Official yet questionable: Examining misinformation in U.S. state legislators' tweets

Yuehong Cassandra Tai*   Roan Buma †   Bruce A. Desmarais ‡

Abstract

We study the roles of elected officials in the dissemination of misinformation on Twitter. This is a particularly salient online population since elected officials serve as primary sources of information for many stakeholders in the public, media, government, and industry. We analyze the content of tweets posted from the accounts of over 3,000 U.S. state lawmakers throughout 2020 and 2021. Specifically, we identify the dissemination of URLs linked to unreliable content. Our starkest finding is that Republicans share more misinformation than do Democrats by an order of magnitude. Additionally, we uncover distinct patterns in the temporal trends of tweets and tweets associated with misinformation across party and state lines. Delving into the content of tweets referencing unreliable URLs reveals discussions of election integrity, abortion, COVID-19 policies, and immigration. Furthermore, consistent with the literature on asymmetric polarization, Republicans exhibit a greater inclination towards engaging in partisan attacks. We also find that state lawmakers often tweet about state-specific topics. These findings enhance our understanding of misinformation, political communication, and state politics.

Keywords: misinformation, Twitter, state legislator, political communication

1 Introduction

The proliferation of misinformation on social media poses a major threat to democracy in the United States (Osmundsen, Bor, Vahlstrup, Bechmann, & Petersen, 2021). Although the influence of political elites on public opinion has been well-documented (Berinsky, 2017; Slothuus & Bisgaard, 2021), we have limited knowledge about the reliability of information shared by those elites, with the exception of some recent studies of U.S. Congress members (e.g., Lasser et al., 2022; Mosleh & Rand, 2021). To advance knowledge in this area, we investigate U.S. state legislators—a population of officials with significantly more members than Congress—who are more reliant on social media to connect with constituents and other stakeholders due to the lack of state and local media sources (T. Kim et al., 2021).

*The Center for Social Data Analytics, The Pennsylvania State University (yhcasstai@psu.edu).
†Vrije Universiteit Amsterdam (roanbuma@live.nl).
‡The Center for Social Data Analytics, The Pennsylvania State University (bdesmarais@psu.edu).

The majority of U.S. state legislators use Twitter (Cook, 2017; T. Kim et al., 2021). We examine tweets from legislators over a two-year period (2020–2021), a considerably longer period than used by previous studies on misinformation shared by American political elites. This period encompasses numerous notable political and social events, such as the COVID-19 pandemic, the 2020 election, and the Black Lives Matter movement. This provides a fertile ground for examining trends and disparities in sharing misinformation across states and parties. To identify misinformation, we focus on the quality of the sources linked by legislators. Examining URLs is a common approach to identifying misinformation in tweets (Bellutta, Uyheng, & Carley, 2022; Chen et al., 2022; Teng, Lin, Chung, Li, & Kovashka, 2022). Analyzing URL quality allows us to capture an array of misinformation content, an approach that complements more specialized treatments of individual topics of misinformation (e.g., elections, see Green, Hobbs, McCabe, and Lazer (2022) and vaccines, see Jamison et al. (2020)).

Analyzing state-level officials provides insights unavailable through studying national-level officials: the variation in misinformation dissemination across states. We find that (1) the temporal trend of tweets containing URLs, excluding those from social media and search engines, differs from the trend in the percentage of tweets with unreliable URLs; (2) the dissemination of unreliable URLs varies significantly across political parties; (3) topics in unreliable tweets include election integrity, abortion, COVID-19 policies, criticism of Biden's domestic policies, Trump's campaign, and immigration; and (4) there is substantial variation across states in the rate at which unreliable URLs are shared.

This study is, to the best of our knowledge, the first analysis of the dissemination of misinformation by state-level officials, examining the largest single population of lawmakers ever studied in this context. Our study contributes to the expanding literature on asymmetric partisan politics, where polarization, affective partisanship, and extremism are stronger on the right due in part to the "conservative media universe" (Grossmann & Hopkins, 2016). We find significant partisan disparities in the dissemination of misinformation, which aligns with patterns of asymmetric polarization given that misinformation is significantly more extreme and sensational (Jerit & Zhao, 2020). Our results also provide new evidence of variation across states within an increasingly nationalized political landscape (Grumbach, 2022; Hopkins, 2018). Accordingly, our findings contribute to research on state politics, digital politics, and legislative politics.

2 Methods & Research Design

Our primary objective is to examine variability in the dissemination of misinformation by state legislators over time, political party, and state. Additionally, we aim to gain insight into the prevalent topics about which state legislators disseminate misinformation. In the following sections, we outline our method for measuring misinformation dissemination, analyze trends in dissemination, investigate partisan differences, explore the topical content of misinformation-laden tweets, and summarize variations observed across states.

Our unit of analysis is tweets from state legislators that include URLs that are not originating from social media or search engines. Following the best practices regarding the trustworthiness of shared information (Grinberg, Joseph, Friedland, Swire-Thompson, & Lazer, 2019; Guess, Nyhan, & Reifler, 2020; Lasser et al., 2022), we assess the credibility of these tweets by evaluating the reliability of the URL domains. For this purpose, we collected URL ratings coded by Media Bias/Fact Check (MBFC, mediabiasfactcheck.com) as our raw reference source, a widely used source in previous research on misinformation (e.g., Chen et al., 2022; Guimaraes, Figueira, & Torgo, 2018; Stefanov, Darwish, Atanasov, & Nakov, 2020). However, we note that MBFC is not the only news/website indexing platform (e.g., OpenSources (Han, Kumar, & Durumeric, 2022)). Since we study aggregate patterns of sharing, and not, e.g., references to specific websites, we expect that our results would be robust to the use of alternative sources for URL classification. Nonetheless, integrating multiple URL sources into a single quantitative study is challenging as specific categorizations (e.g., low fact, questionable) vary across alternative sources.

2.1 Raw Data

We collected 3,345,232 tweets from all 50 states from 2020-01-01 to 2021-12-31 using the Academic Twitter API through the R package academictwitteR (Barrie & Ho, 2021). Following the procedure outlined in T. Kim et al. (2021), we periodically retrieved tweets from legislators' Twitter accounts throughout this period. Of the 8,003 state representatives and senators who were in office during our data collection period, 5,712 legislators, comprising 2,943 Democrats, 2,740 Republicans, and 29 Independents, had at least one Twitter account (T. Kim et al., 2021).[1] Importantly, a significant number of Twitter accounts may have been inactive during the collection period or inaccessible after legislators left office. Despite these restrictions, the collection of all available tweets still encompasses 64% of Democrats, 61% of Republicans, and 55% of Independents (see T. Kim et al. (2021) for further information on account scope and collection). Given that Democrats were more active on Twitter, 70.9% of the collected tweets originated from Democratic legislators, while 28.6% were from Republican legislators, despite the comparable numbers of Democrats (n = 1,885) and Republicans (n = 1,682).

2.2 References for Unreliable URLs

We scraped URL rating details from the MBFC website, including the Source URL, Bias Category, Bias Rating, Questionable Reasoning, Factual Reporting level, and the date the record was last updated. After removing duplicates, our MBFC data includes 5,255 unique URL domains. This data will be useful for future research on the dissemination of misinformation on social media.

We use the term 'unreliable' to refer to the URL categories, as rated by MBFC, that we treat as sources of misinformation. We defined unreliable URLs through the following steps. First, we considered all URLs classified as questionable sources, those having mixed, low, or very low factual reporting, and those designated as conspiracy-pseudoscience (n = 1,829). To refine our references, we retained URLs that were categorized as questionable due to conspiracies, pseudoscience, and failed fact checking and filtered out URLs that were labeled as having questionable sources because of transparency-related and/or ideological bias. We also removed official websites, such as gop.gov and democrats.org. Our goal in thinning out the URLs was to focus on the most misleading content, not just the most politically biased—an important distinction given that we are studying politicians. We ended up with 1,292 unreliable sources. Since not all

[1] Unlike Facebook accounts, we cannot distinguish between legislators' official accounts and campaign accounts based on their account verification.

tweets spreading misinformation include URLs, our process provides a conservative assessment of the scale of misinformation spread by state legislators.

The political leaning of unreliable content on the MBFC list is, on average, skewed to the right (n = 974) compared to the amount of left-leaning unreliable content (n = 43) (see Table 1). In total, the number of “right” labeled sources (n = 1,606) is larger than “left” (n = 968). We deal with this issue later when analyzing party differences through weighting.

Table 1: MBFC Categories: Examples, Total Frequencies, and Bias Label Frequencies

Bias Category	Examples	N	%	Bias Rating*			
				"left"	%	"right"	%
Left bias	CNN, The New Yorker, The Huffington Post, Vox	425	8.1	231	54.4	0	0.0
Left-center bias	BBC News, Bloomberg, CBS News	831	15.8	639	76.9	1	0.1
Least biased	Reuters, Factcheck.org, Poynter, Pew Research	1037	19.7	2	0.2	2	0.2
Right-center bias	Forbes, Fox Business, Le Figaro (FR), NY Post	478	9.1	0	0.0	388	81.2
Right bias	Daily Express (UK), The Sun (US)	331	6.3	0	0.0	194	58.6
Conspiracy-pseudoscience	QAnon, Infowars, 4chan.org, PETA	443	8.4	11	2.5	160	36.1
Questionable source	Fox News, Parler, Breitbart, Occupy Democrats	1386	26.4	66	4.8	857	61.8
Pro-science	Covid.gov, NASA, Sage Journals	170	3.2	7	4.1	0	0.0
Satire	The Onion, Fark, Cracked, Clickhole	154	2.9	12	7.8	4	2.6
Total		5255	100.0	968	18.4	1606	30.6
Unreliable source+	Breitbart, thefederalist.com, townhall.com, theblaze.com	1292	24.59	43	3.3	974	75.2

Except for unreliable source, the categorization is based on the labels provided by MBFC. * Source bias was determined for each MBFC entry by querying the *Bias Rating* variable for the words "left" and "right." 1,585 sources did not include a *Bias Rating*.
+The unreliable source category was created by the authors.

2.3 Analysis data

Since we focused on URL quality, we constructed our analysis data set (n = 383,193) by excluding tweets without URLs and those with URLs linked to social media and search engines. Our analysis data comprises 1,783 Democrats who tweeted 66.63% of the total tweets (n = 255,319), 1,464 Republicans who tweeted 35.57% of the tweets (n = 124,814), and 12 Independents who tweeted the remaining tweets (n = 3,060). In our analysis data set, 13,420 tweets included unreliable URLs. Of these, 12,785 were shared by 575 Republicans (10.24% of Republicans' tweets) and 630 were tweeted by 221 Democrats (0.25% of Democrats' tweets). There is no gold standard against which to compare these percentages. However, in a recent study that used the Twitter streaming API to gather health-related tweets (Singh et al., 2020), researchers found that, of all tweets including URLs, the percentage of tweets including low-quality and/or fake-news URLs was approximately 2%. The rate of questionable URLs shared by Democratic state legislators is relatively low in comparison, while the rate for Republicans is substantially higher.

Although we do not know precisely what drives the dissemination of misinformation by elected officials, we inquire whether the trend in the percentage of sharing unreliable URLs follows the ebb and flow of the total tweets in our analysis data. We analyze the daily tweet counts and the percentage of unreliable tweets shared by Democrats and Republicans, respectively. Figure 1 illustrates the temporal trends of tweet count and the percentage of sharing unreliable URLs by party. Both Democrats and Republicans had their top 10 tweet peaks between mid-March and early April 2020, with a focus on COVID-19 developments, state measures, mitigation and relief policies, and the 2020 census. On peak days, Democrats tweeted around 1,000 times, while Republicans tweeted fewer than 450 times. Notably, the surge in COVID-19-related tweets returned to pre-pandemic levels more quickly for Republicans than for Democrats, aligning with Republicans' perception of COVID-19 as a lesser health hazard (Pew Research Center, 2020). Regarding unreliable tweets, we observe an increasing trend in the percentage of unreliable URLs shared by Republicans with peaks in mid-2021. In contrast, we do not identify a clear trend, either upward or downward, in the percentage of unreliable URLs shared by Democrats. This finding, viewed from the perspective of the political divide, partially runs counter to recent work that notes the increasing prevalence of misinformation on social media (He & He, 2022; Mrah, 2022; Weber et al., 2021). The bottom panel of Figure 1 shows that the average percentage of unreliable URLs over 723 days was around 3.5%. However, Democrats had a maximum of 2%, while Republicans had a maximum of 30%.

This striking pattern could suggest a higher prevalence of unreliable URL sharing by Republicans. However, the MBFC index includes more right-leaning sources (1,606) than left-leaning sources (968). It is possible that right-leaning sources have a higher prevalence of unreliable content than the overall population of URLs. Another possible explanation for this ideological disparity in unreliable URLs is bias in the MBFC source selection process. As we lack precise information about this process and cannot rule out this possibility, we explore whether the observed differences between Democrats and Republicans are attributable to ideological disparities in sources by applying a weighting scheme.

[Insert Figure 1 here]

3 Results

3.1 Party differences in unreliable URL dissemination

In this section, we compare the percentage of unreliable URL dissemination between political parties, adjusting for potential bias in the MBFC URL index. Republicans tend to share right-leaning sources more frequently, while Democrats tend to share left-leaning sources. To address the possibility of over-sampling right-leaning sources in MBFC's construction of the URL list, we introduce a weighting scheme that assumes equal numbers of right- and left-leaning sources in the population. The weighting utilizes the ratio of right- to left-leaning sources in MBFC's source pool, counting each right-leaning and neutral URL as one share and each left-leaning URL as 1.66 (1,606/968) shares to account for hypothetical under-sampling of left-leaning unreliable sources.[2] Legislators with fewer than 10 tweets are excluded from the analysis to avoid misleading percentages. As a result, 838 of 3,582 legislators are excluded.

The weighted partisan comparison is visualized in Figure 2. Since the data is heavy-tailed with a large number of zeros for both parties, a linear-scaled plot is insufficient to capture the majority of the data. Therefore, we employed a pseudo-log (base-10) transformation, which avoids taking the logarithm of zero by adding 1 to the absolute value of x. For large positive numbers, a pseudo-log behaves much like a log (base-10). For ease of interpretation, the labels on both axes utilize the original linear scale values rather than logarithmic scale values.

Our analysis reveals a statistically significant difference in the mean percentage of unreliable URLs shared by Republicans and Democrats ($p < 0.001$ in a two-tailed test). Republicans have a mean percentage of 5.577%, twenty times higher than Democrats' mean percentage of 0.275%. Furthermore, we find that 52.57% of Republican legislators have shared at least one unreliable URL, while only 15.03% of Democratic legislators have done so. A large majority of legislators (70.14%) have not shared unreliable URLs. Variations exist within both parties, although to different degrees. The median percentage of unreliable URLs for Democrats is 0, with a standard deviation of 1.738 and a maximum percentage of 46.948. On the contrary, the median percentage for Republicans is 0.571, with a standard deviation of 10.476 and a maximum percentage of 85.714. To test the sensitivity of the data set weighting, we performed a robustness check without applying the weight. Although the mean percentage for Democrats decreased by 0.04 percentage points, the main result remains robust (see Appendix A for detailed information).

Our findings reveal a significant partisan asymmetry in the dissemination of unreliable URLs, highlighting that Republican state legislators show a considerably higher tendency than Democrats to share tweets containing such URLs. Despite this disparity, the majority of legislators refrained from sharing unreliable URLs during the study period. Research on Congress has identified an increasing level of partisan politics that is not equally divided between parties, with the Republican Party taking a more prominent role in discussions about polarized issues (Hacker & Pierson, 2005). In the subsequent section, we delve deeper into this asymmetry by examining the specific topics in unreliable tweets across parties.

[Insert Figure 2 here]

3.2 Topics in unreliable tweets

To explore the specific topics discussed within the context of unreliable URL dissemination, we

[2] Among unreliable tweets, 13,420 (99.84%) have ideological labels, and only 22 unknown bias URLs get a weight of 1.

trained structural topic models for the full set of unreliable URLs using the *stm* R package (Roberts, Stewart, & Tingley, 2019). In our analysis, we incorporated partisanship and date as covariates in the topic prevalence equation. This functionality of STM allows the likelihood that a token (i.e., word) within a document (e.g., tweet) is drawn from a given topic to depend on attributes of the document (e.g., the author's partisanship, the date of the tweet). Following the best practices and diagnostic procedures outlined by Roberts et al. (2019), we determined the optimal number of topics to be 38. We tested models with varying topic numbers close to 38 and discovered that this number yielded the most understandable set of topics.

Figure 3 presents the top words for each topic based on frequency and exclusivity scores (FREX scores, Airoldi and Bischof (2016)), along with the prevalence of each topic in the models. By examining the top FREX words and reviewing 20 randomly selected associated tweets for each topic, we identified the most prevalent and interpretable topics. These include COVID-19 policies, Trump's 2020 campaign, immigration at the border, critiques of Biden's domestic policies, abortion, and election integrity. The mean proportions of topics across parties are plotted in Figure 4. Dashed lines indicate statistically significant disparities ($p < 0.05$) in topic prevalence across parties for five topics. Republicans demonstrated a greater emphasis on topic 29, criticisms of Biden's domestic policies, topic 1, attributing bias to Democrats in Missouri's audit of Senator Hawley, and topic 3, scrutinizing COVID relief policies and mask mandates. Democrats, on the other hand, exhibited a higher prevalence of topics 30 and 31, which are not easily interpretable.

Our findings fit with the broader results of research on misinformation largely focused on ordinary social media users, not political elites. For example, the prevalence of topics supports that misinformation tends to spread more readily when it pertains to highly polarized topics (Y. M. Kim et al., 2018). The divergence in topics across parties demonstrates that users are more inclined to share misinformation if the perspective presented in the content reinforces their beliefs and partisan views on a polarized subject (Neyazi & Muhtadi, 2021; Yeon Lee, 2020). In our study, this partisanship-driven misinformation is disproportionally prominent for Republicans, reflecting previous findings that the coordinated Republican Party is capable of imposing ideological discipline and engaging in partisan warfare to question opponents' motives (Grossmann & Hopkins, 2016; Theriault, 2013).

[Insert Figure 3 here]

[Insert Figure 4 here]

3.3 Unreliable tweets across states

The last dimension we investigate—a perspective made possible by our focus on state-level officials—is how the dissemination of unreliable URLs varies across states. Through our analysis, we discovered considerable heterogeneity in the proportion of unreliable URLs across different states (Figure 5). Arizona emerges as the foremost purveyor of unreliable tweets (n = 6,342, 28.35%), followed by Alabama (n = 410, 9.73%) and Arkansas (n = 391, 8.41%). When accounting for the number of tweets from Democrats and Republicans in Arizona and employing our weighted mean percentage of unreliable tweets, the expected percentage of unreliable tweets in Arizona should be 3.51% rather than 28.35%. This inflated percentage was driven by the actions of two specific legislators who collectively disseminated the majority of unreliable tweets (see details in Appendix B). This finding fits with the general "bursty" and heavy-tailed nature of digital communication on social media platforms, where a disproportionate volume of interactions are driven by a small number of influential actors (Bessi et al., 2015; Lerman & Ghosh, 2010; Myers & Leskovec, 2014).

[Insert Figure 5 here]

A further examination reveals that states have varying temporal patterns in the percentage of unreliable tweets: some states had more concentrated peaks, while others had more dispersed peaks. For example, Pennsylvania experienced peaks in the second half of 2021, whereas Arizona's peaks spread across both 2020 and 2021 (as depicted in Figure 6).

[Insert Figure 6 here]

To understand the content of unreliable tweets, we sampled 50 tweets in peak days, characterized by the highest absolute number of unreliable tweets, from Arizona, Pennsylvania, Texas, and Tennessee. We found that topics varied. Arizona's unreliable tweets covered a range of topics (the border crisis, AZ's election audit/election fraud, critical race theory/BLM, abortion, COVID-19 measures/leak theory), as did Pennsylvania's (abortion, PA's election audit, and COVID-19 vaccines/leak theory). Texas' unreliable tweets (covering topics like COVID-19/anti-Fauci, abortion, and BLM/police defunding) differed from Tennessee's unreliable tweets (which covered policy funding, BLM/1619 projects, and election fraud/China's intervention).

Recent scholarship on state politics has identified a trend towards nationalization (e.g. Burke, 2021; Zingher & Richman, 2019). This phenomenon entails a diminishing prominence of the characteristics that traditionally define "local politics." Nationalization can be attributed to various factors, including top-down influences stemming from nationally consolidated parties and their alliances, bottom-up behaviors of average voters that align with national political trends, or both (Grumbach, 2022; Hopkins, 2018). Our results regarding this trend are mixed. In tweets containing unreliable URLs, state legislators discuss highly nationalized issues. However, the ebb and flow of attention within states tends to coincide with state-specific events and discussions. For example, a flurry of tweets about the 2020 election audit in Arizona in late June 2021 arose as the ballot recounting effort in Arizona was completed (Bydlak et al., 2021). The patterns we identify are consistent with the process by which the national conversation determines the topics most subject to infiltration by misinformation, and state-specific events drive the timing of misinformation gaining broad traction.

4 Conclusion

In this paper, we present an example of extensive descriptive work that focuses on a highly salient but understudied topic—the dissemination of misinformation by elected officials. There is considerable need for such research in the rapidly growing field of digital politics (Munger, Guess,

& Hargittai, 2021). We identified unreliable tweets posted by U.S. state legislators between 2020-01-01 and 2021-12-31. The temporal trends of tweets diverged from the percentage of unreliable tweets. Although the general trend of tweets remained relatively stable, the percentage of unreliable tweets fluctuated, with variations observed across parties. Our strongest finding is that Republicans share a larger percentage of unreliable URLs than do Democrats—a result that is robust to correction for potential bias in the MBFC's sampling of URLs.

Through the implementation of structural topic modeling, we also identified the key topics discussed within unreliable tweets, encompassing COVID-19, 2020 election integrity, abortion, immigration, and more. Republicans tended to focus on criticisms of Biden and Democrats' public health and economic policies. These findings emphasize that elected officials are subject to the same forces as ordinary social media users—they are prone to sharing misinformation about subjects that are highly polarized politically and consistent with partisan ideology. At the state level, we found variations across states in the percentage and trends of unreliable tweets over time. Prolific sharers of misinformation focused on different aspects and some topics were state specific. This result highlights yet another way in which researchers can take advantage of the comparative nature of state politics research.

Our study extends the examination of asymmetric politics to the state level, providing empirical evidence of local characteristics within the broader trend of nationalized politics (Grossmann & Hopkins, 2016; Grumbach, 2022; Hopkins, 2018). Given the crucial role of state politics in shaping policymaking and the inherent threat misinformation poses to democracy, future research should investigate: 1) the factors underlying the varying degrees and topical focuses of misinformation dissemination across states and 2) the causes and consequences of misinformation dissemination by subnational officials on social media.

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Notes on contributors

Yuehong Cassandra Tai is a Postdoctoral Scholar at the Center for Social Data Analytics, Penn State University. She studies public opinion, public policy, and digital communication with a current focus on misinformation of political elites.

Roan Buma is a student in the research Master's program Big Data for Society, which is linked to the Institute for Societal Resilience at Vrije Universiteit Amsterdam. He is also a junior

researcher at the department of Political Science and Public Administration, at Vrije Universiteit Amsterdam. He received a bachelor's degree in political science from Vrije Universiteit Amsterdam (cum laude). His research is focused on political communication, public opinion, and the consumption of digital media.

Bruce Desmarais is the DeGrandis-McCourtney Early Career Professor in Political Science, Director of the Center for Social Data Analytics, and an Affiliate of the Institute for Computational and Data Sciences at Penn State University. His research is focused on methodological development and applications that further our understanding of the complex interdependence that underlies politics and public policy. Methodologically, he focuses on methods for modeling networks, analyzing text, and running experiments on social systems. Primary application areas of interest to Bruce include public policy diffusion and digital communications involving political elites.

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Figure 1: Daily Count of Tweets and Percentage of Unreliable Tweets Shared by State Legislators, 01/01/2020 - 12/31/2021. Vertical dotted lines indicate the top 10 peak days. Y-scale varies by party.

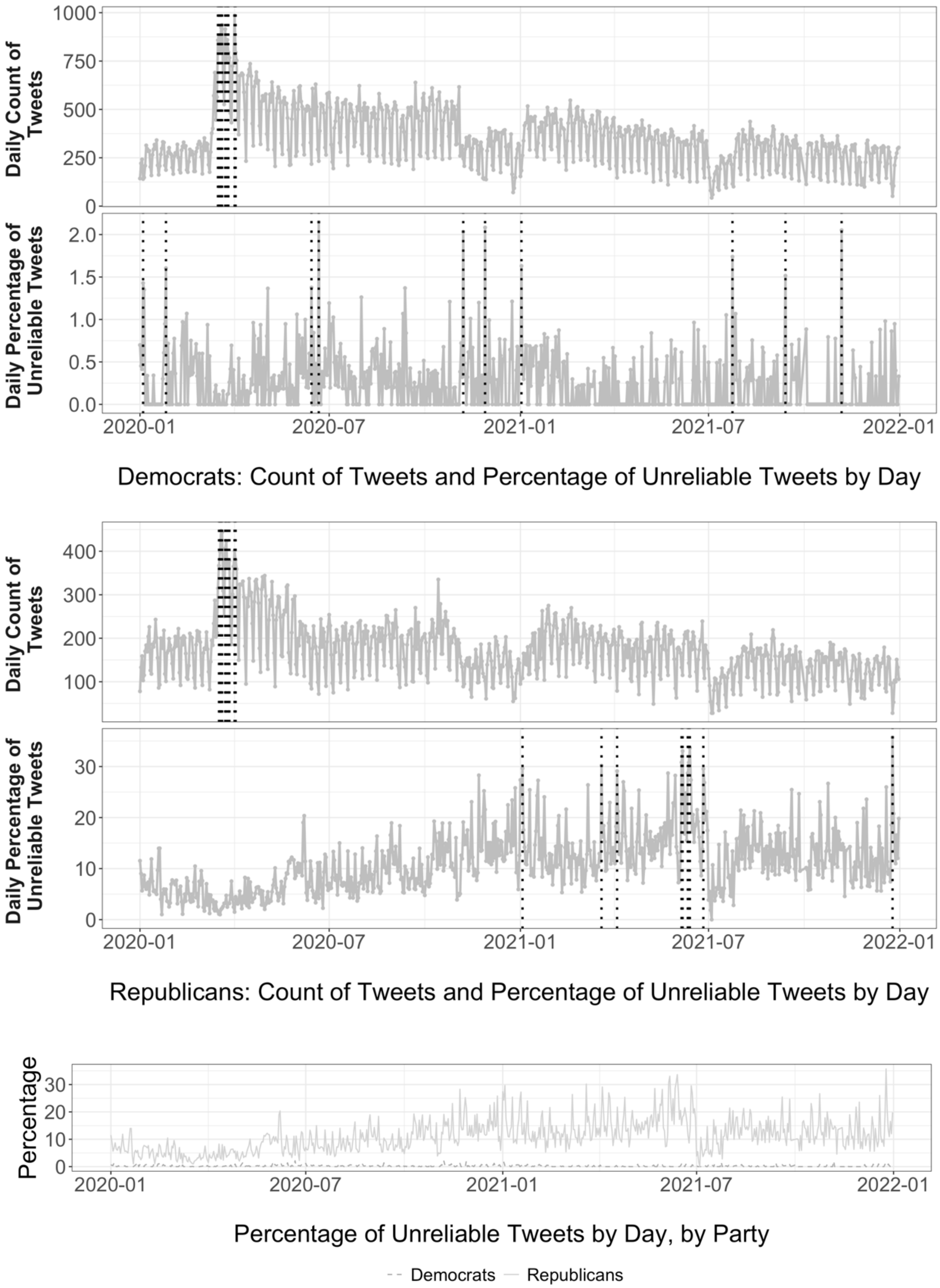


Figure 2: Weighted Percentage of Tweets Per Legislator that Include Unreliable URLs, by Party, in Analysis Dataset Excluding Legislators with Less than 10 Tweets. Both axes use a pseudo-log (base-10) transformation with linear scale labels.

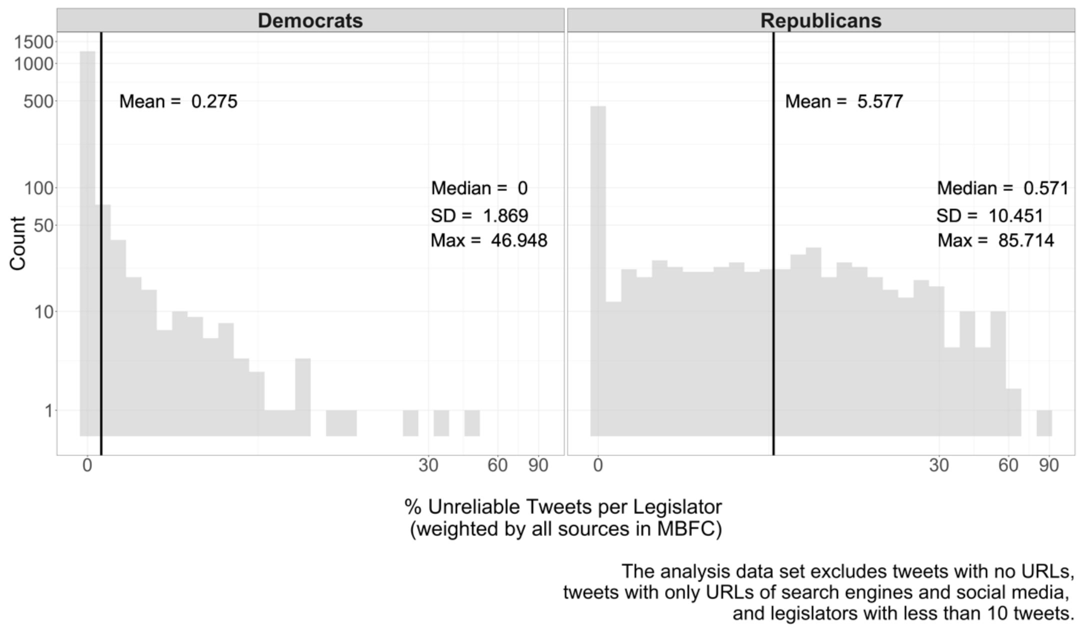


Figure 3: Topics in Legislators' Unreliable Tweets

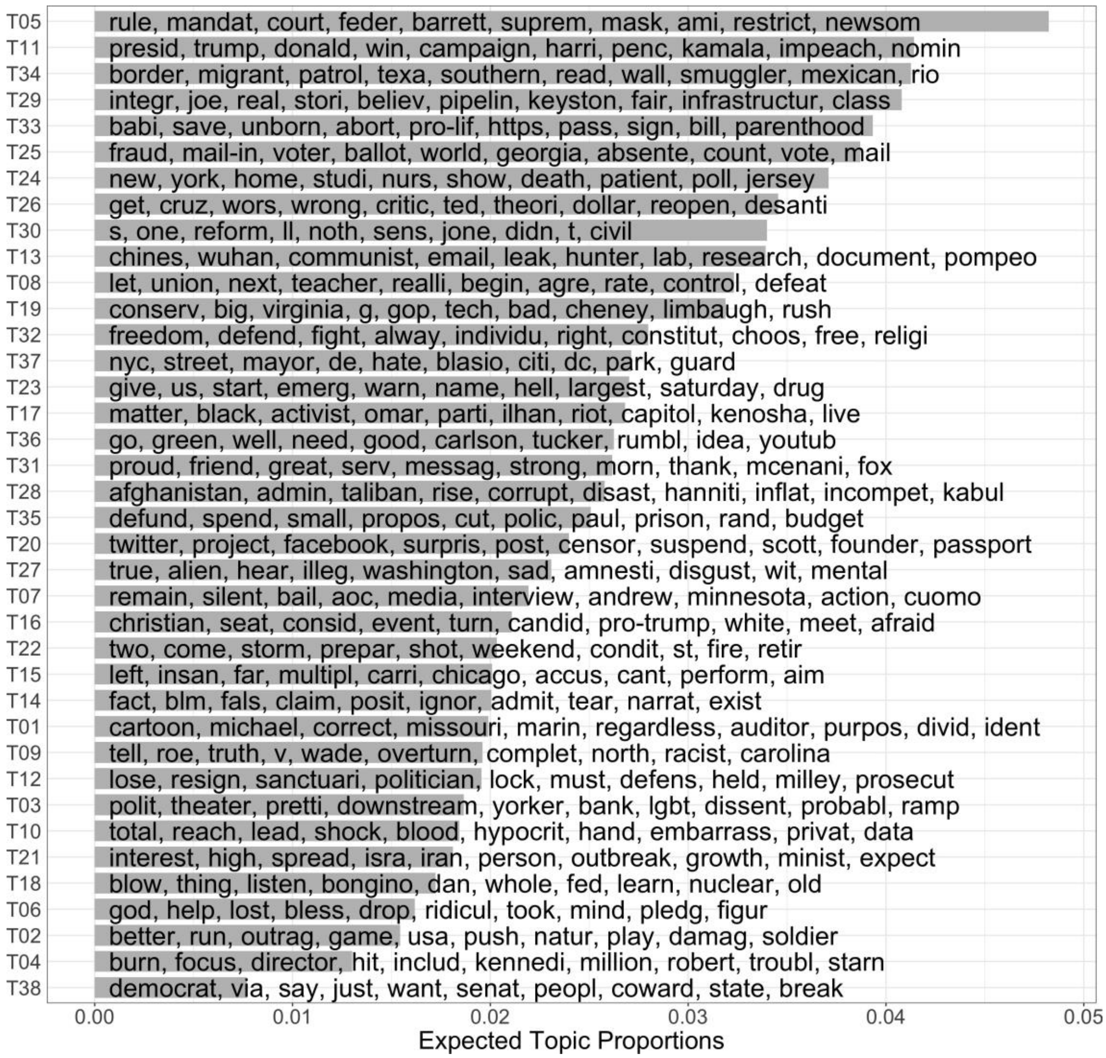


Figure 4: Topic Prevalence in Legislators' Unreliable Tweets, by Party. Horizontal dashed lines indicate that the specific party talks significantly more about the particular topic at 95% confidence intervals.

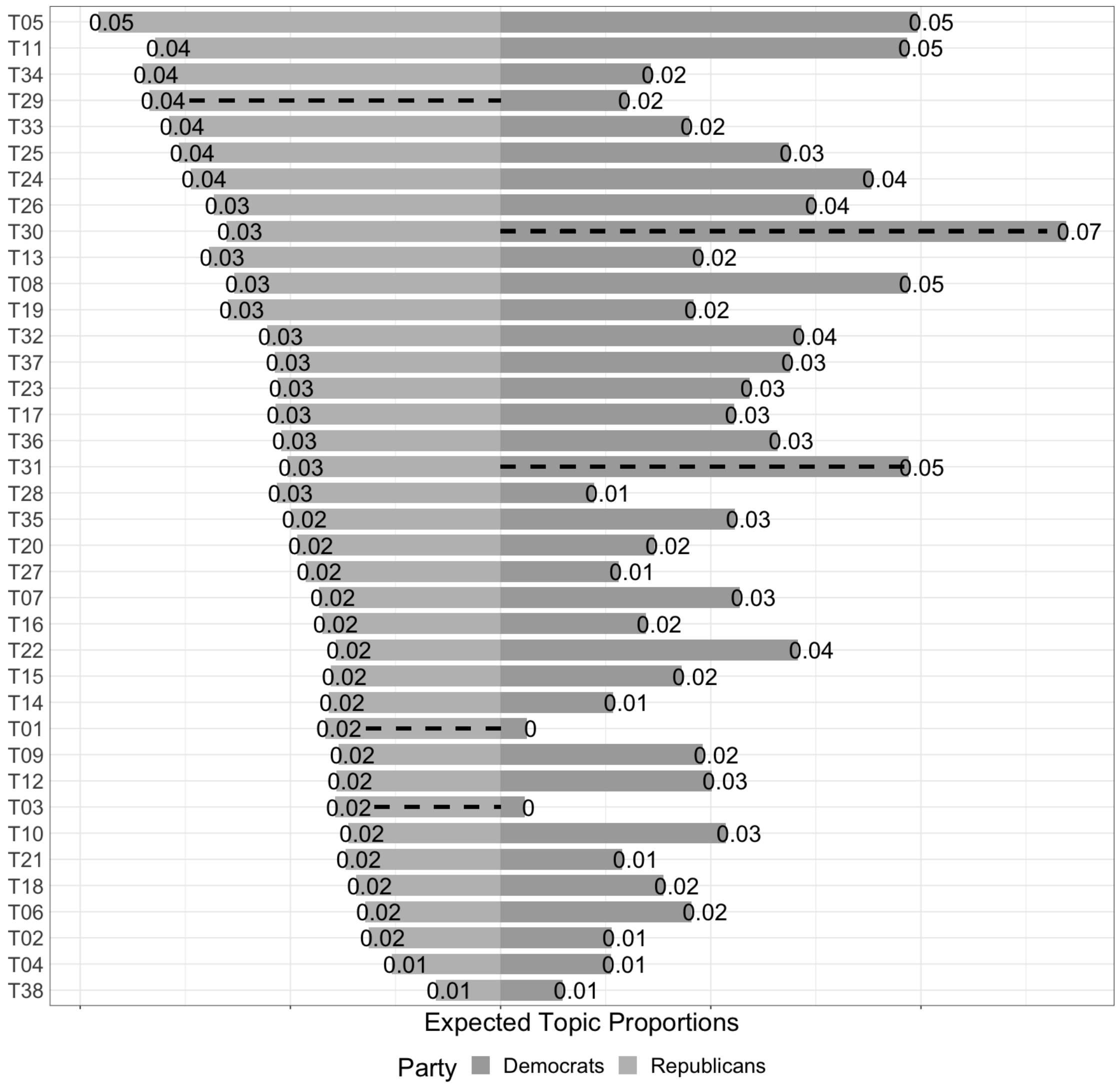


Figure 5: Percentage of Unreliable Tweets Across States, 2020-01-01 to 2021-12-31.

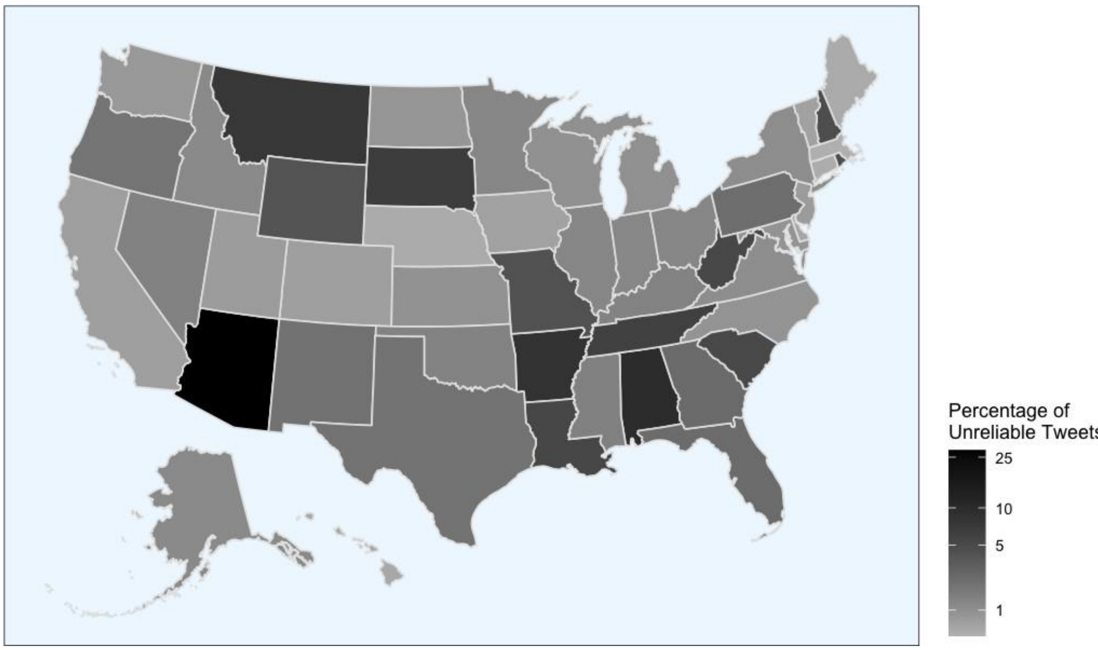
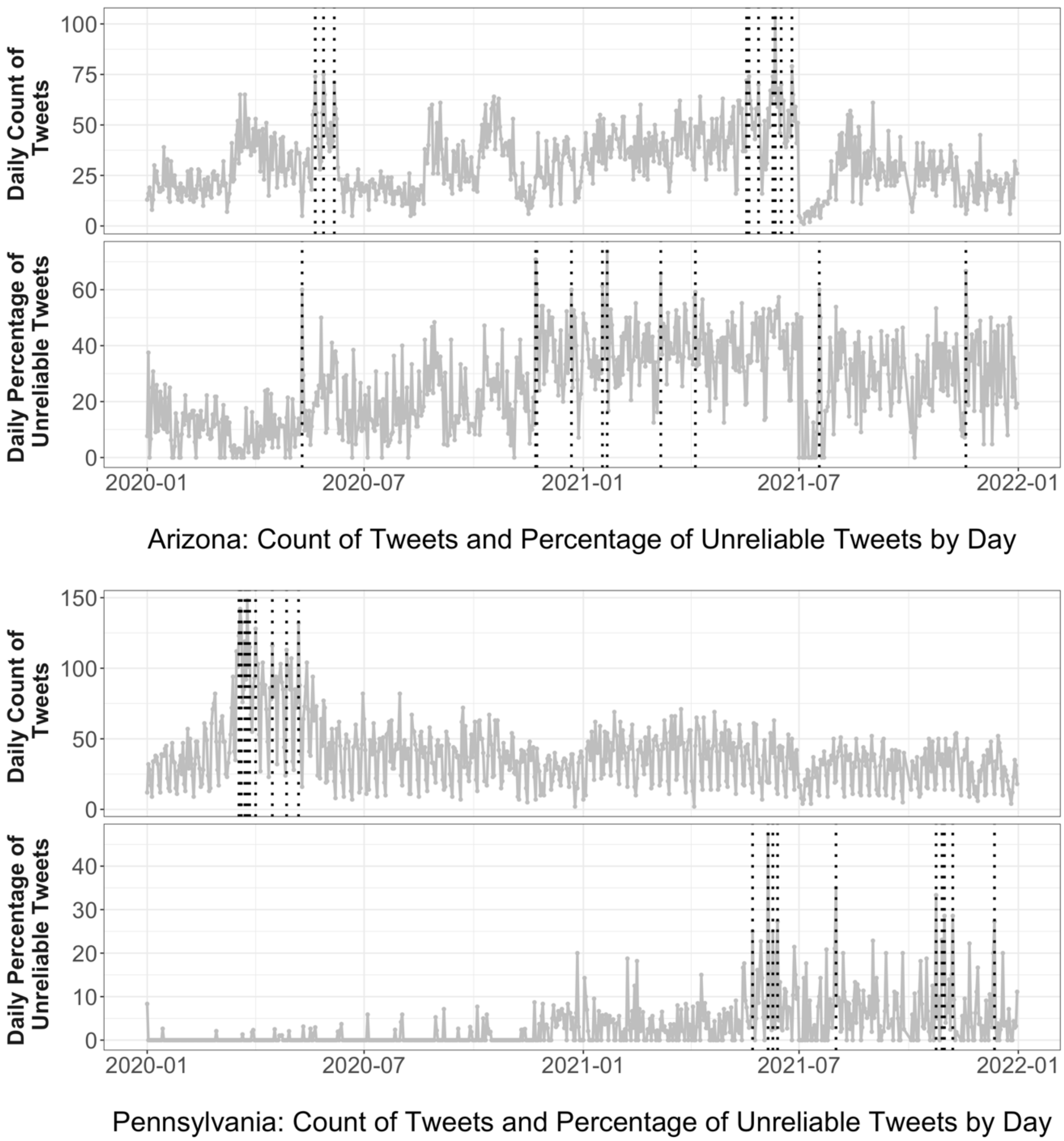
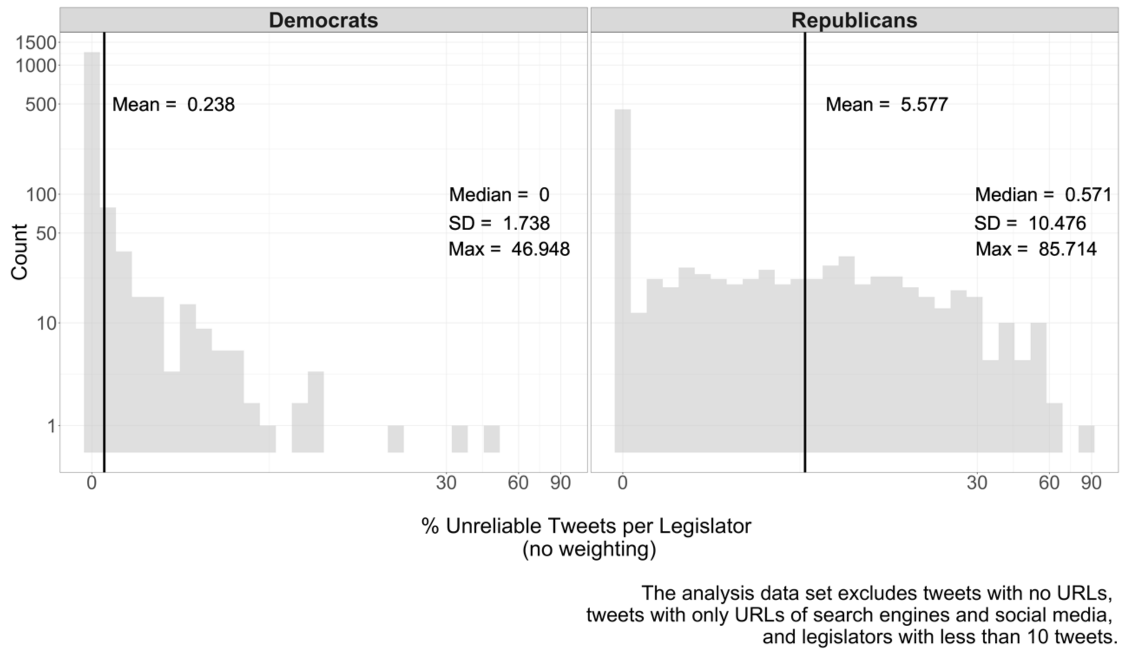


Figure 6: Daily Count of Tweets and Percentage of Unreliable Tweets Shared in Arizona and Pennsylvania, 2020-01-01 to 2021-12-31. Vertical dotted lines indicate top 10 peak days.



Appendix A: Percentage of tweets per legislator that include unreliable URLs, by party, in analysis dataset excluding legislators with less than 10 tweets. Both axes use a pseudo-log (base-10) transformation with linear scale value.



Appendix B: Counts and Cumulative Percentage of Unreliable Tweets by Arizona Legislators who Shared at Least Unreliable Tweets Once, 2020-01-01 – 2021-12-31.