# Co-Spread of Misinformation and Fact-Checking Content during the Covid-19 Pandemic

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**Abstract.** In the context of the Covid-19 pandemic, the consequences of misinformation are a matter of life and death. Correcting misconceptions and false beliefs are important for injecting reliable information about the outbreak. Fact-checking organisations produce content with the aim of reducing misinformation spread, but our knowledge of its impact on misinformation is limited. In this paper, we explore the relation between misinformation and fact-checking spread during the Covid-19 pandemic. We specifically follow misinformation and fact-checks emerging from December 2019 to early May 2020. Through a combination of spread variance analysis, impulse response modelling and causal analysis, we show similarities in how misinformation and fact-checking information spread and that fact-checking information has a positive impact in reducing misinformation. However, we observe that its efficacy can be reduced, due to the general amount of online misinformation and the short-term spread of fact-checking information compared to misinformation.

**Keywords:** Covid-19 · Misinformation · Fact-checking · Social Media.

## 1 Introduction

Recent research indicates that misinformation spreads much faster than true information by exploiting emotions [32]. At the moment, public attention to danger is heightened and fear may influence behaviour [9]. Misinformation about Covid-19 has been rampant on social media [6,5], with some tragic results[1][2]. Studying the spread of misinformation about Covid-19 helps us to understand what information correction the public needs during a health crisis. It also helps to distinguish patterns and timings that are significant in the spread of misinformation.

[1] BBC – The cost of virus misinformation, https://www.bbc.co.uk/news/stories-52731624.

[2] The Guardian – UN warns of deadly effect of Covid-19 misinformation in Pacific, https://www.theguardian.com/world/2020/apr/17/un-warns-of-deadly-effect-of-covid-19-misinformation-in-pacific.

We compare the diffusion of 2,830 misinformation and 734 fact-checking URLs about Covid-19 on Twitter,[3] from early December 2019 to early May 2020 in order to understand the spread of misinformation and fact-checks over time.

First, we analyse how spread differs during the pandemic by observing changes between the initial pandemic onset, the ramping up phase and late pandemic period (Covid-19 level). Second, we study the relative misinformation and fact-checking diffusion patterns by aligning individual URL spreads and analysing how individual misinformation spread after their initial appearance (relative level).

We address the following research questions: Are misinformation and fact-checking information shared similarly? How do misinformation and fact-checking spread patterns vary at the pandemic level and relative level? and How does fact-checking spread affect the diffusion of misinformation about Covid-19?

## 2 Related Work

In this section, we discuss some of the propositions that researchers have made regarding the spread of misinformation and fact-checks on social networks. We highlight the complexity of establishing the impact of fact-checks on misinformation sharing, to which our study contributes.

### 2.1 Misinformation Spread Analysis

Most studies of misinformation spread tend to be focused on early intervention and removal [3]. In this context, many works have focused on the application and extensions of epidemiological models [12,13,3] with additional features like weighted values for particular users [29] or, more recently, information about debunkers and the dynamics of opinion evolution [23]. Notably, Saxena *et al* [23] demonstrated that identifying influential nodes may also help exploit the spread of fact-checked information and impact user opinion over time.

Several works investigate the role of different topological features in misinformation spread [2,30,35,8], finding that some topic/audience interdependencies may increase the spread of misinformation, perhaps related to cultural norms, experiences or values [7]. Likewise, chains or groups of nodes may accelerate the spread of misinformation [22] and, as Xian *et al* demonstrate, individuals can be exposed to and share misinformation across platforms [34]. In the context of the current crisis, Cinelli *et al* [6] analysed spread patterns of different Covid-19 related misinformation across several platforms. The authors noted different diffusion patterns for different types of misinformation on each platform. Researchers are beginning to explore the role of social media *hype* in accelerating both panic and therefore uptake of misinformation about Covid-19 and other viral pandemics on social media [10].

Most researchers agree that the biggest impacts of misinformation happen within a short time span from the initial circulation [26]. Misinformation spikes

[3] Twitter, http://twitter.com.

are prevalent during times of conflict and war [16], and during politic events [15]. Misinformation often accompanies breaking news developments, when people are looking for more details, as well as during disasters, when they might desperately need information about where to go or what to do next [26].

Existing research has mostly focused on analysing misinformation spread alone without much focus on whether fact-checking information impacts the spread of misinformation. Although topological and social features are important for characterising misinformation spread, we decide to leave these features in our study and focus on the co-spread of misinformation and fact-checks with a particular focus on different time periods. We leave additional topological and user analysis as future work.

### 2.2 Fact-Checking Information Spread

Fact-checks are a type of information that is distinct from just "true", or "false" information. Researchers already showed that true information and misinformation spread differently [32]. Fact-checks assess claims for accuracy [31], hence representing a new category of information [11]. At the time of writing, we could not identify work looking computationally at the diffusion of fact-checking in a network, in particular to assess causal relationships to misinformation.

Tambuscio *et al* [28] used agent-based simulations to develop a two parts epidemiological model for defining the "minimal reaction" necessary to get rid of a viral hoax, but this was not transferred to a real dataset. Later work by Kim *et al* [14] used real-world datasets from Twitter and Weibo[4] to model how the network could be mobilised to spread corrective information effectively. Still, these models are meant to predict how future fact-checks may diffuse and not to estimate existing causal relationships.

Researchers have looked at the usefulness of fact-checking from a variety of perspectives. Nyhan and Reifler [21] found that attitudes toward fact-checking in the USA were generally supportive. However, they noted that scepticism toward fact-checking may stem from a lack of trust in fact-checking entities. More recently, Barrera *et al* [4] found that fact-checking did improve voters' knowledge, but did not appear to impact policy, or support for individual candidates. This phenomenon was also reported by researchers in the context of the 2016 USA presidential election [27]. In their exploration of the Australian presidential election in 2017, Aird *et al* found that the number of corrections must outweigh the number of affirmations of the misinforming claim, in order to have a stronger impact on belief and behaviour [1]. Similar findings were echoed in[26].

A recent extensive review of fact-checking literature performed by Nieminen *et al* showed that the corrective potential of fact-checking was a dominate subject of research, but that subjectivity in fact-checking assessment, the overemphasis of fact-checking in the US, and a lack of clarity around correcting beliefs were continued challenges [20]. Assessing the impact of fact-checking from the perspective of individuals consuming fact-checks is difficult to do in laboratory

[4] Weibo, http://weibo.com.

settings. In our work, we focus on assessing the presence and diffusion of both misinformation and fact-checks on Twitter, to explore temporal patterns and evidence of causal relationship.

# 3 Co-Spread of Misinformation and Corrective Information during the Covid-19 Pandemic

The review of existing work investigating misinformation spread shows a gap in understanding the relation and interaction between the corrective information propagated by fact-checking and misinformation spread. We conduct an analysis on the co-spread of fact-checking information and misinformation on Twitter based on the sharing of misinforming URLs that were collected from claim reviews collected from fact-checking websites. The data was collected as part of the misinfo.me platform [17] up to the 4th May 2020.

In our approach, first, we collect Twitter data by looking for the appearance of misinforming URLs that we have collected. Second, misinformation and fact-checks spread is aggregated for three different time periods at two different granularity: 1) From the Covid-19 worldwide spread perspective (Covid-19 level analysis), and; 2) From the initial emergence of a misinforming URL (relative level analysis). This allows for a better understanding of spread at different levels. Third, we perform multiple analyses to investigate how fact-checks and misinformation spread behaviour differs. This analysis allows the identification of significant relations between misinformation spread and fact-checking information, which can be used for designing better methods for spreading fact-checking information on social media. Finally, weak causation and impulse response analyses are performed between fact-checks and misinformation in order to identify if fact-checking information diffusion impacts misinformation spread.

## 3.1 Dataset

For our analysis, we need to create a dataset that contains both misinformation and fact-checking information. We focus our work on Twitter due to its popularity and its accessibility. We rely on COVID19-related reports from fact-checking websites that identify misinforming content by their URLs, and search the occurrences of these URLs in user posts on Twitter.

**Fact-checker URLs Dataset** The dataset of fact-checks comes from the misinfo.me tool [17], that collects URLs that have been fact-checked, labelled and provided with a fact-checker review. The reviews are published by multiple fact-checking websites belonging to the International Fact-Checking Network[5] (IFCN) using the standard `ClaimReview` schema[6], which was defined appositely for the purpose of annotating reviews of claims. The data collection is primarily based

[5] IFCN, https://ifcncodeofprinciples.poynter.org/signatories.
[6] ClaimReview Schema, https://schema.org/ClaimReview.

on the Data Commons `ClaimReview` public feed.[7] From this public feed, ratings are extracted and normalised between $[-1; +1]$ depending on their credibility [18]. Using these ratings, we only select misinforming URLs (ratings $\leq 0$). Although, different levels of misinformation exist (e.g., manipulation, misleading information, forgery, etc.), we focus our investigation on any type of misinformation in order to simplify the analysis. We also keep the URLs of the original fact-checking articles and then filter all the URLs to only get the Covid-19 fact-checks by using a set of relevant keywords[8] based the title and content of the fact-checks. The final URL dataset includes fact-checks published until the 4th of May 2020, with a total of 2,830 distinct misinforming URLs and 734 fact-checking URLs.

**Twitter Dataset** Using the misinforming and fact-checking URLs, we create the Twitter dataset by searching their occurrences on Twitter by adapting an existing Twitter Hashtag crawler that collect posts using Twitter's mobile interface.[9] Out of all the seed URLs, we find posts for only 1,190 distinct URLs for a total of 21,394 posts from 16,308 different users. On average, there are 17.54 posts for each URL ($\sigma = 28.35$, $min = 1$, $max = 232$).

Figure 1 shows the cumulative spread of misinforming and fact-checking information URLs shared over time in our dataset. The figure also shows the amount of Covid-19 casualties and cases over the same period as well as the Covid-19 *initial*, *early* and *late* periods (vertical dashed lines).

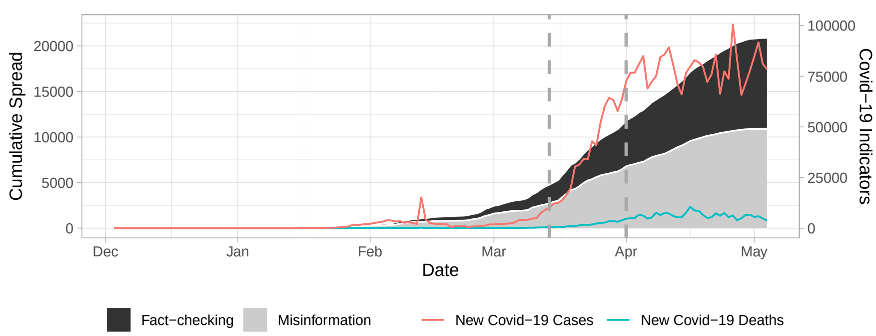


**Fig. 1.** Stacked cumulative spread of misinforming and corrective information URLs over time and amount of Covid-19 casualties and cases over the same time period.

**Covid-19 Cases Dataset** To generate the different time periods at the Covid-19 pandemic granularity, we use the data produced by the European Center

[7] ClaimReview Public Feed, https://www.datacommons.org/factcheck/download.
[8] Twitter Covid-19 keywords, https://developer.twitter.com/en/docs/labs/covid19-stream/filtering-rules.
[9] Twitter Scrapper, https://github.com/amitupreti/Hands-on-WebScraping.

for Disease Prevention and Control (ECDPC).[10] The ECDPC collects daily statistics about the number of Covid-19 cases and causalities worldwide for multiple countries. Although, the data is continuously updated, in our work we focus on the 1st Dec. 2019 to 4th May 2020 period since it matches the data we collected on Twitter. The beginning date is selected as the 1st Dec. 2019 since this date tends to be associated with the first traceable case of the pandemic [33].

### 3.2 Analysed Periods Generation

We analyse the behaviour of fact-checking information and misinformation at two different granularity levels. First, at the pandemic level (Covid-19 level analysis), we are interested in understanding if spread behaviour varies during three different time period within the pandemic based on the the amount of worldwide cases. Second, at the URL level (relative analysis), we are interested in understanding how behaviour differs based on the number of days since the first occurrence of a misinformation-related URL (i.e., a particular misinforming content or its associated fact-checking information). This would show how misinformation and fact-checks spread over time independently from when they were posted.

**Covid-19 Periods** We generate three *initial*, *early* and *late* time periods to analyse fact-checking information and misinformation spreads at the level of the Covid-19 pandemic. We fit multiple linear regression models for the daily worldwide Covid-19 cases curve in order to identify inflection points in the amount of Covid-19 cases [19].

Looking for two inflection points in the curve, the *initial* time period is specified as any tweet posted before Saturday, Mar 14, 2020. *Early* period corresponds to any tweet between Saturday, Mar 14, 2020 and Thursday, Apr 2, 2020. *Late* period is for any posts after Thursday, Apr 2, 2020.

**Relative Periods** To understand sharing behaviour independently from when each URL has been initially shared, we align the initial sharing of each URL so that all the URLs shared in the dataset always start from the same initial time (i.e., we normalise the dates for each analysed URL). We identify the first occurrence of each URL and then obtain the number of times it has been shared per day for each day following its initial appearance.

Following the same approach outlined in the previous section, we use the daily aggregated curve containing all the shared URLs (i.e., misinforming and fact-checking URLs) for identifying the *initial*, *early* and *late* relative time periods by obtaining the inflection point in the daily shared URLs. Using the aforementioned method, the *initial* time period is specified as any URL shares happening within the first 2 days after its first occurrence. The *early* period correspond to share between day 2 and day 14. Finally the *late* period is for any shares happening after 14 days.

[10] ECDC Covid-19 Data, https://opendata.ecdc.europa.eu/covid19/casedistribution/csv.

## 4 Multivariate Spread Variance Analysis

The first part of the analysis is to identify the different patterns of appearance of misinformation and fact-check URLs over varying periods of time. In order to perform such analysis, we use the one way Multivariate ANalysis Of VAriance (MANOVA) and the one way ANalysis Of VAriance (ANOVA) methods. This approach allows us to determine if there are significant differences in information spread between the fact-checking information and misinformation groups in each *initial*, *early* and *late* periods.

### 4.1 Experimental Setup

MANOVA and ANOVA rely on the definition of independent variables and dependent variables. For our analysis, the amount of information spread associated with each information type is our dependent variable whereas each information type (i.e., misinformation and corrective information) is an independent variable.

Since our data does not follow all the assumptions required for the standard ANOVA and MANOVA methods (i.e., multicollinearity, normality and homogeneity), we use non-parametric versions of MANOVA and ANOVA for the analysis, using F-approximations permutation tests. The F-approximation of ANOVA's test, as well as Wilks' Lambda Type Statistic are obtained with their p-value and the associated permutation test p-value.

Our analysis is divided into two different parts for the Covid-19 and relative level analyses: 1) A Non-parametric MANOVA analysis is performed for identifying if there are differences in spread between the different periods and information types, then; 2) Non-parametric ANOVA analysis is then performed if the MANOVA results are significant for each individual time period for determining in which sub-period (i.e., *initial*, *early* and *late*) the pattern differs.

For the non-parametric ANOVA analysis, the Kruskal-Wallis test is used and the p values are adjusted using Bonferroni correction (since multiple dependent variables are analysed). Significant results mean that the behaviour of corrective information and misinformation are significantly different whereas a non-significant result means that the distribution of spread for each time period is non-significant.

### 4.2 Results

In the following section we only report significant results for brevity.

**Covid-19 Period Analysis** The one way MANOVA analysis comparison at the Covid-19 level URL shares for misinforming URLs and fact-checking URLs shows a significant permuted p-value of 0.01. This means that at the Covid-19 pandemic level, there are significant differences in how misinforming URLs and fact-checking URLs spread and that the type of shared URLs has an effect on the amount of shared URLs during the pandemic. Following the significant result of the MANOVA analysis, a one way ANOVA analysis is performed for each Covid-19 time period. The Bonferroni adjusted Kruskall-Wallis tests are only significant for the *initial* ($p = 0.00558$) and *late* ($p = 0.0234$) periods. This result means that sharing behaviour does not differ fundamentally during the *early* Covid-19 period ($p = 1$) whereas sharing behaviour differs in the other periods.

Looking at the individual URLs shares for each time periods, we observe higher deviations in sharing behaviour for misinformation ($\sigma \in \{20.5, 24.9, 26.3\}$) compared to fact-checking information ($\sigma \in \{7.52, 6.94, 11.3\}$). It also appears that fact-checked information is shared less often than the corresponding misinforming URLs in term of means with lower means for all the time periods ($2.42 < 5.88$, $3.60 < 8.73$ and $6.34 < 10$). This suggests that perhaps the types of users that share misinformation is more varied than the types of users that share fact-checks. Similarly, there may be a variation in what misinforming topic attracts the most shares compared to the fact-checking content.

**Relative Period Analysis** The one way MANOVA analysis comparison at the relative URL shares level for misinforming URLs and fact-checking URLs shows a significant permuted p-value of 0. This means that at the relative URL level, there are significant differences in how misinforming URLs and fact-checking URLs spread and that the type of shared URLs has an effect on the amount of spread at different relative time periods.

Following the significant result of the MANOVA analysis, a one way ANOVA analysis is performed for each relative time period. The Bonferroni adjusted Kruskall-Wallis tests are only significant for the *early* ($p = 4.74 \times 10^{-4}$) and *late* ($p = 1.338 \times 10^{-5}$) periods. This means that sharing behaviour during the *initial* ($p = 0.522$) relative period does not differs during that period whereas differences exists when looking at the *early* and *late* periods.

The individual distribution of misinforming and fact-checking URLs for each time period show that the amount of shares tends to be similar across the URL types with a slightly higher spread for the misinforming URLs in general. Interestingly, the highest difference in term of mean and standard deviation between the different URL types appears to be mostly during the initial phase with a more important standard deviation for the misinforming URLs ($\sigma = 12.6$ for misinforming content and $\sigma = 3.31$ for fact-checks).

## 5 Fact-checking Misinformation Impact Analysis

In this section we investigate how the two types of information (fact-checking URLs and misinforming URLs) impact each other. In particular, we are interested in understanding if the spread of fact-checking information has a beneficial impact in reducing the diffusion of misinformation. For this analysis, we focus on modelling the spread of URLs as a Vector AutoRegression (VAR) model using the misinformation and fact-checking URLs as endogenous variables. We perform this analysis at the relative level (i.e., the relative number of days since the first appearance of a URL related to a particular misinformation) and determines if weak causation relations between each information types exists.

### 5.1 Experimental Setup

Although it is not simple to identify causation relations between each information types, it is possible to estimates if the spread of a given information type can be used to predict the spread of another information type using a Granger causality test. In order to compute the Granger causality test we first build a Vector AutoRegression (VAR) model using the combined misinformation spread and fact-checking information for the analysed period. However, since our data is non-stationary, we first integrate each analysed information types so that the spread amount for each day is represented as the difference between the current day value and the previous day value.

A 14 days order value is used for the VAR model based on Akaike's information criterion. Using the VAR(14) model, we perform a bootstrapped Granger causality test for determining if misinformation spread can be associated with fact-checking URL spread or if fact-checking spread can be inferred from misinformation spread.

In order to understand the dynamics that relate fact-checking and misinformation, impulse response analysis is performed as well as Forecast Error Variance Decomposition (FEVD). For the impulse response analysis, we use orthogonal impulse responses in order to evaluate the spread response of the different types of URLs for 14 days steps. This approach allow us to determines how a particular sharing behaviour may affect other types of URLs shares in future. We are particularly interested in determining if an increase in fact-checking information shares trigger a reduction in misinformation diffusion. We run the FEVD with the same 14 days periods in order to obtain the contribution importance of each information types on both misinforming URLs and fact-checking URLs spread.

### 5.2 Results

Using the VAR(14) model, we observe a Granger causality relation showing that fact-checking spread has predictive causality over misinformation spread ($p = 0.02$). This observation is not found in the opposite direction ($p = 0.93$). This result suggests that at the relative-level, change in fact-checking information spread may cause a change in misinformation spread and therefore fact-checking articles have an impact on misinformation spread. Surprisingly, the opposite result shows that fact-checking spread may not be influenced by misinformation.

The impulse response for the orthogonal shock in the amount of shared fact-checking URLs (Figure 2) shows an initial drop in misinformation shares (first day) but mixed results afterwards. Despite this observation, a general downward misinformation spread trend can be observed. This suggests that fact-checking tend to have a short significant impact on the spread of misinformation. A shock in misinformation leads to a sharp drop in misinformation spread. This confirms our previous observation that misinformation spreads tend to occurs mostly after its initial spread and decrease quickly in the following days.

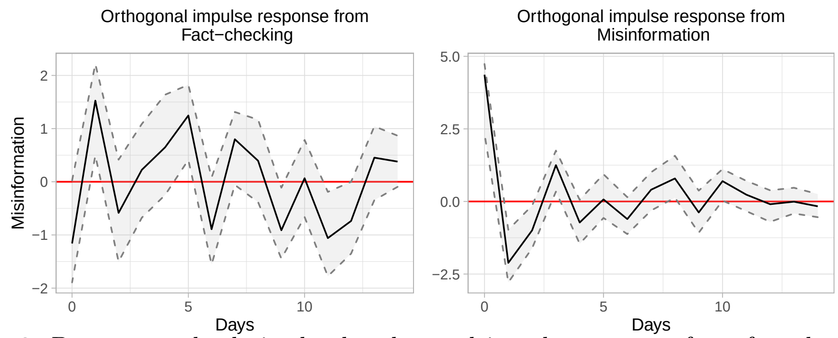


**Fig. 2.** Bootstrapped relative-level orthogonal impulse response from fact-checking shock (95% confidence interval).

The impulse response for the orthogonal shock in the amount of shared misinforming URLs (Figure 3) shows a delayed fact-checking increase two days after the initial misinformation spread. This result suggests that fact-checking spread tend to follow misinformation spread despite a lack of causal relation (i.e., fact-checking articles are created as a response to misinformation). As with the misinformation sharing behaviour, we observe a sharp decrease in fact-checking sharing behaviour after the initial shock as initial sharing behaviour reduces.

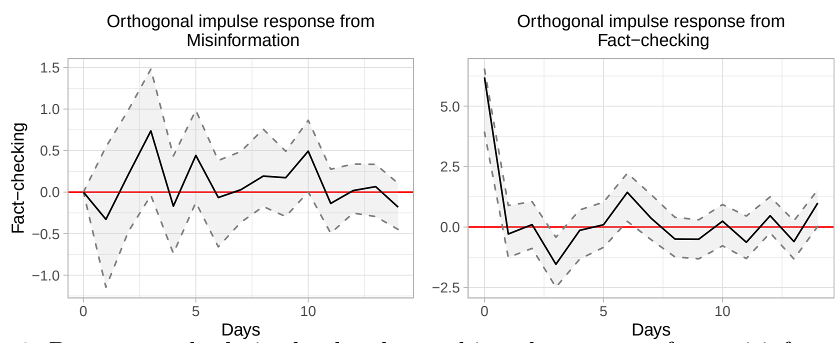


**Fig. 3.** Bootstrapped relative-level orthogonal impulse response from misinformation shock (95% confidence interval).

The FEVD results displayed in Figure 4 show that misinformation spread predictions are directly affected by the spread of fact-checking information with misinformation prediction getting more affected by fact-checking spread as time goes by whereas fact-checking spread appears to be unaffected by past misinformation spread. This result adds to our previous causality observation between fact-checking information and misinformation spread.

## 6 Discussion

Our results show that at the Covid-19 level, fact-checked URLs are less shared (compared to misinformation in term of mean) during all the periods and that the

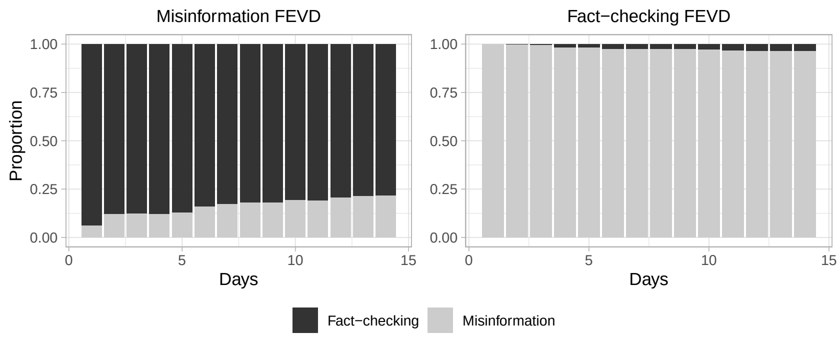


**Fig. 4.** Forecast Error Variance Decomposition (FEVD) for the relative-level misinformation and fact-checking spread.

standard deviation and mean are much higher for misinforming URLs. This indicates that there may be some intrinsic features of misinforming URLs, potentially related to topic or sentiment, for example, that make them more shareable than fact-checks. This echoes previous work that describes the enticement of emotion and novelty in misinformation [32]. Likewise, this also indicates that the communities sharing fact-checks and those sharing misinformation are likely different indicating that previous agent-based models that address the impact of fact-checkers on a network [28,23] may need to be adjusted for lower-than-expected inter-community contact. Finally, significant differences in sharing behaviour appears mostly during the ramping up period of the pandemic (*early* phase) with large variations in deviation and means toward misinformation. This may be explained by the heightened fears and extreme uncertainty concerning the pandemic during that particular period in which the public need for information is outweighing the authority's ability to provide it [9,25,24].

At the relative level, we confirm previous findings showing the initial stage of circulation is associated with highest information spread in general [26]. The absence of significance in general behaviour during the initial period and the observed high difference in standard deviation during that period shows that most difference in spread behaviour happens in the later periods and may be associated with the virality of misinforming content and its ability to spread deeper compared to fact-checks [32]. This result also highlights that the difference in spread may be highly related to the initial amount of shares of a given URL and to external contextual factors rather than the intrinsic properties of the shared URLs (e.g, the relation between the pandemic state and the misinforming URLs topics rather than simply the misinforming URLs topics).

Causality analysis confirms that misinformation spread can be predicted from fact-checking spread. This relation is also confirmed by the FEVD analysis (Figure 4). However, the opposite relation is not observed meaning that fact-checking spread behaviour is not causally related to misinforming behaviour even though impulse analysis show that to some extent misinformation spread shocks tend to lead to an initial increase in fact-checking spread.

Although the previous observation is encouraging, our results (Section 5) show that the reduction in misinformation spread associated with an increase in fact-checking information is mostly temporary. This indicates that the misinformation reduction power of fact-checking is impeded by its apparent inability to be shared over long periods of time. This echoes previous research that suggested that the amount of corrective information may play an essential role in reducing misinformation [1,26]. To this end, better fact-checking campaigns may be required to increase the virality of fact-checking content for increasing its shareability.

## 7 Limitations and Future Work

Although our approach is really accurate, since it does not depends on automatic annotations for identifying misinformation and fact-checks, our data covers only a small amount of misinformation and does not contain variations of the same posts. Similarly, the amount of collected posts is limited by the data collection method. A relatively simple approach for future work would be to use automatic misinformation detection methods coupled with semantic similarity measures to detect content that is already fact-checked but associated with different URLs. We could also combine different data collection methods for improving the fidelity of our study. As our results have shown, additional topological and community analysis is required to better characterise the deviations and mean differences observed in the multivariate spread analysis (Section 6). We plan to increase the granularity of our analysis by obtaining more fine grained information about the users (e.g., demographics) that share misinformation as well as intrinsic misinformation and fact-checking content features such as topical information.

## 8 Conclusion

We have presented an initial analysis of the relation between misinformation spread and fact-checking information during the initial period of the Covid-19 pandemic. Although our results show that fact-checking spread has a positive impact in reducing misinformation, we have found that the impact of fact-checking is seriously impeded by three different factors: the amount of shared misinformation (which is disproportionately higher than fact-checking content), the different communities of fact-check sharers *versus* misinformation sharers, and the short period of time in which fact-checks are likely to spread. To overcome this, it will be necessary to build interaction bridges between fact-checking and misinformation spreaders, and create fact-checking content that is more appealing. This will help create a sustainable fact-checking information spread over time.

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