

# Analyzing the emotional impact of COVID-19 with Twitter data: Lessons from a B-VAR analysis on Italy

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## ARTICLE INFO

### Keywords:

Crisis management  
COVID-19  
B-VAR models  
Twitter  
Positive/negative outbreak indices  
Health policy

## ABSTRACT

The novel coronavirus 2019 revolutionized the way of living and the communication of people making social media a popular tool to express concerns and perceptions. Starting from this context we built an original database based on the Twitter users' emotions shown in the early weeks of the pandemic in Italy. Specifically, using a single index we measured the feelings of four groups of stakeholders (journalists, people, doctors, and politicians), in three groups of Italian regions (0,1,2), grouped according to the impact of the COVID-19 crises as defined by the Conte Government Ministerial Decree (8<sup>th</sup> March 2020). We then applied B-VAR techniques to analyze the sentiment relationships between the groups of stakeholders in every Region Groups. Results show a high influence of doctors at the beginning of the epidemic in the Group that includes most of Italian regions (Group 0), and in Lombardy that has been the region of Italy hit the most by the pandemic (Group 2). Our outcomes suggest that, given the role played by stakeholders and the COVID-19 magnitude, health policy interventions based on communication strategies may be used as best practices to develop regional mitigation plans for the containment and contrast of epidemiological emergencies.

## 1. Introduction

Nowadays, the global crisis of the novel coronavirus 19 which was defined as a pandemic is producing a cross-border worldwide crisis (WHO, 11<sup>th</sup> March 2020). Specifically, among the several definitions of crisis, the "COVID-19 pandemic" can be considered "transboundary" for its rapid diffusion, unclear ending, and ability to cross the boundaries of individual countries [1,2]. This crisis has undermined the structure of health care systems and governments, with severe implications on health, economy, the way of living and on social structure forcing a rise of digital communication. The governments, and particularly their legitimacy, may be heavily threatened by these situations, due to a real (or perceived) scarce capacity in facing cross-boundary crises.

The crisis management of a public organization can be conditioned by several external factors, such as: (i) strong pressures from media and public opinion, (ii) powerful stakeholders acting to shape the crisis response accordingly with their interests, (iii) fragmentation of the political context due to a devolution process and to a power re-distribution, which can produce variations in the response of different actors, (iv) European and international community, which can also play a key role

in shaping the crisis response [3]. In time of crisis, communication has a role both in the response phase and the preparation phase [4]. Communication has been recognized as a tool for coping with traumatic crisis to (i) reduce immediate economic damage; (ii) contain reputational compromise; (iii) contain loss of stakeholder trust [5].

In addition to the factors listed above, several authors have emphasized that other aspects are essential for an effective and well-functioning crisis management such as: leadership, governance capacity, governance legitimacy, decision-making systems and governance tools, and from attention to citizens' perceptions, attitudes and trust in government arrangements for crisis management [6–8].

As leadership, the role of political leaders is fundamental, especially when they must handle a "transboundary crisis" like the COVID-19 pandemic [1]. The 'meaning making' referring to the crises and political communication is among their key strategies that influence preparedness and responses to (current and future) crises.

In terms of governance expressed as coordination and collaboration, both vertically across levels of government and horizontally within government, the fragmentation that can derive from a transboundary crisis challenges the capacity, and the efficacy of the response that

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<https://doi.org/10.1016/j.seps.2023.101610>

Received 3 September 2022; Received in revised form 28 April 2023; Accepted 8 May 2023

Available online 12 May 2023

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depends also on the degree of autonomy of the various actors (i.e., Regions), their level of adaptability and updatability of the measures with an evolving knowledge (e.g. making facial masks obligatory in public spaces) (Lodge and Wegrich 2014; Noordegraaf 2017; [8,9]. [3].

The consequences of the fragmentation are the discrepancies shown in the decentralized healthcare systems due to the trade-off between crisis communication and management. For instance, a recent study by Ref. [10] found that, although the national communication strategy was able to create in Italy a national perception of the first four weeks of the outbreak as a sort of common narrative, significant regional differences in terms of sentiment (positive/negative) seem to be present in Twitter users due to the different capacities of regional health systems to cope the epidemic.

The governance “legitimacy” is another important variable since a low public trust in the adopted government measures leads to scarce collaboration and coordination undermining the governance structures and their processes and amplifying the crises itself [11]. This underlines that the acceptance of and compliance with policy measures depends on the public perception of the coherence, credibility, and effectiveness of the response. How politicians and leaders communicate and deal with uncertainty affects the implementation of crisis management.

This leads to a sort of “co-production” of crisis management: all actors involved (organizations, managers, front-line workers, citizens) will work together both within networks and between the groups to successfully address the crises (Lægveid and Rykkja, 2018; [2,12].

The combination of these factors created high uncertainty in relation to the course of the crisis, and how to manage it (Helsloot et al., 2012, [13].

Although the severity related to the COVID-19 crisis needs a study based on a review of the literature on crises management to individuate best health policy practices, many studies are still limited and focused more on stable/routine situations of crises, rather than on transboundary crises [7,8,13].

Moreover, crisis management and communication were mostly studied in the private sector [13,14], while there is scarce evidence of its effect in public institutions despite, they are among the first actors to be involved.

Handling of crises by private institutions is very different compared to the public ones that may be under greater scrutiny [15] and it is for this reason that communication covers a pivotal role to better understand crisis management and the best way to address it. Institutions need to be transparent, to communicate more frequently with different actors in a constant interaction to learn, adapt and update measures with evolving knowledge [15–17]. This last aspect is particularly critical, because managing interdependencies may be very difficult when situations quickly evolve becoming uncertain and ambiguous [18], and the response should be well-timed and targeted to the different stakeholders’ needs [19].

For these reasons, a crucial aspect is how the communication strategy targets the perception of the real events during a crisis (crisis framing), in terms of the risks and the behaviors to adopt for a resolution [11,20]. In this case, each stakeholder could act as a “station of amplification” of the perception minimizing or maximizing the gap between the perceived and the actual crisis (i.e., top priority, ignoring it or dealing with it in a routine fashion), influencing the dynamics of the crisis perception [11,21]. This last aspect is particularly relevant when the management of crises involves communication on social media.

During the COVID-19 pandemic, social distancing and lockdown moved communication between the different actors (citizens, as well as journalists, experts, and political leaders) to digital channels.

The great amount of information shared on social media became a source of time-critical information for learning more about crisis management. The so-called Big Crisis Data drawn from social media provides updated information on the public concern measuring their reaction to the crisis that can improve the effectiveness of a health policy response [22]. In this sense, Twitter can be used as an official key source of

information by the public institutions in charge of managing the crisis, with the positive effect of reducing uncertainty, shaping emotions, improving the understanding of correct information (i.e., on behaviors to adopt), fix fake news or misunderstanding, supporting discussion and resolution of issues regarding responsibility, blame and adequacy of response, improve cooperation and integration in giving responses to the crisis [10,23]. The growing attention of people (general public) expressed on social media can be explained by an increasing of ‘fear factor’, due to a high number of recent disasters [24], and to a rapid spread of the transboundary crises itself [2,24]. During these crises, most people choose social media to gather information, or to share and accelerate the information, including their opinion, fear, and anxiety [10]. To this respect, it is crucial to study the actors’ perceptions, their role (i.e top leaders), and their interaction with the crisis management strategies, and the crisis communication to guarantee effective health policy response to the crisis itself [25]. At present, the literature on this aspect has been particularly focused on the roleplayed by the experts (Covid scientists) on the leaders/politicians, and citizens that affected the implementation of crisis management generating a trade-off (crisis communication often deviated from expert recommendations) [6,12,26]. The scientific advice on social media shows an essential role of the clinicians’ communication for effective crisis management especially at the beginning of the outbreak. This is shown in a recent study that highlighted the need for a deeper investigation on how some specific categories of stakeholders may have guided positive/negative concerns during the COVID-19 pandemic in Italy [10].

Against this background, our paper complements the existing studies on coronavirus outbreak in three important ways. Firstly, we construct an original and unique database drawn from Twitter, improving on the initial work of [10] we use a sentiment index, known as *polarity*, that we applied to four main key stakeholders, namely people (general public), journalists, politicians and doctors selected according to the review of the state-of-the-art literature on crisis management just discussed above [1,6,12,26]. Specifically, we considered the category of doctors and virologists because it was selected by the Italian government which created a scientific committee of recognized experts. Moreover, this category was extremely active on Twitter and other social media animating the COVID-19 debate and reaching large audiences (i.e they were invited to many interviews and television broadcasts), further amplifying the health policy debate on coronavirus. In this regard, journalists and medical experts became the first source of information for decision-making in crises under conditions of direct threats and high uncertainty significantly impacted on the crises’ perception of the general public. The experts’ responsibility was large, for instance, prof. Roberto Burioni, a recognized virologist, gained on Twitter more than 300k followers, a surprising number for scientific communication that is twice the number of a well-known “star” of the Italian scientific communication on television, Alberto Angela. This anecdotal example demonstrates the framework for communication that has been created by the interaction between experts and media (journalists) and the role of these two categories of stakeholders (doctors and journalists) in amplifying or reducing the perception of real events during a crisis. On the other hand, politicians during COVID-19 faced the challenge of making difficult trade-offs, prioritisations and value judgments. For example, under great time pressure their communication served to encourage people to limit social contacts, avoid traveling, wear masks in closed spaces and encouraged habit changes such as handwashing.

Starting from this scenario the aim of our study using the social listening is to get a better description of the reactions of these four agents to the events during the initial pandemic (when lockdown forced people to online communication), capture the feelings/sentiments of each of them and analyze how they in creating, amplifying, or reducing the positive/negative perception of the crisis may influence each other (looking for the causal directions) during the early phase of the coronavirus in Italy (the first four weeks). Specifically, we monitor their emotional change in three different groups of Italian regions (Group

0,1,2) based on COVID-19 intensity, according to the Conte Government Ministerial Decree (DPCM 8<sup>th</sup> March 2020). By analyzing the feelings of these agents could help the policymakers to obtain real time information on the crisis's perception of these stakeholders reducing the uncertainty of decision making to set up better and early warnings of health policy response to the emergency avoiding to design policy interventions that may be too strict especially in the Phase 2 of the pandemic and adapting the policies to stakeholders needs.

The second contribution is methodological. We investigated the interplay between the emotions/epidemic's perceptions of the four stakeholders for these three groups applying B-VAR models based on Minnesota prior to analyze the longitudinal dataset collected. Since the dataset is short, these models result more appropriate for the dynamical analysis (impulse response functions and forecast variance decomposition functions) and for the forecasting analysis (shown in the appendix). Finally, we discuss the results according to a multidisciplinary approach in the background domain of crisis management, communication, and policy implications.

## 2. Methods

### 2.1. Dataset

In this study, we extracted Twitter data selected for specified health-related keywords such as "COVID-19", "coronavirus", "coronavir- usitalia". The sample period covers the first four weeks of the corona- virus outbreak in Italy (17th February 2020–22nd March 2020) with several days of anticipation and the maturity of the outbreak with the extended lockdown of the entire country. The most relevant episodes during the initial diffusion of the virus are present and it is sufficiently long to perform a robust analysis of the time series trends during the outbreak.

The initial data set includes nearly 4,163,138 tweets from about 62,084 users located in Italy. Associated with each tweet we know the name of the author, his/her location, the timestamp, the number of followers and the impact of the tweet (number of retweets and likes).

Specifically in our analysis we first filtered the users with the help of specific keywords classifying them into four groups of stakeholders: (1) healthcare professionals/famous experts or virologists/doctors; (2) media/journalists; (3) politicians; (4) people/general public.

Secondly, we used the users' location information to filter Tweets according to geography obtaining 523,609 unique tweets from all Italian regions. In this way, we can clearly identify the mood (positive or negative) of the doctors from Lombardy, or the sentiment of the people from Veneto (the statistics per each region are shown in Table 1 and Fig. 1 in the appendix).

Thirdly, considering that the COVID-19 hit in a very different way Italian Regions in the first wave of the epidemic and that Regions have put in place sometimes different recovery health strategies [27], to ensure adequate statistics per category of stakeholders, we considered three different groups of Italian regions (Group 0,1,2). The groups were identified on the basis of their risk exposure according to the Conte Government Ministerial Decree (DPCM 8th March 2020) as follows: i) Group 2: Lockdown of the entire Region (Lombardia, 8th March 2020); ii) Group 1: lockdown of the Regions where the restrictions were on individual provinces and municipalities (Veneto, Emilia Romagna, Pie- monte, Liguria and Marche) and iii) Group 0: the rest of the Italian Regions involved in the second phase of the total lockdown.

### 2.2. Statistical analyses

In this study we first calculated the polarity index to measure the positive/negative feelings of the stakeholders during the epidemic [10]. The sentiment is computed with machine learning methods (for further details see the sentita library [28], according to a manual association of sentiment to a tweet to which it corresponds to a relative subjective

**Table 1**  
Impulse response functions results.

Group 0		
Horizon in years	Doctors vs Journalists	Journalists vs Doctors
0	0	Not significant
1	0.005	
2.5	0.010	
3	Not significant	
10	Not significant	
3	0	
6		
Horizon in years	Doctors vs Public	Public vs Doctors
0	0	Not significant
1	0.0025	
2.5	0.0050	
3	Not significant	
10	Not significant	
3		
6		
Horizon in years	Public vs Journalists	Journalists vs Public
0	0	Not significant
1	0.0050	
2.5	0.007	
3	0.004	
10	0	
3		
6		
Group 1		
Horizon in years	Journalists vs Public	Public vs Journalists
0	0	0
1	0.01	0.025
2.5	0.02	0.06
3	0.01	0.025
10	0	0
3		
6		
Horizon in years	Journalists vs Doctors	Doctors vs Journalists
0	0	Not significant
1	0.02	
2.5	0.03	
3	Not significant	
10	0	
3		
6		
Horizon in years	Politicians vs Public	Public vs Politicians
0	0	Not significant
1	0.01	
2.5	0.015	
3	Not significant	
10	Not significant	
3		
6		
Group 2		
Horizon in years	Doctors vs Public	Public vs Doctors
0	0	0
1	0.05	0.1
2.5	0.10	0.2
3	Not significant	Not significant
10	0	0
3		
6		
Horizon in years	Politicians vs journalists	Journalists vs Politicians
0	0	Not significant
1	0.0050	
3	0.007	
6	0.004	
10	0	

(continued on next page)

Table 1 (continued)

Group 2		
Horizon in years	Doctors vs Public	Public vs Doctors
3		
6		
Horizon in years	Journalists vs Doctors	Doctors vs Journalists
0	0	Not significant
1	0.4	
2.5	0.5	
3	Not significant	
10	0	
3		
6		
Horizon in years	Politicians vs Doctors	Doctors vs Politicians
0	0	Not significant
1	0.2	
2.5	0.3	
3	Not significant	
10	0	
3		
6		
Horizon in years	Politicians vs Public	Public vs Politicians
0	0	Not significant
1	0.04	
2.5	0.05	
3	Not significant	
10	0	
3		
6		
Horizon in years	Journalists vs Public	Public vs Journalists
0	0	0
1	0.05	0.1
2.5	0.10	0.2
3	Not significant	Not significant
10	0	0
3		
6		

score of mood from negative to positive. Joining together the work of many people that evaluated the emotional content of the same set of tweets (the corpus), it is possible to create an “average sentiment” per text. This labeled dataset of tweets becomes then the training set useful to create a supervised machine learning model that is then able to classify other tweets into positive/negative ones.

Then, each tweet is associated with a negative sentiment  $n$  (expressed by a positive numerical value in the range 0,1) and a positive sentiment  $p$  (expressed by a positive numerical value in the range 0,1). The difference between the positive and negative sentiment  $r = p - n$  is called *polarity* and expresses the overall sentiment of the tweet. A negative polarity expresses a negative sentiment, a positive one a positive mood.

Averaging tweet polarity by day we obtain the daily sentiment of the Coronavirus pandemic in Italy. Unlike [10] who analyzed separately the two indices (the positive and negative outbreak sentiment), we decided to compute a unique index for each stakeholder in the Region Groups to easily analyze the effect of the overall polarity in terms of COVID-19 perception and its dynamic.

In the second step, we carried out a dynamic analysis on the sentiments shown during the early weeks of the coronavirus outbreak relative to the abovementioned categories of stakeholders (journalists, people (general public), doctors and politicians) in three different groups of Italian regions, categorized according to the Conte Government Ministerial Decree (DPCM 8<sup>th</sup> March 2020). The short length of our sample represents, however, a limit in the application of the VAR models that, since they typically include many free parameters to estimate may lead to the problem of over-parameterization [29]; Doan et al., 1984; Canova 2007; Kanngiesser et al., 2019).

In this study, we propose a solution to the short length of our sample by modeling the time series of polarity for each stakeholder in the region group employing the B-VAR approach.

The incorporation of the prior distribution of the parameters transforms the VAR model into a more parsimonious model (Bayesian VAR models) while at the same time reduces the problem of dimensionality (overfitting) and it gives a reasonable account of the uncertainty faced by the investigator (for further details see appendix)

Then, we computed the impulse response functions (IRFs) based on B-VAR models to examine whether there exists a significant dynamic relationship between the series of sentiment-polarity relative to a specific stakeholder’s category (and the opposite relationship) in each group of Italian regions (e.g polarity of journalists vs polarity of doctors in Group 0 and vice versa). The IRFs were fitted with a lag length equal to 2 using the Bayesian information criterion (BIC). We estimated all B-VAR models by using the standard Minnesota prior, whose tightness is chosen as follows:  $\lambda_1$  (prior information) is set to a small value since the prior beliefs are informative with respect to the sample information. In this case, the posterior mostly mirrors prior information.  $\lambda_2$  (cross variables lag) is assumed to be larger than zero since the information of

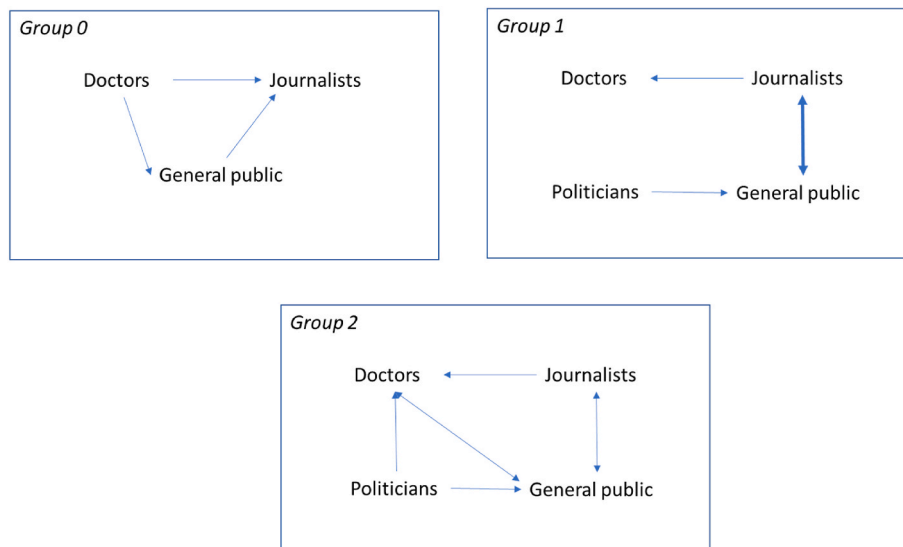


Fig. 1. Actors relationships in each regional group.

cross variable lags is important while  $\lambda_3$  (exogenous variables) is set close to zero since the exogenous variables information is not relevant for our analysis.

Finally, we assess the ability of the models to fit the data by evaluating the *in-sample* model's forecasting performance of B-VAR settings on Minnesota prior against other model specifications (unrestricted VAR model and B-VAR model based on Normal-Wishart prior). As explained above, the Bayesian shrinkage approach effectively recognizes the robust relationships in data, and it replaces the unstable ones with a parsimonious benchmark that is known to have a good forecasting performance (e.g. the random walk with drift). This makes the Bayesian VAR framework very appealing since we do not have to worry about a variable selection procedure.

### 2.3. Impulse response functions results

In Table 1 are shown the IRFs results relative to statistically significant relations between the sentiment-polarity of the stakeholders respectively in the Group 0,1,2 (the Graphs of IRFs are reported in the appendix while the results of not significant IRFs are available upon request).

The results of our analysis show that there is substantial heterogeneity between the macro categories of actors in each Group.

For Group 0, we find a short-term and one-way impact: a) from doctors to journalists; b) from doctors to people; c) from people to journalists. Specifically, an emotional change in the doctors (a positive shock on doctors' polarity index) leads to an increase in journalists' polarity index. In the same way, a worsening of doctors' negative feelings has a negative effect on journalists' negative sentiments (negative polarity shock). Similarly, doctors influence people which in turn affect journalists.

For Group 1, we find a long-term and two-way influence from journalists to people and several short-term one-way influences: a) from journalists to doctors; b) from politicians to people. In detail, a shock on journalists' feelings directly impacts people's emotions and this effect is persistent over time. On the other hand, doctors' emotions positively react to journalists' moods. The same findings we obtain from politicians to people.

Finally, for Group 2 we discover a bi-directional short-run relation from people's sentiments to doctors' sentiments and from people's feelings to journalists' feelings. We also find a direct, significant, and short-lived effect of the polarity index emotional change of journalists to doctors, of politicians to doctors and of politicians to people.

To further understand the relative importance of the stakeholder's sentiment in affecting the other stakeholder's feelings, we also computed the forecast error variance decomposition functions (FEVDs) for the same stakeholders in each region group in the same time horizon of ten days (Fig. 5-6-7a-7b in the appendix), which confirms the robustness of the above results.

### 2.4. Evaluating the performance of the models

In this section, to assess the forecast accuracy of the models since we have a short sample, we first drop the last two observations (holdout sample) and use them for the out-sample forecast. We then use the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE) to compare the models and to ascertain which model shows the smallest forecast errors. We use both measures because RMSE is more sensitive to large deviations from the actual time series, values that become much larger as they are squared. MAE, instead, uses absolute value forecasts without any exponent but sometimes with this index it is difficult to separate a large error from a small one. Table 1 analyzed the accuracy of point forecasts by reporting the RMSE and MAE of sentiment/feeling for each category of stakeholder in the three Region Groups (0,1,2)

The results of the forecasting reported in Table 2 show that: (a), an unrestricted VAR model performs poorly; (b) a B-VAR model based on

Minnesota prior is better than an unrestricted VAR model and a B-VAR model based on Normal Wishart prior. We conclude that B-VAR with Minnesota prior, outperforms both the unrestricted VAR model and the B-VAR model based on Normal Wishart prior. The results are robust and qualitatively similar using both the RMSE and MAE.

## 3. Discussion

This paper provides an analysis of the three groups of regions where there are different interplays among the four main actors of our investigation. As shown in Fig. 1 which summarizes the results of the abovementioned IRFs we find that the higher the intensity and the impact of the COVID-19 spread, the higher the influence and the interaction between the actors expressed by the sentiment polarity. This result underlines the relevance of identifying agents that act as 'stations of amplification' of the public perception [21], since they may influence (increase or decrease) the gap between the public perception of the crisis and the actual crisis itself with significant consequences on the efficacy of health policy interventions.

Specifically, the higher the gap between the public perception of the crisis and the actual crisis itself due to the communication of key actors and higher may be the impact of their communications on the efficacy of health policy actions. Thus, measuring the perception/feelings of the main stakeholders during the early weeks of the pandemic and their influence can help to improve the health interventions starting for example from specific surveys on health policies conducted allowing this "alternative communication styles". Traditionally, measuring the level of acceptance of health policies has been conducted by direct surveys. For instance, the Italian demographic institute IPSOS for the first 15 weeks of the pandemic measured the "optimism" of a small sample of the population with direct phone interviews. These methods read the situation and can also describe the level of optimism, although they do not distinguish between different actors. Moreover, we believe that to be a reliable support for health policy measurement, these surveys lack systematicity as they a) were not consistently targeting the same population sample b) do not present alternative communication styles nor different ways of phrasing the same message to discover its impact. They were not conceived to measure different communication styles, but instead to propose alternative narratives that do exist in social networks where these ones can eventually become dangerous "conspiracy" theories. Measuring the impact of these narratives is possible on social networks as the direct sentiment polarity associated with these messages perturbs the overall level. Social networks have virtually all possible narratives and their impact is reflected in the sentiment level. For this reason, while surveys remain a fundamental tool for measuring a specific issue, social media allow a more extended and articulated analysis where "alternative narratives" coexist with official ones and are in part responsible for the observed change we estimated over time. Finally, in social media there is no interviewer effect that can condition the answer in a well-known psychological effect. We then argue in favor of social listening as a tool to explore larger audiences and to use its general sentiment levels for policy intervention and better communication style.

In detail, one of the most relevant findings of this study is the influence on people (general public) of the doctors, in particular in the Group that includes most of the Italian regions (Group 0) and in Lombardia was the first region registering infections and maintaining a primacy of a number of cases and deaths in Italy (Group 2). One possible reason is that doctors and experts have a clear vision of the potential negative impacts and tend to react quickly to the negative effects of the coronavirus diffusion influencing people and journalists. In this case, the doctors have a dominant role in the crisis communication for regional and national policymakers because they communicated on social media at the beginning of the outbreak and this aspect clearly impacted the public perception of the crisis, making the doctors important stakeholders for "surveillance strategies" in monitoring the COVID-19 disease. This suggests that they as "hands-on practitioners" and "front-line

**Table 2**  
Forecasting VAR versus B-VAR.

Group 0	RMSE	MAE
<b>Doctors vs Journalists</b>		
Standard VAR	0.68	0.53
	0.77	0.62
Minnesota prior	0.34	0.26
	0.51	0.53
Normal-Wishart prior	0.43	0.51
	0.67	0.69
<b>Doctors vs Public</b>		
Standard VAR	0.72	0.67
	0.63	0.86
Minnesota prior	0.45	0.44
	0.27	0.22
Normal-Wishart prior	0.71	0.65
	0.68	0.69
<b>Public vs Journalists</b>		
Standard VAR	0.18	0.19
	0.28	0.25
Minnesota prior	0.10	0.16
	0.21	0.20
Normal-Wishart prior	0.17	0.17
	0.24	0.26
Group 1	RMSE	MAE
<b>Journalists vs Public</b>		
Standard VAR	0.21	0.29
	0.27	0.25
Minnesota prior	0.13	0.19
	0.21	0.23
Normal-Wishart prior	0.46	0.35
	0.31	0.26
<b>Journalists vs Doctors</b>		
Standard VAR	0.19	0.21
	0.13	0.22
Minnesota prior	0.09	0.15
	0.11	0.18
Normal-Wishart prior	0.17	0.28
	0.26	0.27
<b>Politicians vs Public</b>		
Standard VAR	0.45	0.46
	0.61	0.50
Minnesota prior	0.38	0.39
	0.26	0.22
Normal-Wishart prior	0.48	0.43
	0.51	0.46
Group 2	RMSE	MAE
<b>Doctors vs Public</b>		
Standard VAR	0.53	0.75
	0.27	0.26
Minnesota prior	0.35	0.45
	0.23	0.15
Normal-Wishart prior	0.48	0.58
	0.29	0.22
<b>Politicians vs Journalists</b>		
Standard VAR	0.24	0.25
	0.12	0.18
Minnesota prior	0.16	0.16
	0.09	0.08
Normal-Wishart prior	0.18	0.13
	0.11	0.09
<b>Journalists vs Doctors</b>		
Standard VAR	0.37	0.28
	0.63	0.86
Minnesota prior	0.28	0.20
	0.58	0.61
Normal-Wishart prior	0.31	0.27
	0.60	0.62
<b>Doctors vs Politicians</b>		
Standard VAR	0.25	0.27
	0.13	0.26
Minnesota prior	0.14	0.16
	0.06	0.17
Normal-Wishart prior	0.23	0.23
	0.09	0.24

**Table 2 (continued)**

Group 2	RMSE	MAE
<b>Politicians vs Public</b>		
Standard VAR	0.21	0.22
	0.81	0.87
Minnesota prior	0.13	0.15
	0.15	0.21
Normal-Wishart prior	0.15	0.16
	0.19	0.27

workers” [9], are the key source of resilience and crisis communication also on social media, because it seems they can anticipate anomalous peaks of negative/positive sentiments of both people and journalists giving useful information for health policy best practices in fighting the COVID-19 diffusion.

However, since the doctors are mostly focused on the epidemic spreading and lethality, they could have influenced respectively the negative side of the epidemic perception of the people and of the journalists framing it in terms of dimensions and severity and, consequently, changing its significance related to the agenda status (i.e., a top priority) [11]. These results are confirmed by the existing literature that showed the high influence of experts (scientists) on the people’s perceptions [6, 26]. The dominant role at the beginning of the epidemic of actors with specific expertise (i.e. clinicians/doctors) underlines a big risk in increasing the gap between the people’s perception of the crisis and the actual crisis [30].

Another important finding of our research is that the people showing a negative sentiment (panic, fear) under the impact of COVID-19 is influencing the journalists’ mood in Group 0. Since social media shows an important role in spreading fear among people, correct communication of the crisis is essential for effectively managing a crisis [24].

It is worth pointing out that the politicians seem to have a marginal role in Group 0. There was a lack of online salience of the leadership of politicians, considering that, among the strategic activities of political leaders in crises management, the ‘meaning making’ task refers to political communication (i.e., an activity aimed at collecting and distributing information, reducing uncertainty from internal as well as external perspectives, maintaining or increasing the credibility and legitimacy) [13]. The absence of the politicians’ voice in the Twitter arena of the most influencing interactions might also be seen as challenging in terms of people’s trust and perception of government actions, and governance legitimacy, which are all determinant factors of successful crisis management [7,8].

Finally, we find in Group 1–2 a significant effect of journalists’ emotions on doctors and people’s feelings. When the situation of the COVID-19 diffusion is getting worse the information provided by the journalists influences doctors. This is a clear case of the “strong” reaction of doctors and people to negative/positive news showing the pivotal role of journalists’ communication in the perception of the crises. These results confirm that the journalists remain ‘stations of amplification’ on Twitter [21], as they can intensify or attenuate negative and positive perceptions of the crisis.

Overall, among the three stakeholders groups, the doctors show a significant Twitter influence that impacts both people (Group 2-0) and journalists (Group 0). It seems that the doctor’s behavior was fundamental especially, at the beginning of the coronavirus spread, when the first lockdown was imposed in the Lombardy region (23 February). However, the analyses show that communication must be carefully tailored in the three cases. In the more severe situation (i.e., when the impact of coronavirus spread is larger) communication management is rather complicated because all the actors are involved, and they influence each other with a dynamical effect. In these cases, the health policy’s interventions should be targeted to the specific regional situation to cope in an efficient way with the crisis itself.

This result seems to confirm that when there is an increase in the relationships’ complexity that is growing up with the crises magnitude

communication and coordination among different actors become difficult [12]. This aspect is an additional and relevant finding of our research, considering that vertical as well as horizontal coordination between networks and groups can be undermined by communication problems [12]. Nevertheless, unprecedented crises with a rapid spreading and high level of uncertainty, such as the COVID-19 outbreak, leave public institutions unprepared and do not allow for standard solutions, and processes-contingency plans (if available) should be prepared and deployed on time for an immediate and specific response to minimize the negative impact of the crises [31]. In this context, social listening may help policymakers in the phase of preparation of strategic planning to mitigate the crisis and adapt the crisis management system in response to identified potential vulnerabilities.

#### 4. Conclusions

Several crises, such as the COVID-19 pandemic, could have a long-lasting impact or not having a rapid or neatly defined conclusion, adding a great pressure on political and administrative institutions that need to be ready, able to detect and develop response measures under conditions of uncertainty and short time constraints. Crisis management and communication are key-drivers when dealing with a transboundary crisis and a huge plethora of actors.

Twitter social listening is useful to investigate whether there is an immediate threat and what it constitutes, whether it needs to be addressed urgently and how it should be countered. This research is focused on citizens, doctors, journalists and politicians, as key agents in social networks during health crises.

Our aim is to assess whether there are significant relationships in terms of sentiment/feelings between these four categories of stakeholders (journalists, people, doctors, and politicians) in three different groups of Italian Regions (0,1,2) grouped according to the Conte Government Ministerial Decree (DPCM 8<sup>th</sup> March 2020). The analysis considers the early phase (four weeks) of the coronavirus outbreak in Italy taking into consideration the decentralized nature of the Italian healthcare system (the degree of autonomy of the various public institutions (Regions)) that in an emergency could have an impact on the efficacy of the health policy response [3].

The innovative features of this study are the following. First, the analysis complements the literature on crisis management and health policy by focusing on the role of communication of the main actors during a pandemic. To the best of our knowledge, this is the first study on the role of healthcare workers on the crisis perception on Twitter, in terms of their potential influence on positive and negative feelings. The analysis of the behaviors of these actors is crucial for decision-making in crises under conditions of direct threats and high uncertainty.

Second, social media listening represents a useful and innovative tool to cope with outbreaks starting from the perceptions shown during the epidemic of individual groups of actors. In fact, several studies demonstrated that analyzing Twitter discussions it is possible to capture “early warning signals”, to geo-localize anomalous infections and monitor their development for now-casting health policy interventions [32–34]. In our study, using a polarity index, we monitor the emotional change (positive/negative sentiment) of different categories of stakeholders to identify the early signals of crisis perception through the communications on Twitter of the agents who played the most important role during the pandemic. Given the nature of the Covid crisis and its uncertainty listening to these stakeholders represents the best strategy to get their support for a crisis policy and to justify its adequacy when the measures are taken ex-post under pressure and uncertainty [9].

Finally, given the short length of our sample, this study proposes the Bayesian VAR econometric tools. The preference for the Bayesian methods relies on the fact that they are particularly well suited in handling time series even when the dataset covers a limited number of observations; they are an a-theoretically grounded way to impose

judgmental information and a priori beliefs in the model; they improve the dynamical analysis and the forecast performance when the VAR is unstable, and they do it by reducing the bias and the standard error. The use of the impulse response functions and the variance decomposition functions allows us to investigate the long-run dynamic relationship between the variables of interest. Further, we employ an out-of-sample forecast analysis to ascertain the goodness fit of the B-VAR estimation. Our results show that the B-VAR procedure based on Minnesota prior specification is acceptable for the parameter estimation given the available data. We use two criteria to evaluate forecasting models which include Roots Mean Square (RMSE) and Mean Absolute Error (MAE). In general, the values of the RMSE and MAE for all B-VAR models based on Minnesota prior are the lowest. The B-VAR models based on Minnesota prior should be considered as appropriate models for forecasting and dynamical analysis with respect to VAR approaches and other B-VAR specifications when the dataset is short.

In sum, our findings confirm that the journalists are ‘stations of amplification’ on Twitter [21], because they can intensify or attenuate negative and positive perception of the crisis (especially in Groups 1–2). However, this study suggests that doctors, namely hands-on practitioners and front-line workers [9], are key-drivers sources of resilience and crisis communication also on social media, because it seems that their feelings about the pandemic can directly anticipate negative, or positive sentiments of both people and journalists in the most part of the Italian regions (Group 0), including Lombardia that had the highest number of cases of COVID-19 in Italy (Group 2).

Starting from these points our research underlines how social listening provides useful information to improve policy performances as well as the adoption of health strategies in response to the COVID-19 crisis. However, the acceptance of and compliance with policy measures depends on the public perception of the coherence, credibility, and effectiveness of the response. Thus, how politicians, journalists, and doctors (virologists, epidemiologists) communicate and deal with uncertainty affects the implementation of crisis management. The ability to adapt the crisis management system and the corresponding measures as the pandemic unfolds on social listening, is essential for effective health policy strategies. A constant interaction and coordination of the governments and policymakers with these networks of actors (i.e. journalists, doctors) may help them to learn, adapt and update measures with evolving knowledge improving the health policy interventions.

Despite social listening offers relevant information on the main stakeholders’ crises perception during the COVID-19 epidemic, it is important to notice that official communication is not always able to counteract the natural tendency of modern social media to produce a large amount of fake news, manipulated content, and even conspiracy materials. The influence of these narratives can make a portion of the population resist or contrast health measures. It is well known the case of misinformation on “vaccine adoption” that is a source of resistance reducing the efficacy of vaccination campaigns. To make things even more complicated, recent emerging Artificial Intelligence tools (at the time of COVID-19 chat-bots were multiplying the voices of users, generating the content, and creating engagement, while nowadays the powerful large language models such as ChatGPT that can create entire sophisticated stories) can favor spreading fake messages to larger audiences, with potentially harming effects. In this context, an effective communication style should support policy implementation by leveraging on the same techniques used by marketing fake narratives. According to Ref. [35]; institutions frame messages using a combination of factual (simple information), inferential (inferring or directly mandating specific behavioral responses) and other more specialized and context-specific contents (e.g. value-related or symbolic communications) [23]. Thus, policy communication should carefully measure the emotional content and response of the users to the announcements, evaluating the related emerging risks, and eventually manage information in order to counteract misinformation, raise concern, generate positive reactions or avoid the escalation of negative reactions [23]. In

fact, while the debate and the democratic space should be respected as fundamental civil rights, an incorrect communication style, charged with negative feelings can greatly hurt the policy actions. As for the high uncertainty of a developing pandemic, with the possibility of several seasons of disease outbreaks, policy announcements should carefully control the sentences, avoiding conveying uncontrolled statements or negative feelings, but also showing moderate optimism. We believe that the only way to achieve these goals is with continuous testing and measurement of the response to select the best messages to counteract misinformation. In fact, if the weapons of misinformation are based on the positive/negative content of a message and often on the presence of reassuring messages (such as “Covid-19 will disappear in the hot season as all respiratory major diseases”) these methods should, instead, be used for better scopes to pass the fundamental and lifesaving messages. Misinformation nowadays is a big limit of media campaigns; it can alter or reduce policy efficacy and it is a limitation of our analysis. The stakeholders and their sentiments, and their reciprocal influence can be in part altered by fake news. Optimism can be driven by fake reassuring announcements or be the response to an excess of optimism. As an anecdotal example, during the first weeks of the pandemic, several political leaders affirmed that “Milano should not stop” (“Milano non si ferma”) harming the efficacy of the lockdown measures by trying to diminish the level of threat posed by the pandemic. In turn, this created a backlash in the medical community which saw this announcement with sceptic eyes. While misinformation is a fundamental limit in the ability to measure response, its typical appearance can be studied, and the same “viral marketing” used as a tool to spread lifesaving messages. Information can be framed by selecting some aspects of a perceived reality, making them more salient, so promoting ‘a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation’ [20]: 52). We stress here that counteracting conspiracy should be done with continuous testing of the citizen response to announcements, with different communication strategies and a careful evaluation of the efficacy of each measure. As pandemics are likely to happen again in the future a modern health policy framework should be able to test and deploy an effective and convincing narrative. Finally, more research should be done on the role that these actors can play in a

global crisis scenario. There is room to understand not only the impact of the stakeholders and their mutual influence, but also the necessity to quantify the effect of incomplete and wrong information on each of them. Research then address this multidimensional challenge, moving from the sentiment analysis to the impact estimation of each political decision and all interplay: from social media to the political arena and to the economic condition, actors that on the medium-long term may play a big role. In this sense, the impact of the communication on the efficacy of the health policy response can be measured with dedicated surveys/questionnaires involving a statistically meaningful sample of the population. For instance, one can ask in a randomized interview about the intention of people to follow a specific health policy mandate (for instance take a shot of a vaccine). If the survey is conducted with the correct timing - during the health crisis and before/after a specific policy announcement - reaching a representative sample, the responses can measure the actual perception of the policies. The caveats in this process are the following: a) reaching a representative sample of the population at a regional level if possible; b) avoiding influencing the responders with incorrect wording of the question (interviewer conditioning effect). These points, starting from the feasibility of the process, the survey implementation and correct administration, are left for future research.

#### CRediT authorship contribution statement

Sabina De Rosi: Conceptualization, Writing - original draft, Writing - review & editing.

Milena Lopreite: Supervision, Methodology, Software, Validation, Formal analysis, Investigation, Visualization, Writing - original draft, Writing - review & editing.

Michelangelo Puliga: Resources, Data curation, Methodology, Writing - original draft, Writing - review & editing.

Milena Vainieri: Conceptualization, Writing - original draft, Writing - review & editing.

#### Data availability

Data will be made available on request.

## Appendix

### Statistics per regions of geolocalized tweets

Although Lombardia has more inhabitants than Lazio many tweets come from news agencies whose headquarters located in Rome, also the tweets of national political leaders refer to Rome. Moreover, in Rome there is the Spallanzani hospital that is the national institute responsible for infectious diseases (Table 1).

In Fig. 1 (below) we show the Italian regions grouped according to their inner risk in the COVID-19 outbreak (DPCM of 8<sup>th</sup> March 2020). Interestingly the geographical pattern is not obvious with Northern regions belonging to a group that also comprehends the Southern regions. In Fig. 1 stands out the Lombardia (in bold font) as the center of the major contagion. This is not surprising considering the spread of covid in Lombardia.

**Table 1**

Statistics per region of geolocalized tweets (from the location field in the user description).

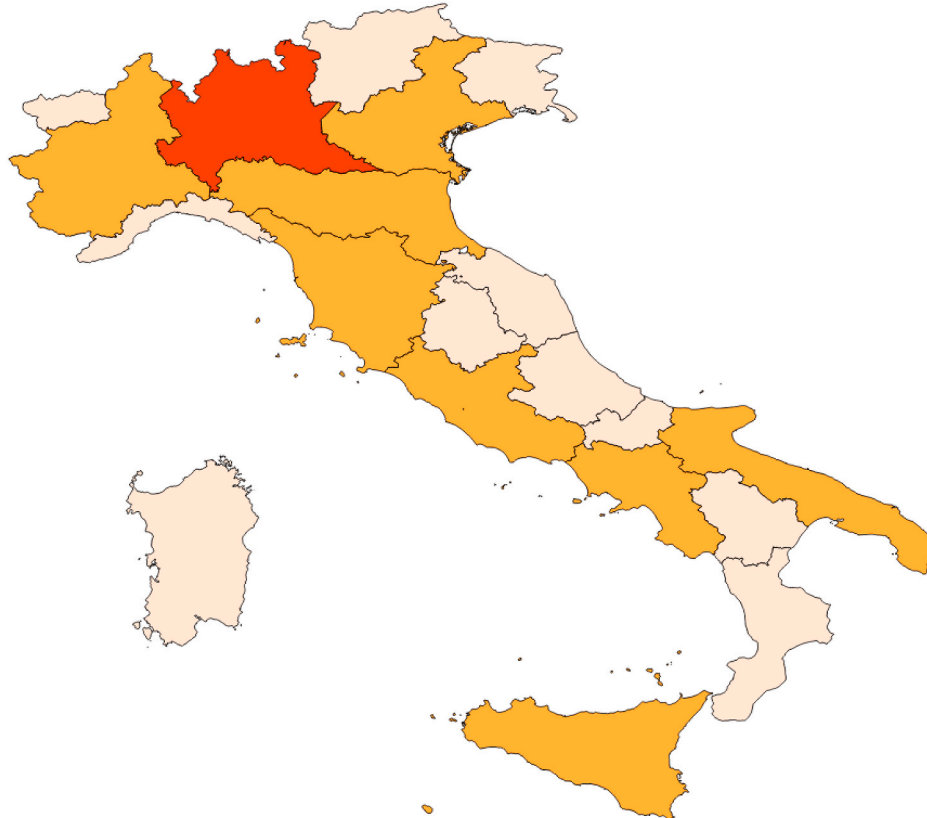
Regions	Tweets
Abruzzo	10426
Puglia	19833
Basilicata	4958
Calabria	9542
Campania	39728
Emilia-Romagna	39388
Friuli-Venezia Giulia	11459
Lazio	107451
Liguria	16555
<b>Lombardia</b>	<b>87277</b>
Marche	12258
Molise	1615

(continued on next page)



**Table 1** (continued)

Regions	Tweets
Piemonte	33588
Sardegna	10823
Sicilia	29318
Toscana	34063
Trentino-Alto Adige	5790
Umbria	9310
Valle d'Aosta	958
Veneto	39269
TOTAL	523609



**Fig. 1.** The three Italian Region Groups clustered according to the DPCM of 8<sup>th</sup> March 2020

**B-VAR models**

In the Bayesian inference, the *prior*, *likelihood* and *posterior distributions* are the key drivers.

In contrast to the classical frequentist approach, where the process generating the data (DGP) is random and the parameters are known and fixed, in the Bayesian statistics anything uncertain is regarded as the parameters that are considered random and to which it is assigned a probability distribution (prior probabilities).

While the prior distributions are based on the knowledge of the parameters of interest (non-sample information), the likelihood captures the information in the sample.

Specifically, if we assume that  $Y$  are the available data and  $\theta$  are the parameters of interest that we want to estimate, the Bayes' theorem combine the prior information  $p(\theta)$  with the information contained in the data (likelihood function- $L(\frac{Y}{\theta})$ ) yields a posterior distribution  $p(\frac{\theta}{Y})$  that generally has the same density function of the prior. This posterior contains the beliefs of the investigator about the model parameters after looking to the data:

$$p\left(\frac{\theta}{Y}\right) \propto L\left(\frac{Y}{\theta}\right) * p(\theta) \tag{1}$$

To discuss the application of the Bayesian analysis to the VAR models we start from a VAR (q), given by:

$$Y_t = c + \sum_{j=1}^q BY_{t-j} + u_t \quad t = 1, \dots, T \quad u_t \sim N\left(0, \sum_u\right) \tag{2}$$

Where  $c$  is an  $N \times 1$  vector of deterministic variables,  $Y_t$  is an  $N \times 1$  vector of the endogenous variables and  $u_t$  is an  $N \times 1$  vector of error terms.

The parameters which describes the VAR model are  $c, B$  for  $l = 1, \dots, q$ , the variance-covariance matrix  $\sum_u$  and the lag length  $q$ .

We can re-write the VAR ( $q$ ) in matrix notation as follows:

$$Y = XB + U \tag{3}$$

Where.

- (a)  $Y_t = (y_{1t}, \dots, y_{Nt})'$ . The matrix dimension is  $T \times N$  (number of observations  $\times$  each dependent variable).
- (b)  $X = (x_1, \dots, x_T)'$  with  $X_t = (1, y'_{t-1}, \dots, y'_{t-q})'$ . The matrix dimension is  $T \times k$  where  $k = NP + 1$ . (number of observations  $\times$  each lagged dependent variable).
- (c)  $B = (c, B_1, \dots, B_q)'$ . The matrix dimension is  $k \times N$  (number of constant/autoregressive terms  $\times$  each lagged dependent variable).
- (d)  $U = (u_1, \dots, u_T)$  collects the error terms. The dimension is  $T \times N$  (number of error terms  $\times$  each dependent variable).

In this study we adopt the Litterman-Minnesota prior [29,36] where the coefficients of the matrix  $B$  are *a-priori* represented as a random walk with drift (independent and normally distributed). In this case the beliefs of the investigator can be specified in the following way:

$$B \sim \left( \beta_0, \sum_u \right) \tag{4}$$

In which  $\beta_0$  is the prior mean and  $\sum_u$  represents a measure of dispersion on the uncertainty of the prior beliefs.

To apply the random walk hypothesis to equation (2) it requires the mean of the coefficient matrix on the first lag,  $B_1$  to be equal to an identity matrix (the coefficient on the diagonal) and the prior mean ( $\beta_0$ ) of the elements  $B_l$  (with  $l > 1$ ) outside the diagonal to be equal to zero.

Thus, in a small sample size introducing the prior distribution over the parameters of the unrestricted VAR model we can reduce the tendency of the VAR models to be over-parameterized and we obtain more accurate forecasts than VAR models.

More in detail, the so-called Minnesota [29,36] prior considers a normal prior on a parsimonious set of parameters with the matrix of variance-covariance  $\sum_u$  known, fixed, and a priori selected to be diagonal.

If we replace  $\sum_u$  with its estimate from the data  $V_0$  we obtain the prior distribution of  $B$  based on the Minnesota prior as a *priori* normal and conditional upon the variance-covariance matrix  $\sum_u$ :

$$p\left(B \middle/ \sum_u\right) \sim N(\beta_0, V_0) \tag{5}$$

Given the VAR model we can group the explanatory variables of each equation into three blocks: 1) the own lags of the dependent variable; 2) the lags of the other dependent variables; 3) exogenous variables [37]. Following [37] since the prior covariance matrix  $V_0$  is diagonal we do not specify all the elements of  $V_0$  but we select only the following scalars:

$$V_{ij} = \begin{cases} \frac{\lambda_1}{q^2} \text{ for coefficients on lag } r \text{ for } r = 1, \dots, p \\ \frac{\lambda_2}{q^2} * \frac{\sigma_{ii}}{\sigma_{jj}} \text{ for coefficients on lag } r \text{ of variable } J \neq i \\ \lambda_3 * \sigma_{ii} \text{ for coefficients on exogenous variables} \end{cases} \tag{6}$$

The vector  $\lambda_i$  (with  $i = 1, 2, 3$ ) that collects the hyperparameters describing the features of the Minnesota prior (the tightness or weight attaching to the prior in random walk) is set as following:

- (a)  $\lambda_1$  reflects how closely the random walk approximation must be imposed. In general, this parameter determines the relative weight of prior information. If  $\lambda_1$  is large, the prior is too uninformative, and the posterior estimates collapse into an unrestricted VAR model. If it is low and close to zero, the diagonal elements of matrix  $B$  shrink towards one while the other coefficients (outside the diagonal) towards zero. In this case the prior information dominates.
- (b)  $\lambda_2$  sets the relative cross-variables weight. If  $\lambda_2$  is close to zero, the off-diagonals elements of matrix  $B$  shrink towards zero. Otherwise, if  $\lambda_2 = 1$  there is no difference between the lags of the dependent variable and the lags of other variables.
- (c)  $\lambda_3$  regulates the relative information contained in the exogenous variables (i.e., a constant; dummy variables).

After setting the prior covariance, the B-VAR model turns out a normal distribution of the posterior.

*Impulse response functions Graps*

Figs. 2-3-4 (4a, 4b) display the IRFs that show statistically significant relations between the sentiment-polarity of the stakeholders respectively in the Group 0,1,2. In each impulse response graph, the shaded regions show the posterior coverage intervals corresponding to the 95% of the Bayesian credible sets obtained through Gibbs sampling using 1000 iterations. Moreover, in each row of Figs. 2-3-4 (4a, 4b) we represent the IRFs that show the relations between the couple of stakeholders (i.e., in the Group 0 we divided three relationships: a) doctors vs journalists; b) doctors vs public; c) public vs journalists). We described the response of the stakeholder's sentiment-polarity to a shock (emotional change) from another stakeholder for the bivariate B-VAR models in a time span of ten days until this effect dissipates.

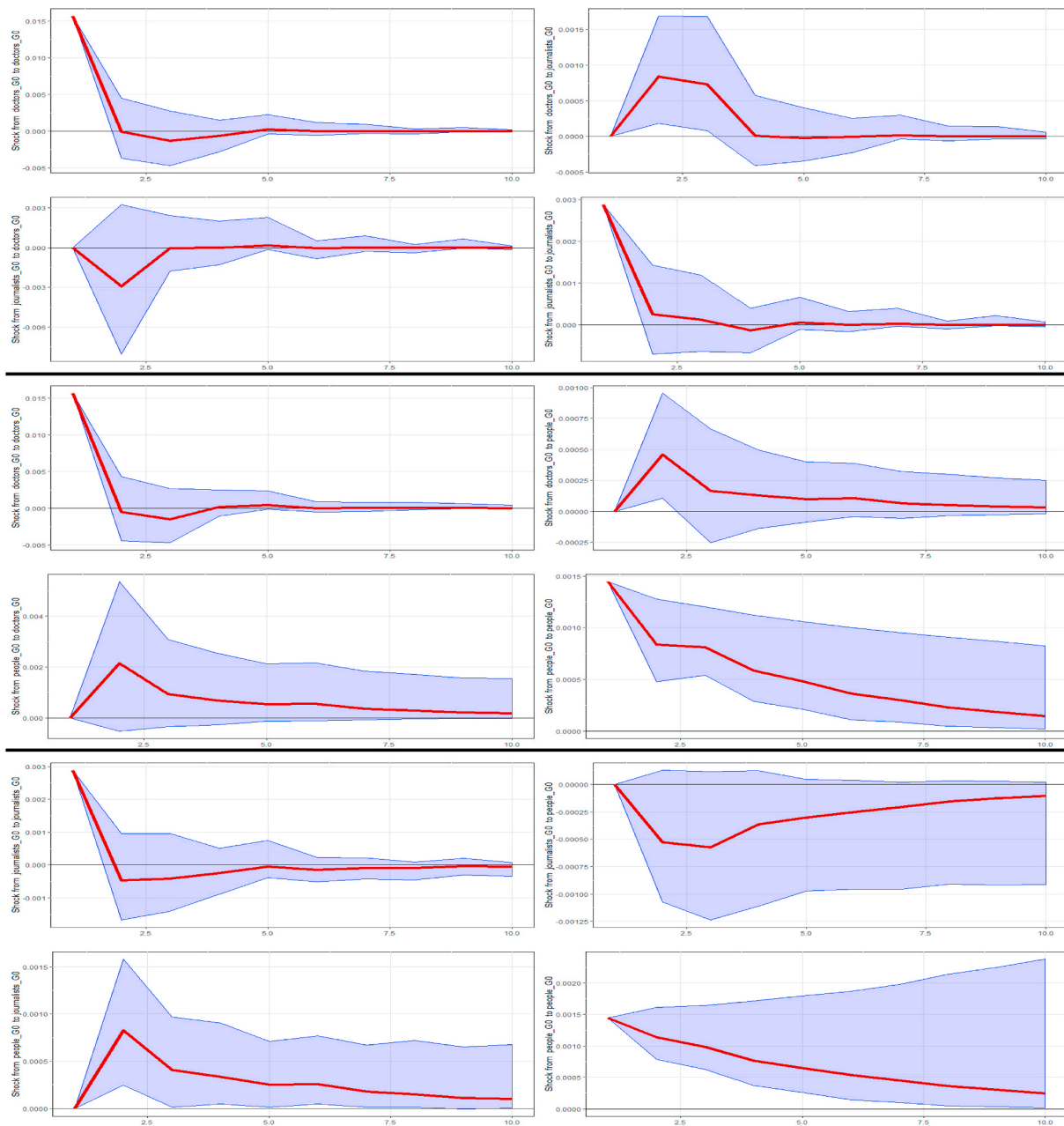


Fig. 2. Impulse response functions with 95% credible intervals (Group 0)

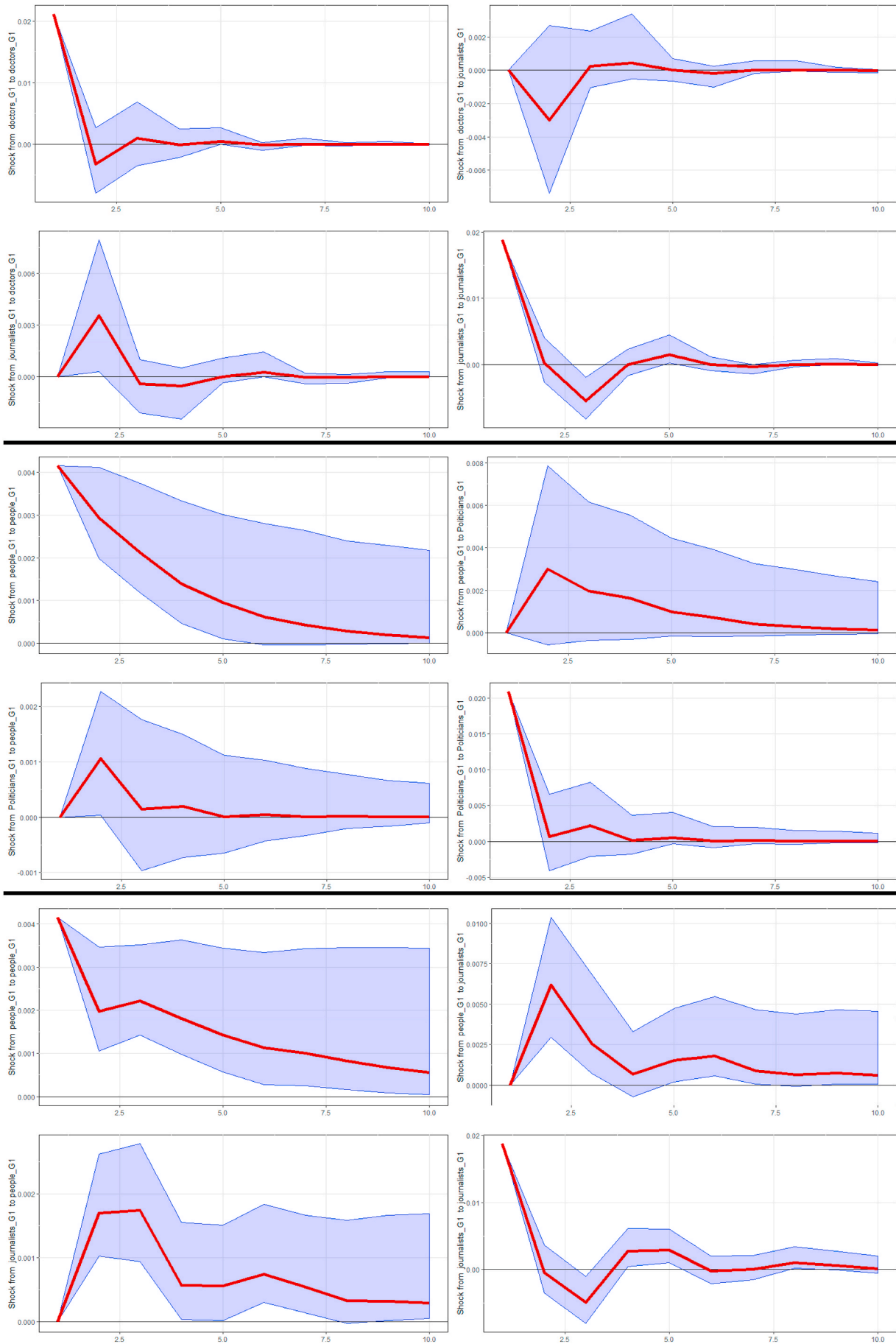


Fig. 3. Impulse response functions with 95% credible intervals (Group 1)

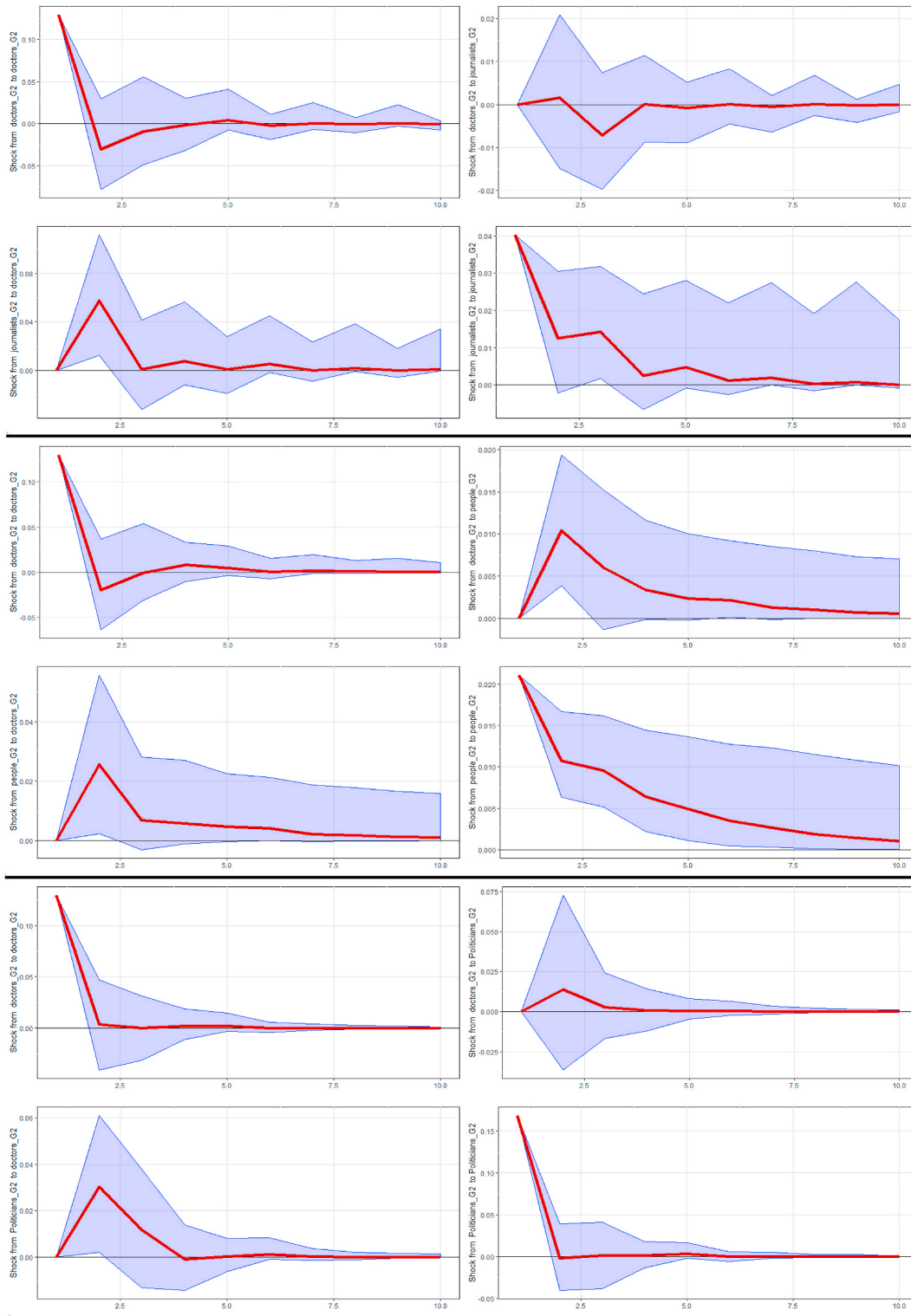


Fig. 4a. Impulse response functions with 95% credible intervals (Group 2)

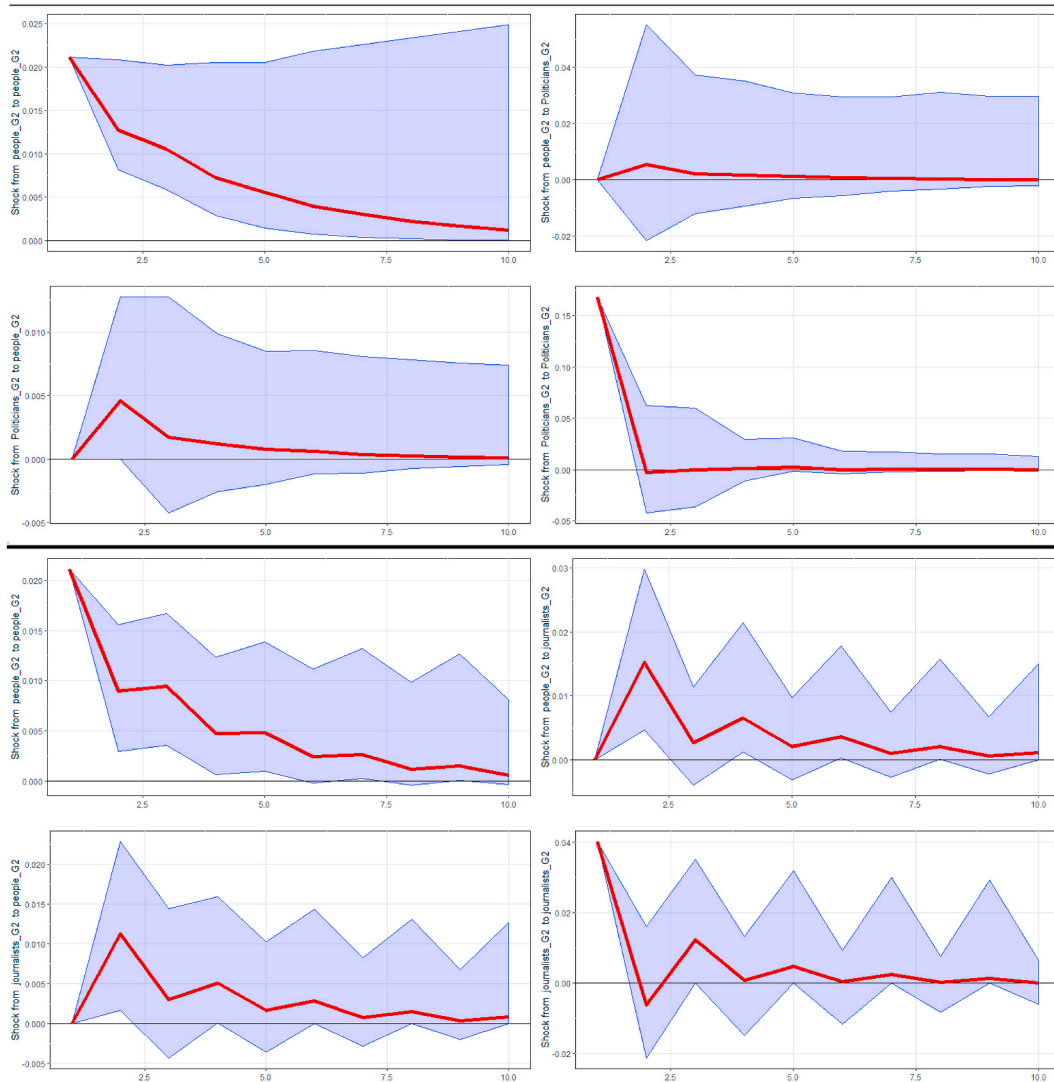


Fig. 4b. Impulse response functions with 95% credible intervals (Group 2)

In sum, for the Group 0 in Fig. 2, we find short-lived and direct relationships that go as follows: a) from doctors to journalists (first row, second column); b) from doctors to people (third row, second column); c) from people to journalists (sixth row, first column). Specifically, a growing of doctors’ negative feelings due to the pandemic leads to an increase of journalists’ negative sentiment. We obtain similar findings for the other relationships: an increase of doctors’ panic negatively impact on people that, in turn affect journalists.

For the Group 1 in Fig. 3, we find bi-directional relationships from journalists to people (fifth row, second column; sixth row, first column): an increase of journalists’ fear strongly impacts on people sentiments and vice versa; Again, similarly, we discuss the following one-way relationships: a) from journalists to doctors (second row, first column): b) from politicians to people (fourth row, first column).

Finally, for the Group 2 in Fig. 4a and b, we discover more complex relationships (two-way): a) from people to doctors (fourth row, first column; third row, second column- Fig. 4a); b) from people to journalists (third row, second column; fourth row, first column-Fig. 4b) and one way relation: c) from journalists to doctors (second row, first column-Fig. 3a); d)from politicians to doctors (sixth row, first column-Fig. 3a); e) from politicians to people (second row, first column-Fig. 3b).

Forecast variance decomposition functions Graphs

The results of forecast variance decomposition functions, shown in Fig. 5-6-7a-7b, are in line with the impulse response functions and confirm that the polarity index of doctors is the fluctuations dominant source of public in the Group 2 (see first plot in the second row of Fig. 7a) and Group 0 (see second plot in the third row of Fig. 5). We also find in the Group 1 a significant influence of journalists on doctors and on public (see third plot in the second row and, third plot in the sixth row of Fig. 6).

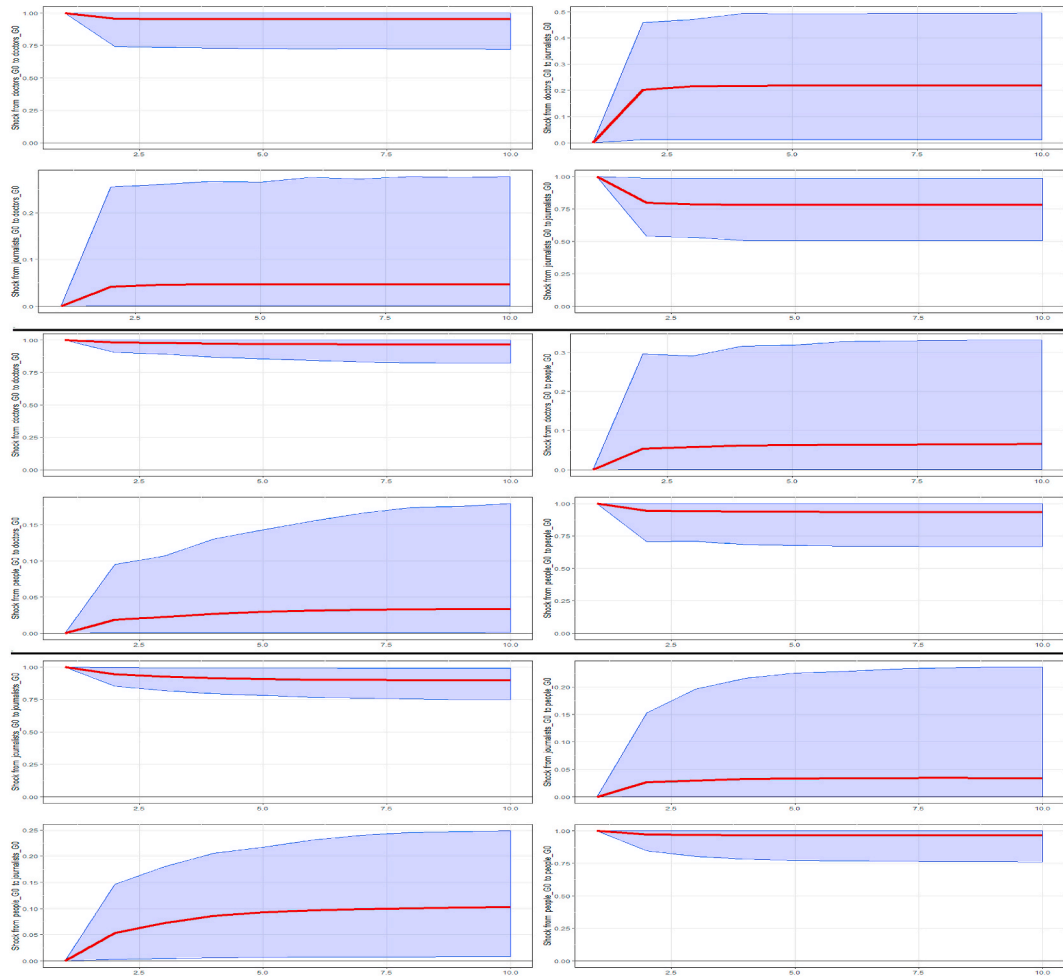


Fig. 5. Forecast Variance Decomposition functions with 95% credible intervals (Group 0)

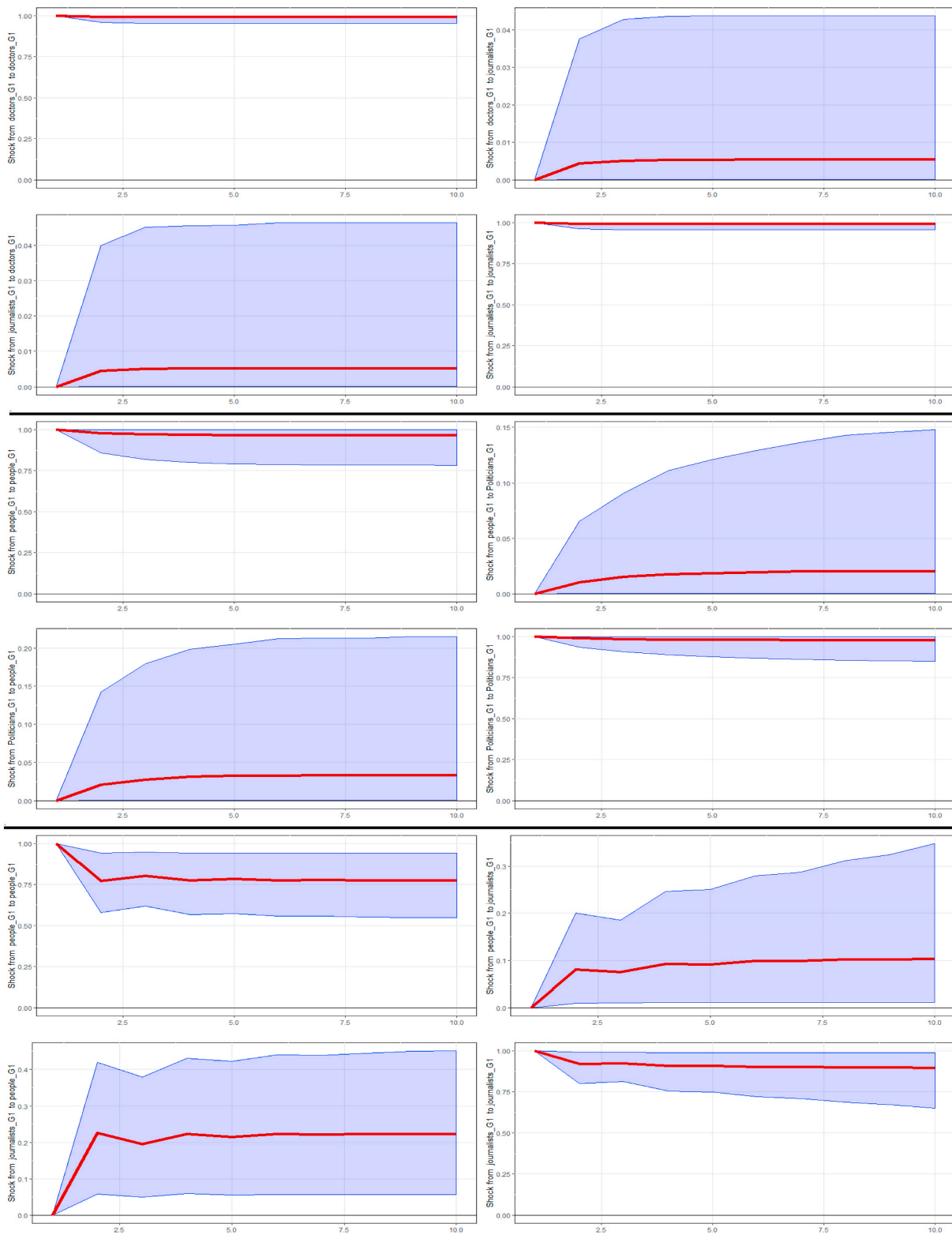


Fig. 6. Forecast Variance Decomposition functions with 95% credible intervals (Group 1)



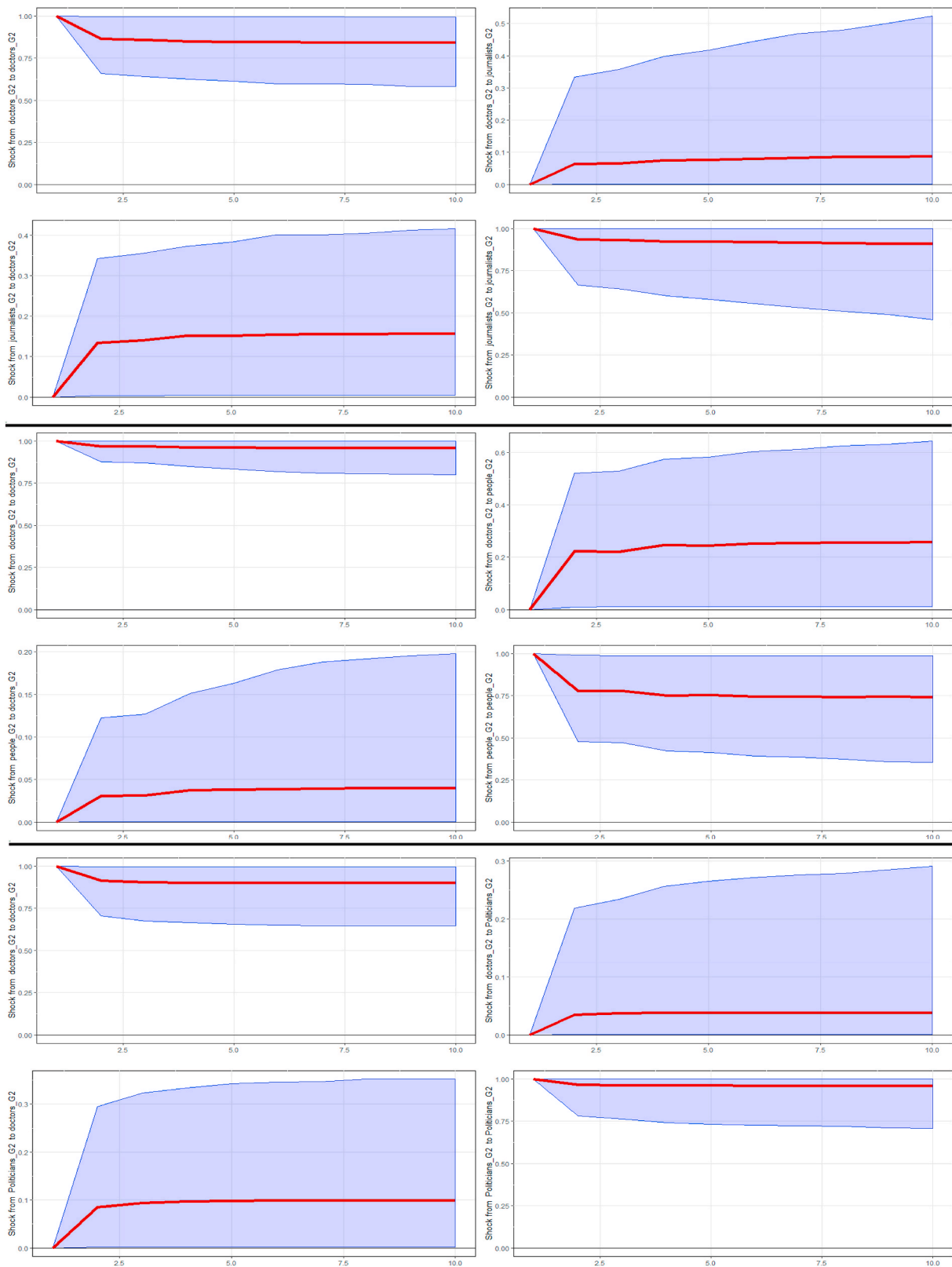


Fig. 7a. Forecast Variance Decomposition functions with 95% credible intervals (Group 2)

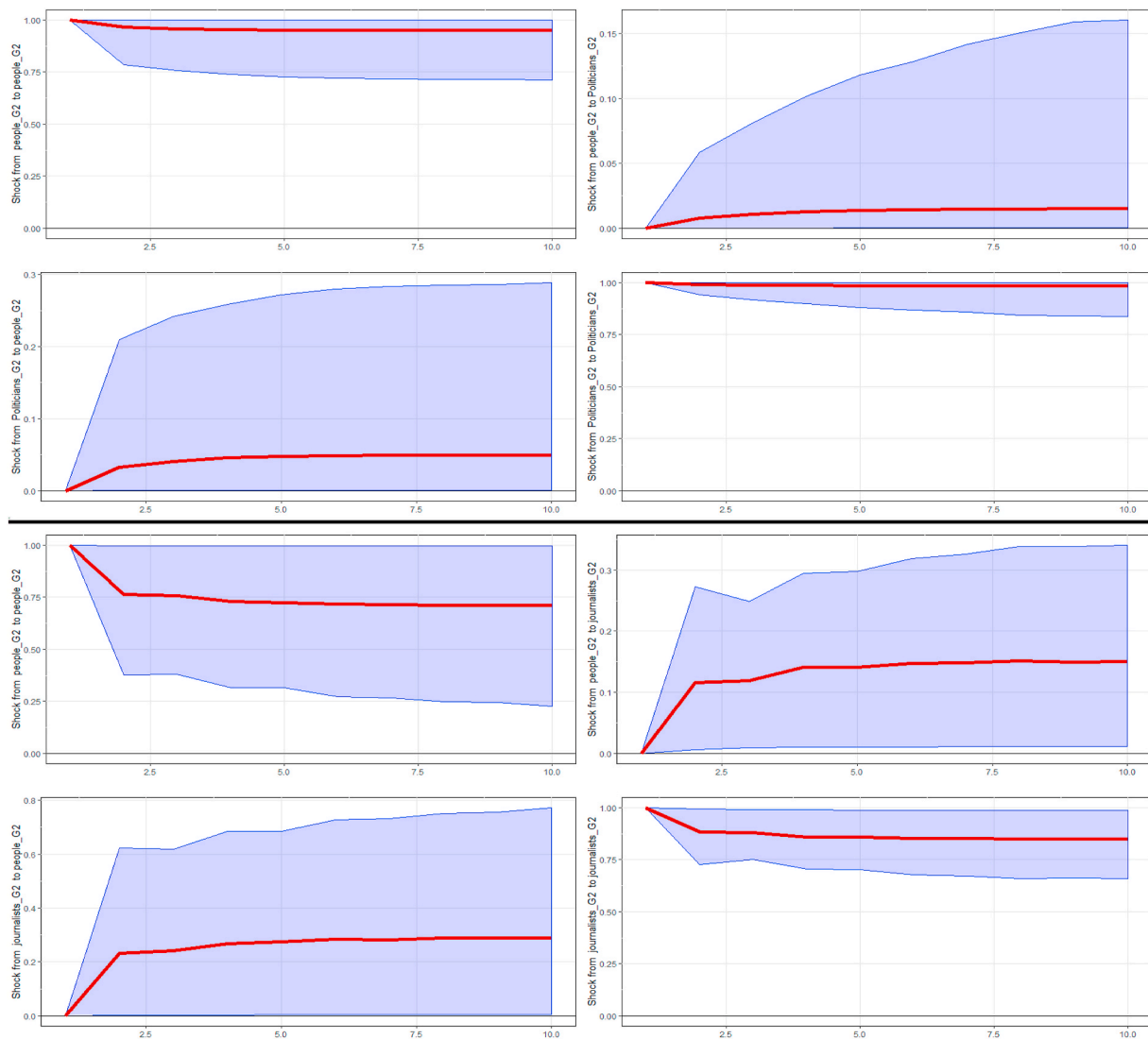


Fig. 7b. Forecast Variance Decomposition functions with 95% credible intervals (Group 2)

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