	358 (4.3%)	715 (3.4%)	17,877 (6.8%)	1989 (0.2%)	1 (1.2%)	0 (0%)

Appendix C: Misinformation-related topics at the source level for traditional media

In the main analysis, we used the number of mentions to track misinformation-related topics in our streams at the unit level: articles, TV segments, Twitter posts, or surveys. Number of mentions indicates how many times a given topic appears in a given stream at a given time across units, providing a direct measure of misinformation discussion. As a point of contrast, in a supplementary analysis we also measured a topic's spread by determining the proportion of sources (newspapers and TV channels) discussing the misinformation-related topic. This proportional measure captures how broadly misinformation has penetrated media discourse overall—without over-counting larger sources that publish more articles or segments.

The patterns described in the main text are similar whether we measure misinformation at the mention level or at the source level. The rise in misinformation at the source level was just as striking as described above: The proportion of newspapers discussing any misinformation grew from 5.34% before the debates to 7.86% after debate 2, while the proportion of TV channels doing so grew from 2.55% to 4.33% over the same period. In newspapers, considering the proportion of sources that mentioned a misinformation-related topic, *Biden personal attacks* and *taxes* surged around debate 1 from 5.2% to 14.8% and from 4.4% to 15.6%, respectively. While *taxes* rivaled *Biden personal attacks* around debate 1 by this measure, *taxes* still dropped off by debate 2 to 8.0%. *COVID-19* and *climate* were more prevalent when considered at the source level, with the former peaking around debate 1 (at 10.9% of sources, from 5.7% pre-debate) and the latter climbing through debate 2 (reaching a considerable 16.2%, from 7.6% pre-debate). However, the biggest difference in the source analysis is that *election integrity* outpaced all other topics—it was stable between 27% and 29% across time—while in the mentions-based analysis *Biden personal attacks* ranked first starting around the first debate.

Source-based analysis of TV channels yields similar findings to analysis of newspapers, but with smaller magnitudes: *Biden personal attacks* peaked at 12.8% around debate 1, *election integrity* dominated (but dropped from 14.5% pre-debate to a stable 13.1%), and *COVID-19, climate,* and *taxes* reached lower peak levels: 9.8% around debate 1, 4.0% around debate 2, and 7.8% around debate 1, respectively. However, *racism* and *healthcare* climbed to 6.0% and a surprising 10.3% of sources around debate 2, diverging from newspapers but reproducing the pattern in TV mentions.

Table 1. *Misinformation-related topic mentions (and proportions) at source level: Newspapers and TV channels.*

Misinformation-related topic and date range	**Newspapers**			**Television channels**		
	Pre-debate	**Post-debate 1**	**Post-debate 2**	**Pre-debate**	**Post-debate 1**	**Post-debate 2**
Biden personal attacks	457 (5.2%)	515 (14.8%)	406 (21.1%)	1,732 (2.6%)	3,294 (12.8%)	1,753 (12%)
Campaigning	815 (9.3%)	201 (5.8%)	90 (4.7%)	1,765 (2.7%)	316 (1.2%)	63 (0.4%)
Climate	661 (7.6%)	314 (9.1%)	311 (16.2%)	1,668 (2.5%)	608 (2.4%)	582 (4%)
Courts	0 (0%)	6 (0.2%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
COVID-19	499 (5.7%)	377 (10.9%)	186 (9.7%)	3,428 (5.2%)	2,513 (9.8%)	1,104 (7.6%)
Economy	216 (2.5%)	125 (3.6%)	59 (3.1%)	1069 (1.6%)	598 (2.3%)	504 (3.5%)
Election integrity	2,345 (26.8%)	998 (28.8%)	522 (27.1%)	9,545 (14.5%)	3,373 (13.1%)	1,906 (13.1%)
Foreign relations	0 (0%)	0 (0%)	18 (0.9%)	0 (0%)	0 (0%)	0 (0%)
Healthcare	191 (2.2%)	143 (4.1%)	54 (2.8%)	692 (1.1%)	931 (3.6%)	1,508 (10.3%)
Immigration	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Law enforcement	182 (2.1%)	64 (1.8%)	11 (0.6%)	528 (0.8%)	77 (0.3%)	3 (0%)
Military	573 (6.6%)	241 (6.9%)	130 (6.8%)	342 (0.5%)	182 (0.7%)	56 (0.4%)
Racism	214 (2.4%)	88 (2.5%)	176 (9.2%)	419 (0.6%)	516 (2%)	880 (6%)
Taxes	386 (4.4%)	541 (15.6%)	154 (8%)	2,286 (3.5%)	2,021 (7.8%)	475 (3.3%)
Number of source-mentions[35]	6,539	3,613	2,117	23,474	14,429	8,834
Number of sources	8,744	3,469	1,923	65,863	25,773	14,578
Proportion of sources that mention misinformation[36]	5.34%	7.44%	7.86%	2.55%	4.00%	4.33%

[35] Number of "source-mentions" indicates the number of times any source in this time period mentions any myth. Each source can be counted multiple times, so this figure may be higher than the total number of sources.

[36] This proportion indicates the prevalence of misinformation across sources—that is, the number of sources that mentioned any misinformation-related topic divided by the number of sources in that stream. It is calculated by topic and averaged across all 14 topics, hence its lower baseline than mentions per unit.

Appendix D: Breakdowns of traditional media

As a supplementary analysis, we grouped newspapers and TV channels by partisan leaning and region and compared misinformation counts between these different groups. We grouped by partisan leaning (left vs. right) using Media Bias Fact Check leanings for newspapers (see Table 2 below for these groupings) any by creating groups of TV channels with a common partisan leaning: Fox News and Newsmax for pro-Republican, MSNBC and CNN for pro-Democrat. We also analyzed only those papers and channels in "purple" or "battleground" states outside of the upper Midwest. Media in these states warrant special attention due to their often-deciding role in close national elections; this includes North Carolina, Florida, Arizona, Nevada, and Georgia.[37] Table 1 below shows the results.

Table 1. *Misinformation-related topic mentions for newspapers and television by partisan leaning and purple states.*

Category of misinformation	Liberal newspapers	Conservative newspapers	Purple state newspapers	Liberal TV	Conservative TV	Purple state TV
Biden personal attacks	4,699 (47.1%)	4,074 (24.8%)	952 (19.4%)	427 (14.5%)	3,197 (59.6%)	76 (18%)
Campaigning	580 (5.8%)	838 (5.1%)	284 (5.8%)	130 (4.4%)	207 (3.9%)	7 (1.7%)
Climate	695 (7%)	1,486 (9%)	431 (8.8%)	101 (3.4%)	371 (6.9%)	36 (8.5%)
Courts	4 (0%)	1 (0%)	4 (0.1%)	0 (0%)	0 (0%)	0 (0%)
COVID-19	374 (3.7%)	1,012 (6.2%)	327 (6.7%)	358 (12.1%)	131 (2.4%)	27 (6.4%)
Economy	126 (1.3%)	277 (1.7%)	90 (1.8%)	70 (2.4%)	215 (4%)	15 (3.6%)
Election integrity	2,395 (24%)	5,748 (35%)	1,950 (39.8%)	1,410 (47.8%)	999 (18.6%)	173 (41%)
Foreign relations	2 (0%)	10 (0.1%)	5 (0.1%)	0 (0%)	0 (0%)	0 (0%)
Healthcare	57 (0.6%)	261 (1.6%)	73 (1.5%)	50 (1.7%)	49 (0.9%)	8 (1.9%)
Immigration	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Law enforcement	72 (0.7%)	151 (0.9%)	49 (1%)	26 (0.9%)	23 (0.4%)	1 (0.2%)
Military	288 (2.9%)	647 (3.9%)	190 (3.9%)	15 (0.5%)	28 (0.5%)	5 (1.2%)
Racism	205 (2.1%)	477 (2.9%)	112 (2.3%)	125 (4.2%)	91 (1.7%)	10 (2.4%)
Taxes	487 (4.9%)	1,452 (8.8%)	432 (8.8%)	235 (8%)	53 (1%)	64 (15.2%)
TOTAL	9,984 (100%)	16,434 (100%)	4,899 (100%)	2,947 (100%)	5,364 (100%)	422 (100%)

From this analysis we derived the following two supplemental findings.

[37] We did not break down tweets or surveys in these ways because we do not have geographic data for those sources.

Supplemental Finding 1: Liberal newspapers focused more on Biden personal attacks but less on election integrity than did conservative newspapers.

Liberal newspapers accounted for a disproportionate share of coverage of *Biden personal attacks* (47.1% of misinformation in liberal newspapers, vs. 24.8% in conservative papers) despite the generally higher levels of misinformation in conservative newspapers (16,434 mentions vs. 9,984 in liberal papers; see Table 1 below for complete numbers).[38] In contrast, conservative newspapers accounted for a greater share of coverage of *election integrity* (35.0% vs. 24.0% in liberal papers). While conservative newspapers' coverage of misinformation may be expected due to the conservative candidate's propensity to advance claims that fact checkers label as misinformation, the coverage among liberal outlets may be due to their efforts to debunk those claims against the more liberal candidate. These results also suggest partisan news outlets may avoid discussing misinformation less than they avoid factual critiques of their preferred candidate, complicating the power of partisanship to drive some coverage decisions (Budak et al., 2016).

The "purple" or "battleground" states often pivotal in national elections focused on the same topics as did newspapers overall: the *Biden personal attacks, election integrity*, *climate*, and *taxes* topics. However, they focused less on *Biden personal attacks* (19.4% vs. 27.7% overall), more on *election integrity* (39.8% vs. 34.0% overall), and marginally more on *COVID-19* (6.7% vs. 5.6% overall) and *taxes* (8.8% vs. 8.0% overall; see Table 1 below for complete numbers). The slightly greater focus on pandemic misinformation may reflect interest in the overall topic given the mounting COVID-19 cases in these states through the campaign season, while the relative increase in *election integrity* and *taxes* may reflect greater concern about incumbent Trump's narrative and leadership than about Biden's supposed family issues.

Supplemental Finding 2: Conservative TV channels focused more on Biden personal attacks but less on election integrity than did liberal channels.

As Figure 1 below shows, liberal TV channels accounted for a disproportionate share of coverage of *election integrity* (47.8% of misinformation on liberal channels, vs. 18.6% on conservative ones), despite the generally higher levels of misinformation on conservative channels (5,364 mentions vs. 2,947 on liberal channels; see Table 1 below for complete numbers). In contrast, Figure 2 shows that conservative TV channels accounted for a much greater share of coverage of *Biden personal attacks* (59.6% vs. 14.5% on liberal channels). These partisan tendencies are more pronounced and inverted when compared with newspaper coverage. Much as media streams differ in their carrying capacity for political content (Jang & Pasek, 2015), these results suggest that streams also diverge in how partisanship drives responses to misinformation—that is, in what false claims liberals and conservatives deem essential to discuss.

[38] We underestimate the greater level of misinformation coverage in conservative newspapers by including in our sample more liberal- than conservative-leaning newspapers (69 vs. 37, respectively).

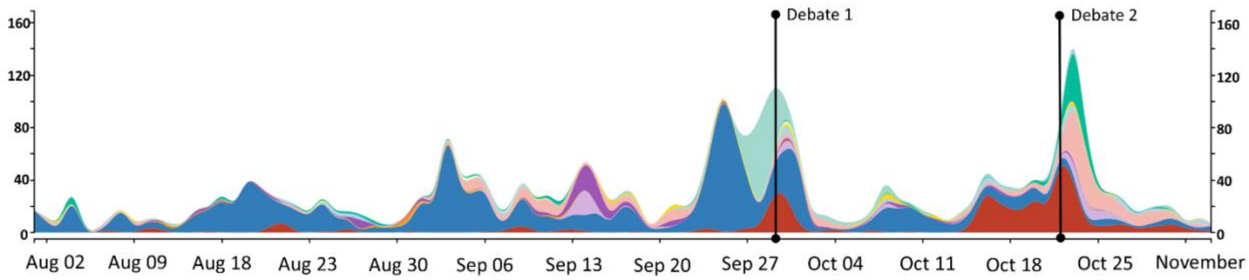

Figure 1. Mentions over time of misinformation-related topics on liberal TV channels. *The key topics depicted are Biden personal attacks (red), election integrity (blue), taxes (light green), Covid-19 (pink), campaigning (purple), climate (light purple), and racism (green). For an interactive version, click here.*

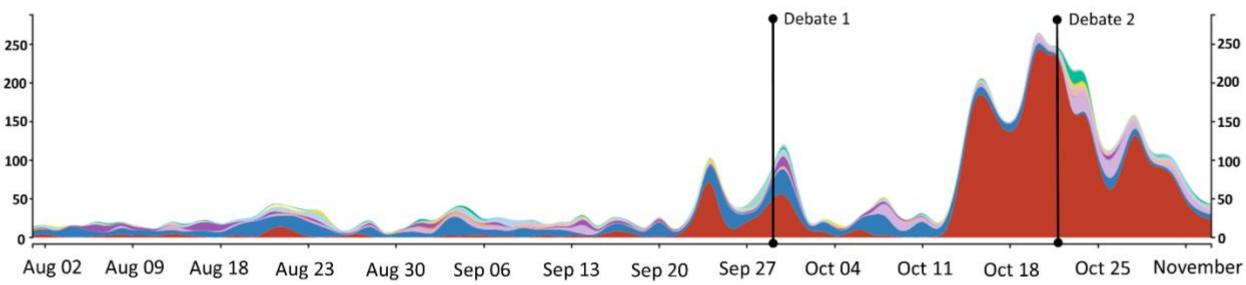

Figure 2. Mentions over time of misinformation-related topics on conservative TV channels. *The topics depicted are Biden personal attacks (red), election integrity (blue), climate (light purple), campaigning (purple), and racism (green). For an interactive version, click here.*

TV in purple states focused on the same misinformation-related topics as did cable TV (and newspapers) overall: the *Biden personal attacks, election integrity*, *climate*, and *taxes* topics (see Table 1 above for complete numbers). However, they focused less on *COVID-19, healthcare,* and *racism* (6.4%, 1.9%, and 2.4% vs. 11.3%, 6.0%, and 5.0% overall), and more on *election integrity* and *taxes* (41.0% and 15.2% vs. 32.7% and 11.3% overall). Such trends largely mirror the pattern in purple-state newspapers, with less focus on *COVID-19*, *healthcare*, and *racism* similarly suggesting more concern (arguably) over Trump's candidacy than Biden's.

Finally, Table 2 lists newspapers by partisan leaning and those in purple states.

***Table 2**. Newspapers by partisan leaning and in purple states.*

Liberal	**Moderate**	**Conservative**	**Purple states**
Alabama Public Radio	Associated Press	alabamanewscenter.com	Albuquerque Journal
Anchorage Daily News	Chattanoogan.com	Albuquerque Journal	Arizona Republic
Arizona Republic	columbian.com	arkansasonline.com	Asheville Citizen-Times
Arkansas Times	Des Moines Register	Boston Herald	Atlanta Journal-Constitution
Asheville Citizen-Times	Duluth News Tribune	Carroll County News	Augusta Chronicle
Atlanta Journal-Constitution	Financial Times	Chicago Tribune	Courier-Journal (Louisville)
Bangor Daily News	Gephardt Daily	Columbus Dispatch	Des Moines Register
Business Insider	Green Bay Press-Gazette	courierpress.com	Fort Worth Star-Telegram
Chicago Sun-Times	journalrecord.com	dailypress.com	goupstate.com
cleveland.com	keloland.com	Dallas Morning News	Houston Chronicle
Concord Journal	Lansing State Journal	Desert Sun	Kansas City Star
courant.com	Longview News-Journal	Detroit News	Las Cruces Sun-News
courier-journal.com	New Bern Sun Journal	eastidahonews.com	Las Vegas Review-Journal
DelawareOnline.com	Quad City Times	gjsentinel.com	Las Vegas Sun
Detroit Free Press	registerherald.com	inforum.com	New Bern Sun Journal
East Bay Times	Reuters	Juneau Empire	News-Sentinel (Fort Wayne)
Honolulu Star Advertiser	Sioux City Journal	Las Vegas Review-Journal	Northwest Arkansas Democrat-Gazette
Houston Chronicle	syracuse.com	New York Post	Plain Dealer (Cleveland)
idahostatejournal.com	The Daily Gazette	Omaha World-Herald	postandcourier.com
indystar.com	The Post and Courier	OregonLive.com	Richmond Times-Dispatch
Jackson Free Press	The Waterloo-Cedar Falls Courier	postandcourier.com	St. Louis Post-Dispatch
laramielive.com	WLTZFirstNews.com	Press of AC	Star Tribune (Minneapolis)
Las Cruces Sun-News		Republican American	SunSentinel
Las Vegas Sun		Shreveport Times	Tampa Bay Times
Lincoln Journal Star		Springfield News-Leader	Tennessean
Los Angeles Times		SunSentinel	The Columbus Dispatch
Milwaukee Journal-Sentinel		Tennessean	The Dallas Morning News
New Haven Register		The Post-Crescent	Winston-Salem Journal

New York Times		The Spokesman Review	WLTZFirstNews.com
NJ.com		thegazette.com	
PennLive.com		TNonline.com	
POLITICO		Tulsa World	
Portland Press Herald		unionleader.com	
Providence Journal		Washington Times	
qctimes.com		wcax.com	
Register-Guard		West Central Tribune	
San Francisco Chronicle		Winston-Salem Journal	
San Jose Mercury News			
Santa Barbara Independent			
seattletimes.com			
sevendaysvt.com			
sltrib.com			
St. Louis Post-Dispatch			
Stamford Advocate			
startribune.com			
Talking Points Memo			
Tampa Bay Times			
The Atlantic			
The Baltimore Sun			
The Boston Globe			
The Commercial Appeal			
The Denver Post			
The Hill			
The News-Times			
The York Dispatch			
theadvocate.com			
TIME			
USA Today			
Washington Post			

Appendix E: Correlations between media streams across topics

Table 1. *Correlations between media streams for each of the five most prevalent topics in at least one media stream.*

Misinformation-related topic	**Newspapers and TV**	**Newspapers and Twitter**	**TV and Twitter**	**Trump Twitter and Biden Twitter**
Biden personal attacks	0.878***	0.553***	0.495***	0.450***
COVID-19	0.548***	0.300**	0.289***	0.055
Election integrity	0.603***	0.169	0.388***	0.01
Healthcare	0.177***	0.192	0.191***	0.031
Racism	0.978***	0.778***	0.712***	0.463***

Note: * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Appendix F: Dictionary validation

An essential step in workflows involving dictionaries (conceptually related word or phrase lists) is to check whether they mean what we think they mean—that is, to validate them in the study context (Grimmer & Stewart, 2013). The question here is how effectively our dictionaries capture media discussion of our misinformation-related topics, as opposed to unrelated conversation about a different topic. While there are different approaches for testing the validity of dictionaries, our approach is to manually annotate a random set of posts identified by the dictionaries as being misinformation-related.[39]

Our validation procedure involved hand-coding a sample of 101 social media posts (tweets) for three of the most common misinformation-related topics (*climate change*, *Biden personal attacks*, and *election integrity*) and three of the least common (*healthcare*, *taxes*, and *military*) on social media. We randomly selected sample tweets from those tweets that matched a phrase in one of the myth dictionaries. For each topic, we selected a single phrase list related to a specific false claim: respectively, these are claims about Hunter Biden, his laptop or the Ukraine scandal; about the election being "rigged" or issues with mail-in ballots; that the California forest fires were caused by forest mismanagement (not climate change); that prices of insulin and other prescription drugs were falling; that Trump paid millions of dollars vs. $750 in federal income tax in 2016 and 2017; and that Biden called military members "stupid bastards." For the most frequent topics, each tweet was triple coded by independent coders; 18 coders each labeled approximately 50 tweets. For the least common topics, each tweet was double coded, and the first author resolved any disagreements. In both cases, coders answered two questions to determine the high-level topic and the specific topic of the post. These questions and the response options are shown in Table 1.

[39] Here we measure precision of our dictionary as opposed to coverage. Given that our dictionaries are non-exhaustive and may leave out phrases relevant to our myths, we have likely undercounted the misinformation conversation.

Table 1. *Coding options for our two dictionary validation exercises.*

Question	**Options for frequent topics validation**[40]	**Options for infrequent topics validation**
Q1. Which high-level topic is the post about?	*Biden's family/personal life*	*Healthcare*
	Trump's family/personal life	
	Election integrity	*Taxes*
	Climate change	
	Health	*Military*
	Economy	
	None of the above	
Q2. Which specific topic is the post related to?	*The election being "rigged"/issues with mail-in ballots*	*Prices of insulin and other prescription drugs are falling*
	Hunter Biden, his laptop or the Ukraine scandal	
	Forest mismanagement as a cause of the wildfires in CA	*Trump paid millions of dollars vs. $750 in federal income tax in 2016/2017*
	The US having the greatest economy in the history of the country	
	Serious people (like Fauci) saying that masks are not important	*Biden called military members "stupid bastards"*
	None of the above	

Based on the hand-coding results, we measured our dictionaries' accuracy, or the proportion of tweets flagged as pertaining to a misinformation-related topic that were actually about that topic. For the most frequent topics, we also measured their task-based agreement, or the proportion of coders that agreed on the most common label for a given tweet; and their inter-rater reliability, or the overall consistency between coders (as measured by Krippendorff's alpha). While task-based agreement measures reliability at the task level, accuracy and alpha are computed at the question level—that is, they compare across topics and across myths. Table 2 shows our validation results for the most frequent topics using all of these metrics.

[40] Cells in *italics* in the center and right columns were used to select tweets for validation purposes—in other words, we expected these topics to be represented in our sample. The false claims not in italics were included to increase the number of options given to coders, making the test more rigorous.

Table 2. *Dictionary validation results for most frequent topics.*

Level of measurement	**Task-based agreement**	**Alpha**	**Accuracy**
Topic (Q1)	0.932	0.863	0.970
Myth (Q2)	0.908	0.818	0.954

The task-based agreement for both questions is over 0.9, and the alpha score for both questions is over 0.81, indicating that independent coders tend to assign the same topic and myth to a given tweet. These results suggest high reliability in our phrase-based method for identifying misinformation-related social media content. Moreover, the very high accuracies (over 0.95) demonstrate that the hand-selected topic and myth for a given tweet typically match the topic and myth predicted by phrase matching, evidencing the validity of our dictionary-based method for the most frequent topics. Table 3 shows the resulting accuracies for each of the least common topics we validated.

Table 3. *Dictionary validation accuracies for least frequent topics.*

Level of measurement	***Healthcare* topic**	***Taxes* topic**	***Military* topic**
Topic (Q1)	0.989	1.00	0.593
Myth (Q2)	0.851	0.842	0.593

These accuracies are also generally high, reaching full or nearly full general agreement about the *taxes* and *healthcare* topics and about 0.84 for their specific myth. However, both accuracies for the *military* topic were 0.59, due almost entirely to two overly broad phrases indicating names of political importance: "Andrew Bates" and "Karen Johnson." The former was a campaign official who sought to contextualize Biden's comments, while the latter was mentioned specifically in Biden's speech to service members—but tweets selected by matching these phrases rarely relate to the relevant myth (about Biden's "stupid bastards" comment). Nonetheless, these results overall suggest that such imprecise phrases were rare and that our less common topics are also effective in capturing misinformation discussion in the media.