Misinformation versus Facts: Understanding the Influence of News Regarding COVID-19 Vaccines on Vaccine Uptake

Hanjia Lyu, 1 Zihe Zheng, 2 Jiebo Luo 1

1 Department of Computer Science, University of Rochester, Rochester, NY
2 Goergen Institute for Data Science, University of Rochester, Rochester, NY
hlyu5@ur.rochester.edu, zzheng18@u.rochester.edu, jluo@cs.rochester.edu

Abstract

Background: There is a lot of fact-based information and misinformation in the online discourses and discussions about the COVID-19 vaccines.

Method: Using a sample of nearly four million geotagged English tweets and the data from the CDC COVID Data Tracker, we conducted the Fama-MacBeth regression with the Newey-West adjustment to understand the influence of both misinformation and fact-based news on Twitter on the COVID-19 vaccine uptake in the U.S. from April 19 when U.S. adults were vaccine eligible to June 30, 2021, after controlling state-level factors such as demographics, education, and the pandemic severity. We identified the tweets related to either misinformation or fact-based news by analyzing the URLs.

Results: One percent increase in fact-related Twitter users is associated with an approximately 0.87 decrease ($B = -0.87, SE = 0.25, p < .001$) in the number of daily new vaccinated people per hundred. No significant relationship was found between the percentage of fake-news-related users and the vaccination rate.

Conclusion: The negative association between the percentage of fact-related users and the vaccination rate might be due to a combination of a larger user-level influence and the negative impact of online social endorsement on vaccination intent.

Introduction

Many people read news on social media today, yet the veracity of the news is not guaranteed. Waszak, Kasprzycka-Waszak, and Kubanek (2018) studied the top shared health web links on Polish social media platform and found that 40% of the most frequently shared links contain fake news. Fake news regarding the COVID-19 pandemic is particularly concerning. By identifying and analyzing 1,225 pieces of COVID-19 fake news, Naeem, Bhatti, and Khan (2021) concluded that fake news is pervasive on social media, putting public health at risk. Among these health-related fake news, vaccine-related news (Wu, Lyu, and Luo 2021) has the most fallacious content (Waszak, Kasprzycka-Waszak, and Kubanek 2018). A recent study showed that misinformation induced a decline in intent of 6.2% in the UK and 6.4% in the USA among those who previously intended to take the vaccine (Loomba et al. 2021). To support the COVID-19 vaccination, Rzymski et al. (2021) suggested to track and tackle emerging and circulating fake news. Montagni et al. (2021) argued to increase people’s ability to detect fake news. Additionally, collaboration with the media and other organizations should be used, given that citizens do not support the involvement of government authorities in the direct control of news (Marco-Franco et al. 2021). By studying the anti-vaccination sentiment on Facebook, Hoffman et al. (2019) concluded that it would be valuable for health professionals to deliver targeted information to different sub-groups of individuals through social networks. In this study, we intended to examine the scale and scope of the influence of misinformation and fact-based news about COVID-19 vaccines on social media platforms on the vaccine uptake. To summarize, this work (1) quantitatively analyzed the effect of fake news and fact-based news on the vaccine uptake in the U.S. using the Fama-MacBeth regression with the Newey-West adjustment and (2) compared the user characteristics of the fact-related and fake-news-related users. Seemingly counter-intuitive, the percentage of fact-related users is significantly negatively associated with the vaccination rate while no significant correlation is found between the percentage of fake-news-related users and the vaccination rate. The fact-related users have relatively more social capitals than the fake-news-related users. Most of the frequent keywords in the user descriptions of the fake-news-related users are political.

Material and Method

Data Sets

Twitter Data We used the Twitter API to collect the related tweets that were publicly available. More specifically, the Twitter streaming API was used. The search keywords and hashtags are COVID-19 vaccine-related or vaccine-related, including “vaccine”, “vaccinated”, “immunization”, “covidvaccine”, and “#vaccine” Slang and misspellings of the related keywords were also included which are composed of “vacinne”, “vaccine”, “antivax” and “anti vax”. The tweets that were only related to other vaccine topics like MMR, autism, HPV, tuberculosis, tetanus, hepatitis B, flu shot or flu vaccine were removed using a keyword search.

https://www.tweepy.org/, Accessed June 9, 2021

1The capitalization of non-hastag keywords does not matter in the Tweepy query.
Moreover, since this study focused on the tweets posted by the U.S. Twitter users, we used the geo-location disclosed in the users’ profiles to filter out the tweets of non-US users. Similar to [Lyu et al. (2020)], the locations with noise were excluded. Nearly four million geotagged tweets as well as the retweets posted from April 19, 2021 to June 30, 2021 were collected. The average number of geotagged tweets per state is 79,894 (Min= 2,796, Max = 715,871, SD = 119,637).

CDC COVID-19 Data The daily state-level number of people with at least one dose, confirmed cases, and deaths per hundred were extracted from the CDC COVID Data Tracker [Centers for Disease Control and Prevention (2021)].

Census Data Multiple factors including demographics, socioeconomic status, political affiliation and population density have been found to be related with people’s intent to accept a COVID-19 vaccine [Lyu et al. (2021); Lazarus et al. (2021)]. These were considered as control variables in our study. From the latest American Community Survey 5-Year Data (2015-2019) [U.S. Census Bureau (2020)], we collected (1) the percentage of male persons; (2) the percentage of persons aged 65 years and over; (3) the percentage of Black or African American alone; (4) the percentage of Hispanic or Latino; (5) the percentage of Other; (7) the percentage of persons aged 25 years and over with a Bachelor’s degree or higher; (8) the percentage of persons in the labour force (16 years and over); (9) per capita income in the past 12 months (in 2019 dollars); and (10) the percentage of urban population. For these control variables, the state-level numbers were extracted.

2020 National Popular Vote Data The results of the 2020 national popular vote [Wasserman et al. (2020)] were used to estimate the political affiliation of individual states. Since the sums of the shares of Biden and the shares of Trump are almost equal to 100%, we only selected the shares of Biden. To keep the consistency among the variables, the state-level shares were chosen.

Tweets Classification

On the one hand, automated fake news detection methods have been proposed by multiple studies. To characterize fake news, Zhou and Zafarani (2019) represented the spread network in different levels and confirmed that the network of misinformation is more-spreaded, farther in distance, and denser. Horne and Adali (2017) found that fake news has longer titles, uses simpler sentences, and is more similar to satire compared to real news. Sentiment of the content was also proven to be an important feature used to detect fake news [Bhutani et al. (2019); Jin et al. (2017a)].

Using this approach, we assumed that the Twitter users did not post a tweet containing a link to fake news outlets or fact-based news outlets just to indicate whether or not they thought the content was fact or fake. Example tweets are as follows:

- This article in [fake-news-related URL] is apparently fake/ a fact.
- This article in [fact-related URL] is apparently fake/ a fact.

Instead, we assumed that the Twitter users shared a similar opinion with the content they posted. To verify the as-

3 https://www.cjr.org/, Accessed January 31, 2022
Table 1: Variables of interest.

| Variables                                                                 |
|---------------------------------------------------------------------------|
| **Dependent**                                                            |
| Daily new vaccinated people per hundred (7-day average)                   |
| **Independent**                                                          |
| (1) Percentage of fake-news-related (fake news, conspiracy theories, unreliable contents, or extremely biased news) tweets (7-day average) |
| (2) Percentage of fact-related tweets (7-day average)                    |
| **Control**                                                              |
| (1) Percentage of male persons                                           |
| (2) Percentage of persons aged 65 years and over                         |
| (3) Percentage of Black or African American alone                        |
| (4) Percentage of Asian alone                                            |
| (5) Percentage of Hispanic or Latino                                     |
| (6) Percentage of Other                                                   |
| (7) Percentage of persons aged 25 years and over with a Bachelor’s degree or higher |
| (8) Percentage of persons in the labor force (16 years and over)         |
| (9) Per capita income in the past 12 months (in 2019 dollars)            |
| (10) Percentage of urban population                                      |
| (11) Daily new cases per hundred (7-day average)                         |
| (12) Daily new deaths per hundred (7-day average)                        |

sumption and the robustness of our approach, we randomly sampled 100 unique tweets from both identified fake-news-related (fake news, conspiracy theories, unreliable contents, or extremely biased news) and fact-related tweets, respectively, and inspected whether or not they met our assumptions. After manually reading the sampled tweets, we found all of them met our assumptions. In fact, the majority of the content are just a short sentence that summarizes the content to which the URL links.

**Preprocessing**

The daily state-level number of people with at least one dose, confirmed cases, deaths per hundred were transformed using a two-step procedure. First, we calculated the lag-1 differences of these three variables. Next, we smoothed the data using a simple moving average. According to the CDC vaccination data (Centers for Disease Control and Prevention 2021), there is a seasonal pattern inside the number of daily new vaccinated people (i.e., the lag-1 difference). The number normally reaches the highest on Thursdays or Fridays, and approaches the lowest on weekends. Therefore, we applied a 7-day moving average to the vaccination data. To maintain the consistency, the lag-1 differences of confirmed cases and deaths were processed in the same way.

As for the Twitter data, since Twitter users could post tweets repeatedly, the series of (1) the percentage of unique Twitter users who posted fake-news-related tweets, and (2) the percentage of unique Twitter users who posted fact-related tweets were only processed with a 7-day moving average.

**Fama-MacBeth Regression**

In our study, we attempted to analyze five time series data, but most of them are non-stationary. For example, the time series of the vaccination data show a declining trend during our study period. Noticeably, the vaccination data, at this stage, has already been transformed into the lag-1 difference. To avoid the spurious regression problem, which might lead to an incorrectly estimated linear relationship between non-stationary time series variables (Kao 1999), we conducted the Fama-MacBeth regression (Fama and MacBeth 2021) with the Newey-West adjustment (Newey and West 1986), which has also been applied in several previous studies to address the time effect in areas such as finance (Loughran and Ritter 1996), public health and epidemiology (Wang et al. 2021). The optimal number of lags was selected automatically using a nonparametric method (Newey and West 1994). Apart from the time series data, we added control variables from the aforementioned data sources including the Census data and the 2020 National Popular Vote data. Table 1 summarizes the dependent, independent, and control variables.

**Results**

Using the aforementioned URL-based tweet classification method, we detected 26,998 fake-news-related (fake news, conspiracy theories, unreliable contents, or extremely biased news) and 456,061 fact-related tweets. There were 10,925 unique Twitter users who were associated with fake news, while 159,283 were associated with fact-based news. Interestingly, 6,839 were associated with both fake news and fact-based news, which accounted for 62.6% and 4.3% of the fake-news-related users and fact-related users, respectively. This suggested that people who were associated with fake news were more likely to be associated with fact-based news, but not the other way around.

The state-level percentages of fake-news-related and fact-related Twitter users were presented in Figures 1a and 1b. Overall, there is clear segregation between the states with more users associated with fact-related tweets and the states with more users associated with fake-news-related tweets. They tend to be geographically close to each other within the same group. For instance, there are more users associated with fact-related tweets in New York, Connecticut and Massachusetts. Higher percentages of users associated with fake-news-related tweets are observed in the Southeast of
the U.S.

We conducted the Fama-MacBeth regression with the Newey-West adjustment of the 7-day average number of daily new vaccinated people per hundred, on the 7-day average percentages of unique fake-news-related (fake news, conspiracy theories, unreliable contents, or extremely biased news) and fact-related Twitter users, during the period when all U.S. adults were eligible for COVID-19 vaccines, while controlling other factors. The CDC vaccination data might not reflect the intention to receive vaccination when the vaccines were not available for all the U.S. adults. We thus set the start date of the study period to be April 19, 2021 because, according to the Reuters, President Joe Biden moved up the COVID-19 vaccine eligibility target for all American adults to April 19. The regression was conducted using approximately 3-month data (from April 19, 2021 to June 30, 2021).

Figure 1 shows the state-level vaccination rates as of June 30, 2021. Compared to Figures 1a and 1b, we found that some of the states with relatively lower vaccination rates tend to have both higher rates of fake-news-related and fact-related users, perhaps an indication of higher disagreement (e.g., Montana, Idaho, and Wyoming). Table 2 summarizes the results of the Fama-MacBeth regression, which suggests a significant effect of the fact-based news on the vaccination rates. The percentage of fact-related Twitter users is negatively associated with the vaccination rates: one percent increase in fact-related Twitter users is associated with an approximately 0.87 decrease \((B = -0.87, SE = 0.25, p < .001)\) in the number of daily new vaccinated people per hundred. This is consistent with the findings of Loomba et al. (2021), where they conducted a questionnaire-based randomized controlled trial to quantify the effects of exposure to online misinformation around COVID-19 vaccines over vaccination intent. The percentages of people holding negative opinions (“leaning no” and “definitely not”) about COVID-19 vaccines indeed increase after exposure to factually correct information. It is also noteworthy that the increase is consistent across all four experiment settings in their study. However, what is inconsistent between our findings and theirs is the effect of misinformation. They found the exposure to misinformation induces a decline in vaccination intent, while, as shown in Table 2, we did not find significant relationship between the percentage of fake-news-related users and the vaccination rate.

For the control variables, on the one hand, some of them variables are significantly associated with the vaccination rate. As for the race and ethnicity, the percentage of Asian alone \(B = 0.39, SE = 0.19, p < .05\) is positively associated with the vaccination rate, while the percentage of Black or African American alone is negatively associated \(B = -0.23, SE = 0.06, p < .001\). With respect to the educational level, one percent increase in the percentage of persons aged 25 years and over with a Bachelor’s degree or higher is associated with an approximately 5.56e-3 increase \((B = 5.56e-3, SE = 1.38e-3, p < .001)\) in daily new vaccinated people per hundred. Socioeconomically, per capita income (in 2019 dollars) is negatively associated with the vaccination rate \(B = -3.92e - 6, SE = 1.12e - 6, p < .001\). One percent increase in the percentage of urban population is associated with a 4.72e-4 increase \((B = 4.72e-4, SE = 2.27e-4, p < .05)\) in the vaccination rate. The vaccination rates are higher among the states with a relatively higher percentage of people voting for Biden \((B = 5.31e - 3, SE = 1.09e - 3, p < .001)\). On the other hand, gender, Hispanic or Latino, Other, the numbers of daily new confirmed cases and deaths are not found to be significantly associated with the vaccination rate.

To better understand the discrepancy in the effects of misinformation (fake news, conspiracy theories, unreliable contents, or extremely biased news) on vaccination intent between our findings and the findings of Loomba et al. (2021), we dived deep into the user characteristics by comparing the social capitals (e.g., the number of followers) of two groups of Twitter users - one group composed of the users who have posted fake-news-related tweets but have not posted fact-related tweets, the other composed of the users who have posted fact-related tweets but have not posted fake-news-related tweets. Since the social capitals are not normally distributed, we performed the Mann-Whitney rank test with the Bonferroni correction on the numbers of followers, friends, statuses, favorites, and listed memberships. There is significant evidence \((p < .05)\) to conclude that the social capitals of these two groups of users are different. Specifically, the users who have posted fact-related tweets but have not posted fake-news-related tweets have more followers, friends, statuses, listed memberships, and give more favorites (i.e., likes). Moreover, by performing the proportion z test over the percentages of verified users be-

Table 2: The results of the Fama-MacBeth regression with the Newey-West adjustment.

| Variable           | B     | SE    | t-stat | p value |
|--------------------|-------|-------|--------|---------|
| Fake news          | -0.34 | 0.59  | -0.58  | 0.566   |
| Fact-based news    | -0.96*** | 0.27 | -3.53  | < .001  |
| Male               | -1.23 | 0.95  | -1.29  | 0.201   |
| 65 years and over  | 0.15  | 0.12  | 1.28   | 0.206   |
| Black              | -0.23*** | 0.06 | -3.84  | < .001  |
| Asian              | 0.39* | 0.19  | 2.01   | 0.048   |
| Hispanic           | -0.11 | 0.10  | -1.17  | 0.244   |
| Other              | 0.07  | 0.15  | -0.50  | 0.616   |
| Bachelor           | 5.56e-3*** | 1.38e-3 | 4.04  | < .001  |
| Labor              | -4.24e-3*** | 8.61e-4 | -4.92 | < .001  |
| Income             | -3.92e-6** | 1.21e-6 | -3.24 | 0.002   |
| Urban              | 4.72e-4* | 2.27e-4 | 2.08  | 0.041   |
| Confirmed cases    | 0.41  | 0.41  | 0.99   | 0.325   |
| Deaths             | -28.96| 24.27 | -1.19  | 0.237   |
| Biden shares       | 5.31e-3*** | 1.09e-3 | 4.90  | < .001  |
| const              | 0.86  | 0.44  | 1.94   | 0.056   |

Note. * p < 0.05, ** p < 0.01, *** p < 0.001.

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1. https://www.reuters.com/article/us-health-coronavirus-usa/all-american-adults-to-be-eligible-for-covid-19-vaccine-by-april-19-biden-idUKKBN2BT1IF?edition-redirect=uk Accessed June 9, 2021
Figure 1: State-level visualization of (a) fact-related, (b) fake-news-related (fake news, conspiracy theories, unreliable contents, or extremely biased news) tweets (b), and (c) COVID-19 vaccination rates. The percentages of unique Twitter users associated with fact-related and fake-news-related tweets were used for Panels (a) and (b). Percentages of population receiving at least one dose of COVID-19 vaccine as of June 30, 2021 were used for Panel (c).

We identified a significant negative correlation between the percentage of the U.S. Twitter users who were associated with fact-based news and the U.S. COVID-19 vaccination rates during the period when all U.S. adults were eligible for the COVID-19 vaccines. We found no significant effects of misinformation (fake news, conspiracy theories, unreliable contents, or extremely biased news) on the vaccination rates. The negative relationship between the fact-based news and the vaccination rate is consistent with the questionnaire-based randomized control trials conducted by Loomba et al. (2021). However, we found discrepancy in the effects of misinformation. As acknowledged by Loomba et al. (2021), their study “does not replicate a real-world social media platform environment where information exposure is a complex combination of what is shown to a person by the platform’s algorithms and what is shared by their friends or followers” (Bakshy, Messing, and Adamic 2015). By comparing the user characteristics of the fact-related and fake-news-related users, we found significant evidence that the fact-related users tend to have greater online influence as they have more followers, friends, statuses, listed

Figure 2: User descriptions of the users who have either posted fact-related or fake-news-related tweets but not both.

Discussions

We identified a significant negative correlation between the percentage of the U.S. Twitter users who were associated with fact-based news and the U.S. COVID-19 vaccination rates during the period when all U.S. adults were eligible for the COVID-19 vaccines. We found no significant effects of misinformation (fake news, conspiracy theories, unreliable contents, or extremely biased news) on the vaccination rates. The negative relationship between the fact-based news and the vaccination rate is consistent with the questionnaire-based randomized control trials conducted by Loomba et al. (2021). However, we found discrepancy in the effects of misinformation. As acknowledged by Loomba et al. (2021), their study “does not replicate a real-world social media platform environment where information exposure is a complex combination of what is shown to a person by the platform’s algorithms and what is shared by their friends or followers” (Bakshy, Messing, and Adamic 2015). By comparing the user characteristics of the fact-related and fake-news-related users, we found significant evidence that the fact-related users tend to have greater online influence as they have more followers, friends, statuses, listed
memberships, give more favorites (i.e., likes), and are more likely to be verified users. We further qualitatively compared the words extracted from the user descriptions of these two groups of users and found clear differences. The fake-news-related users tend to have similar user profiles as more political keywords such as “maga”, “conservative” and “Trump” were observed in the user descriptions. As a result, in our study, the number of detected fact-related users is almost 15 times of the number of detected fake-news-related users. These findings indicate a combination of a smaller online influence and a tendency for selective exposure to homogeneous opinions (Vicario et al., 2019; Del Vicario et al., 2016) that may create echo chambers (Costa et al., 2020; Schmidt et al., 2018).

At first glance, it might be counterintuitive that more fact-related news is associated with lower vaccination rate. However, this pattern was consistently found in both survey-based studies (Loomba et al., 2021; Chadwick et al., 2021) and our social media-based study. The reason could be that more fact-related news about the vaccines might raise not only more discussions but also more concerns. This non-positive perception of the vaccines might induce a decline in the vaccination intent among the people who were hesitant. Chadwick et al. (2021) conducted a survey-based study to explore the implications of online social endorsement for the COVID-19 vaccination program. They found the effects of online social endorsement are complex in terms of the people who consume them. The people who give less priority to active monitoring of news are more likely to be associated with discouragement of vaccination compared to the people who actively seek news. It is notable that the users we captured using our methods are the ones who posted tweets. Based on our results, the people who have posted fact-related tweets but have not posted fake-news-related tweets have a relatively larger audience. The people among the audience who do not post fact-related tweets can be considered as less active than the people who posted. Therefore, according to the findings of Chadwick et al. (2021), these people might become more vaccine hesitant after consuming a growing amount of the news, which could be the reason of a negative association we found in our study. Future research can further explore this pattern by investigating the effects of online social endorsement on vaccination intent (Chadwick et al., 2021) using social media data in real-world environments.

With respect to the control variables, the patterns are in line with the ongoing vaccination trends (Centers for Disease Control and Prevention, 2021). In June 2021, the estimated percents of people 18 years and older in White alone, not Hispanic or Latino, Black or African American alone, and Asian alone were 66.8, 56.7, and 85.0, respectively. Our results also show a negative association between the percentage of Black or African American alone, a positive association between the percentage of Asian alone with the vaccination rate. No statistically significant relationship was found between the percentage of persons aged 65 and over, which is within our expectation, since this demographic group was among the first batches who were eligible for the COVID-19 vaccines in the U.S. By the time of our study period, over 78% of the people aged 65 years and over have already received at least one dose (Centers for Disease Control and Prevention, 2021). Echoed with Bertoncello et al. (2020), the states with more people holding a Bachelor’s degree or higher tend to have higher vaccination rates.

The findings of our study should be interpreted with caution as there are still limitations in terms of the representativeness of online behaviors and the potential biases in the type of people using Twitter. However, multiple previous studies have shown that these kinds of online activities are representative of real-world patterns in many areas such as diet (Abbar, Mejova, and Weber, 2015; Gore, Diallo, and Padilla, 2015) and public health (Lyu et al., 2021; Paul and Dredze, 2011). More importantly, as also shown in our study, social media-based studies to some extent overcome the challenges encountered using survey-based methods (Loomba et al., 2021). Ideally, a future research direction is to explore the combination of both survey-based and social media-based methods to improve robustness while addressing the drawbacks of both methods.

Moreover, this work employed a method to identify fake-news-related and fact-related tweets only using the URLs fact checked by human experts, which could potentially cause a sample bias since not all fake-news-related or fact-related tweets contain URLs. However, one of the advantages of this approach over other text-based machine learning or deep learning methods (Jin et al., 2016, 2017b; a) is its high precision rate. Shahi and Nandini (2020) presented a multilingual cross-domain dataset of 5,182 fact-checked news articles for COVID-19. This dataset was annotated manually. They used a BERT-based classification model (Devlin et al., 2018) for fake/fact detection. The overall precision was only 0.78. Although this result was achieved without fine-tuning, it suggests that there are gaps in the precision rate between expert-labeled and machine-detected results. In the future, we intend to combine these methods to detect fake news more reliably. In addition, other advanced time series models can be explored to perform the regression analysis for spatial and temporal patterns.

Conclusion

In this study, we identified the tweets related to either misinformation (fake news, conspiracy theories, unreliable contents, or extremely biased news) or fact-based news posted from April 19, 2021 to June 30, 2021 on Twitter. After performing the Fama-MacBeth regression with Newey-West adjustment, we found the percentage of fact-related users is significantly associated with the vaccination rate. We did not find a significant relationship between the percentage of fake-news-related users and the vaccination rate. We further compared the user characteristics of the fact-related and fake-news-related users and found fact-related user have significantly more social capitals. The fake-news-related users are similar to each other in terms of social capitals as well as their user descriptions. Our findings are mostly consistent with the findings of previous survey-based studies. More importantly, we conducted our study by passively observing the social media data in an attempt to address the issue that
previous survey-based studies did not replicate a real-world social media platform environment, enabling us to have a better understanding of the mechanism of the relationship between vaccine-related news and vaccination rates.

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