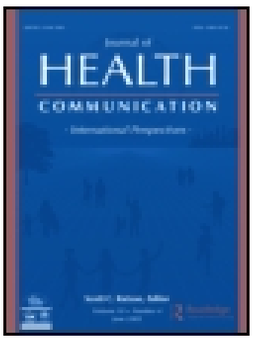

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ARTICLE

The Framing of COVID-19 in Italian Media and Its Relationship with Community Mobility: A Mixed-Method Approach

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Media framing of epidemics was found to influence public perceptions and behaviors in experiments, yet no research has been conducted on real-world behaviors during public health crises. We examined the relationship between Italian news media coverage of COVID-19 and compliance with stay-at-home orders, which could impact the spread of epidemics. We used a computational method for framing analysis (ANTMN) and combined it with Google's Community Mobility data. A time-series analysis using vector autoregressive models showed that the Italian media used media frames that were largely congruent with ones used by journalists in other countries: A *scientific frame* focusing on symptoms and health effects, a *containment frame* focusing on attempts to ameliorate risks, and a *social frame*, focusing on political and social impact. The prominence of different media frames over time was associated with changes in Italians' mobility patterns. Specifically, we found that the *social frame* was associated with increased mobility, whereas the *containment frame* was associated with decreased mobility. The results demonstrate that the ways the news media discuss epidemics can influence changes in community mobility, above and beyond the effect of the number of deaths per day.

Despite facing multiple outbreaks of infectious diseases in recent years, the world was caught unprepared for the spread of severe acute respiratory syndrome coronavirus 2 (COVID-19, Brueck, 2020). In addition to its relatively high infection and death rates, particularly among the elderly, and its physical symptoms, including fever, coughing, and shortness of breath, the virus caused unprecedented social and economic interruptions (Anderson, Heesterbeek, Klinkenberg, & Hollingsworth, 2020). During public health crises, people seek timely and accurate information about health and social threats, and effective ways to mitigate risks (Austin, Fisher Liu, & Jin, 2012). As was the case with prior epidemics, official evidence-based information at early stages was scarce and inconclusive, leading to uncertainty, anxiety, and depression (Wang et al., 2020). Under these circumstances, people often turn to the mass media for answers (Djerf-Pierre & Shehata, 2017). Unfortunately, studies have pointed to inadequacies in media coverage of epidemics that may lead to detrimental effects (Ophir, 2018).

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The effects of media coverage of epidemics on perceptions and behaviors were previously assessed through experiments using fabricated diseases and articles (Ophir, 2019) or through surveys relying on self-reports (Motta, Stecula, & Farhart, 2020; Ophir & Jamieson, 2018). Although a few studies examined the impact of media coverage on real-world behaviors, they were limited focusing only on volume (Tizzoni, Panisson, Paolotti, & Cattuto, 2020) and lacked a specific focus on the effects of media frames during epidemics. Moreover, the intentional and behavioral outcomes measured in prior studies were largely limited to information seeking and vaccination intentions, as opposed to actual behaviors (e.g., Lu, H., APPC 2018-2019 ASK Group, Winneg, K., Jamieson, K. H., & Albarracín, D, 2020; Romer & Jamieson, 2020).

Our study fills these gaps by examining the effects of media frames on compliance with a stay-at-home order during COVID-19. Specifically, we harness the unique characteristics of COVID-19 and its unprecedented impact on citizens' lives to examine the real-world effects of media coverage on community mobility (Lasry et al., 2020). Using a mixed-method approach, combining computational unsupervised machine learning for identification of media frames (Walter & Ophir, 2019) and Google's COVID-19 community mobility data

(Aktay et al., 2020), we demonstrate how the prevalence of media frames impacted compliance with governmental mobility restrictions. Our study focuses on Italy, one of the early epicenters of COVID-19 (Nacoti et al., 2020). Italy documented the first two cases of COVID-19 in Rome on January 31st and the first case of death from COVID-19 was reported on February 22nd. Starting March 8th, the region of Lombardy and other northern provinces were put under a lockdown. On March 12th the World Health Organization declared COVID-19 to be a pandemic, and three days later the Italian government extended the lockdown to the whole country (Pepe et al., 2020; Torri et al., 2020).

The Media Coverage of Epidemics

During crises, the flow of timely and accurate information is essential for people to make sense of potential threats, and could increase trust in health organizations (Maitlis & Sonenshein, 2010; Veil, Reynolds, Sellnow, & Seeger, 2008; Weick, 1988). Specifically, the public wishes to learn about risk information, including physical and nonphysical threats, and actions individuals and organizations could take to mitigate risks (Reynolds & Seeger, 2005). However, even if health organizations provide rich information on their websites and social media, people often obtain their health information not from official sources but the mass media (Djerf-Pierre & Shehata, 2017). Similarly, health information found and shared on social media (Singh et al., 2020) often also quotes or directs to articles from the news media (Conway, Kenski, & Wang, 2015).

The information available on news media during public health crises is limited, incomplete, and often inadequate (Ophir, 2018). Journalists tend not to simply amplify the messages of health organizations (Reynolds & Seeger, 2005; Veil & Ojeda, 2010), but to instead process, edit, and change information based on their needs and routines, such as the evaluation of newsworthiness (Galtung & Ruge, 1965) and the construction of media frames (D'Angelo, 2018; De Vreese, 2005). Framing was defined differently in various disciplines and contexts (Cacciatore, Scheufele, & Iyengar, 2016), but here we rely on the emphasis framing approach (D'Angelo, 2018; Entman, 1993), and its focus on journalists' reliance on frames as central organizing ideas (Gamson & Modigliani, 1989). This approach is arguably more suitable for understanding of journalistic work than alternative approaches (D'Angelo, 2018), such as equivalency frames (e.g., gain and loss frames, see Kahneman & Tversky, 1984).

Multiple studies have looked at the social construction in general, and framing specifically, of epidemics (Powers & Xiao, 2008). For example, scholars examined the coverage of the AIDS crisis with its early focus on marginalized groups, and identified unique frames such as the *containment* one (Ungar, 1998). Others (Powers & Gong, 2008) identified frames used in the coverage of SARS in Hong Kong's media, including a frame that focused on the political implications of the outbreak, with a focus on governmental failures. Some employed general frames, like human interest and conflict (An & Gower, 2009), or episodic and thematic frames (Lee & Basnyat, 2013) to analyze coverage of HIN1. Others (Shih, Wijaya, & Brossard, 2008) developed framing typologies specific for the coverage of epidemics (specifically, uncertainty, action, reassurance, conflict, and new evidence). In another study, Kott and Limaye (2016) examined the prevalence of four frames: medical, sociopolitical, human interest, and unconfirmed information.

Prior studies relied in large on deductive, theory-driven approaches. While deductive approaches are crucial for the development and application of existing theories, inductive approaches can help us identify emerging or changing frames, as media coverage can change drastically over time with changes to journalistic routines, practices, and across contexts (Van Gorp, 2010). Inductive approaches, at least the frame detection phase, can help us identify changes in the application of frames, thus allowing to develop and advance current theories of framing. The Analysis of Topic Model Networks (ANTMN) method attempted to combine the benefits of inductive and deductive approaches, by identifying frames inductively, and then implementing a deductive, theory-based knowledge at the interpretation level (Walter & Ophir, 2019). In the next section, we discuss the rationale behind the method used in this study.

Conceptualization and Operationalization of News Frames

A central concept to communication research, framing is often described as a "fractured paradigm" (Entman, 1993). First, disagreement exists among researchers regarding the nature of frames themselves. For example, scholars differ on whether they perceive media frames to be different from other theoretical concepts, such as second-level, or attribute, agenda-setting (McCombs & Ghanem, 2001). While the debate is important and ongoing, solving the disagreements is beyond the scope of our work here. Instead, in this study, we follow the conceptualization (Scheufele & Iyengar, 2014) that is congruent with the method we follow (Walter & Ophir, 2019) and defines our measured construct as media frames. Yet, we acknowledge the debate remains open.

A second debate revolves around the optimal method for the measurement and estimation of news frames. Many have attempted to develop valid, reliable, and efficient approaches to frame measurement (Van Gorp, 2010). The most common strategy employs a deductive manual coding, based on predefined, theoretically driven codebooks (Matthes & Kohring, 2008). This approach, while common, received criticism for relying on prior knowledge, which limits the analytical lenses and introduces potential researcher biases (Van Gorp, 2010). Manual coding of large corpora is also inefficient, requiring vast resources in terms of time, money, and manpower. Even in the presence of sufficient resources, human readers are better equipped for the close-reading of specific texts, and not for identifying complex linguistic patterns across large corpora (Grimmer & Stewart, 2013).

In response to the challenges of bias and efficiency, computational researchers suggested automated ways for the identification of frame elements (Baden, 2018; Van Gorp, 2007) and

their automated clustering into frame packages (Gamson & Modigliani, 1989). Specifically, to reduce the reliance on prior theoretical knowledge (Matthes & Kohring, 2008) and biases (Tankard, 2001), scholars suggested identifying frame elements inductively (Van Gorp, 2010) before automatically clustering them based on their co-occurrence in documents (Matthes & Kohring, 2008). Such an approach was seen as consistent with the definition of frames as repeatedly invoked news patterns (Entman, Matthes, & Pellicano, 2009).

Following van Gorp (2010), scholars developed multiple *unsupervised machine learning* approaches that did not depend on prior theoretical knowledge. For example, Baden (2018) conceptualized clusters of co-occurring words in a network as frames (Baden, 2018). Others preferred to identify frames using topic modeling, a method that infers the thematic structure of a corpus in terms of "topics" (sets of frequency distributions of words) from the co-occurrence of words in documents (Blei, Ng, & Jordan, 2003). However, while some (e.g., DiMaggio, Nag, & Blei, 2013) have argued that "many topics may be viewed as frames" (p. 578), others rebutted this argument, claiming that the theoretical meaning of individual topics remains largely unclear, and is sensitive to decisions made by researchers in the modeling stage (Maier et al., 2018).

In response to the limitations of using either semantic networks or topic modeling for the identification of frames, a recently developed approach, ANTMN (Walter & Ophir, 2019), combined the two approaches into an integrated process that maximizes the advantages of each, while limiting their disadvantages. Specifically, ANTMN uses topic modeling for the identification of frame elements, and network analysis for understanding the relationship between them. Importantly, as opposed to other recent work (DiMaggio et al., 2013), ANTMN does not posit that individual topics are frames. Instead, in ANTMN topics serve as frame elements that are being transformed into a semantic network based on co-occurrence in documents (Baden, 2018), before being clustered into frame packages using a community detection algorithm (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). For a full description of the method's rationale and steps see Walter and Ophir (2019).

The Content and Effects of Media Frames of Epidemics

The application of ANTMN allowed researchers (Ophir, 2018) to efficiently study the content of different media frames employed across epidemics, and to examine whether media frames adequately communicated the information health organizations hope to convey during crises (Reynolds & Seeger, 2005). Unfortunately, while crisis and risk communication models strongly recommend providing the public with information about risks (health and social) and response (individual and organizational), Ophir (2018) found that media frames in American media tended to focus only on some of these aspects while omitting others. Specifically, he found that the *scientific frame*, which focused on the viruses' biology and health impact (e.g., symptoms and death tolls) mostly contained health risks information, and to a lesser degree information on organizational response. The *pandemic frame*, discussing attempts to block diseases from entering a country with measures like quarantines, was dominated by a discussion of organizational response, and largely omitted all other information types. Lastly, the often-used *social frame* focused exclusively on the diseases' impact on social, political, and economic institutions. While frames are not exclusive and news articles can combine information from different frames (Walter & Ophir, 2019), he found that in the case of epidemics, the media tended to focus only on one frame at a time (Ophir, 2018). In addition, all three frames analyzed largely ignored the crucial component of individual response information. In other words, when covering epidemics, American news media consistently failed to provide the public with practical advice for what individuals and communities could do to effectively reduce risks (Bandura, 1990).

While the effects of media coverage during epidemics were theorized before, including suggested effects on beliefs and attitudes, such as perceived-efficacy and perceived-severity (Bandura, 1990), trust (Veil et al., 2008) and behavioral intentions and compliance (Covello, 2003; Jamieson, 2015; Reynolds & Quinn, 2008), empirical evidence remains relatively scarce. The few studies showing media effects during epidemics tend to focus on volume and not content (Tizzoni et al., 2020). To date, the only study to examine the effects of media frames specifically used a controlled experimental design (Ophir (2019), finding that exposure to frames impacted perceptions of certainty and self-efficacy (Bandura, 1982). Those perceptions, in turn, influenced intentions to comply with public health organizations, as well as scientific uncertainty (Yang et al., 2020). Specifically, Ophir (2019) found that articles focusing on health risk information without providing solutions, yielded lower self-efficacy and trust.

While this experimental design excel in internal validity, effects may be different during a real epidemic. On one hand, during real crises, people feel frightened, confused, and susceptible (Reynolds & Seeger, 2005) and may therefore by more attentive to information about the disease, and media effects may be stronger. On the other hand, during a real epidemic, the public is exposed to a constant stream of information, and the effects of new information may be incremental. In other words, if people were already informed about the health risks of COVID-19, exposure to yet another article emphasizing that risk may only have a limited effect. Our study uses real-world data to complement prior experimental findings with such an approach that emphasizes external, ecological validity.

To examine the effects of real-world coverage of epidemics on real-world public behaviors we first examined whether the Italian media covered the COVID-19 epidemic using the same media frames (scientific, pandemic, and social) that were found in prior research using a similar method (Ophir, 2018), but in the context of American media and different diseases:

RQ1: What frames were used in the coverage of COVID-19 in Italian mainstream media?

Prior experiments (Ophir, 2019) did not find differences in intention to comply with public health organizations between participants exposed to different frames. However, as argued earlier, research on the effects of frames of epidemics is very limited and scarce, and the lack of findings in a particular study could result from many factors, including the artificial nature of experiments. Additionally, experimental studies relied on self-report of intentions to comply, and not on actual compliance. In this study, we examine the real-world effects of media frames on actual compliance in the form of community mobility–changes in mobility patterns that indicate compliance with stay-at-home orders (Lasry et al., 2020). Due to scarcity of prior evidence, and the fact that we could not hypothesize specific directional differences before first learning which frames were used by the Italian media during COVID-19, we opted to avoid directional hypotheses and suggested a research question concerning the association between media coverage and the nationwide Italian stay-at-home order:

RQ2: Was the prominence of the media frames identified in RQ1 associated with different levels of compliance with public health organizations?

Method

Data Collection

Media Data consisted of 3918 full articles were collected from Factiva. We conducted a search of newspaper articles in Italian, in five highly circulated national Italian newspapers, Corriere della Sera, La Repubblica, La Gazzetta dello Sport, La Stampa, and Il Sole 24 Ore, between September 21st, 2019 and April 24, 2020. As of April 2020, the sum of the circulation of the 5 newspapers under study accounted for 28% of the total circulation of Italian newspapers (http://www.adsnotizie.it/index.asp). We used the keywords COVID OR corona OR coronavirus. Like in prior research (Ophir, 2018), we consider articles mentioning COVID-19 only in passing to be part of the general discourse around the disease, and all were maintained in the analysis.

Community Mobility Data was collected using Google's community mobility data (https://www.google.com/COVID-19/mobility/), which provides aggregated metrics of mobility, measured from de-identified data obtained from Google users' mobile devices. Each report shows changes in daily movements to six location categories (retail & recreation, grocery & pharmacy, parks, transit station, workspaces, and residential -i.e., people's homes, which indicates reduced mobility and thus higher compliance with the stay-at-home order) with respect to a baseline, defined as the median value of data collected between January 3 to February 6, 2020. We collected mobility data for the same time period for which media content was analyzed. According to Google, the data include all Android users in Italy who turned on their Location History setting on their mobile devices. For privacy reasons, Google does not provide information about the users and the sample (including size and distribution). Due to the need for users to turn on location services and the lack of detailed information about specific demographics, the data should be interpreted with caution concerning generalizability to the whole Italian population.

Italian government-issued mobility restrictions were controlled in our models as covariates. We used the national lockdown date of March 11, 2020. According to the strict nationwide stay-at-home order of March 11, outdoor activity (in isolation) was allowed only within a 500-m radius from one's home, access to parks was prohibited, and grocery shopping was limited to purchasing "essential items" (mostly food).

Procedure

To answer RQ1 and examine the news frames used by Italian media in the coverage of COVID-19, we followed the multi-step procedure suggested in ANTMN (Walter & Ophir, 2019). In its first step, ANTMN automatically identifies frame elements by estimating a topic model, where each topic represents a frame element. In the second step, a network of topics is calculated where topics are nodes and edges represent their co-occurrence in news articles. Finally, a community detection algorithm is used to cluster topics (frame elements) into coherent frame packages. We briefly describe each step below.

Topic modeling is an unsupervised machine learning method for the analysis of textual data. 'Topics' are frequency distributions of words that co-occur in documents and are expected to share thematic meaning, calculated using Latent Dirichlet Allocation (LDA) and Gibbs Sampling (Blei et al., 2003). To choose the optimal model, we used perplexity scores for different candidate models, with the number of topics (k) ranging from 5 to 100 in skips of 5, and alpha hyperparameter levels of 0.01–0.5. We used 10-fold cross-validation to get average perplexity scores over 10 iterations per model. We calculated the maximum point for the second derivative of all perplexity score changes moving from a model with k value to a model of (k + 5) value, representing the range of k at which enlarging k offers diminishing returns. Based on the results of this exhaustive process we chose the optimal k value of 35 and an optimal alpha level of 0.2. To interpret and label topics, we examined three types of information; the words with the highest loading over each topic, the words that are both prevalent and exclusive to each topic, and the full articles most representative of each frame. The qualitative reading and labeling were conducted by a native Italian speaker and a public health communication expert. The top 10 unique words for each topic can be found in Table 3 (words were translated into English by an Italian-speaking researcher).

A Topics Network was drawn using pairwise cosine similarities between topics based on co-occurrence in articles. Based on this adjacency matrix, we constructed a network in which topics served as nodes and co-occurrence in articles as edges. The result is a fully connected, undirected, weighted network, where edges provide information on the extent to which topics are related (between 0 and 1). Drawing on recent comparative analyses (Yang, Algesheimer, & Tessone, 2016) we employed the modularity maximization method offered by Blondel and colleagues (Blondel et al., 2008), often referred

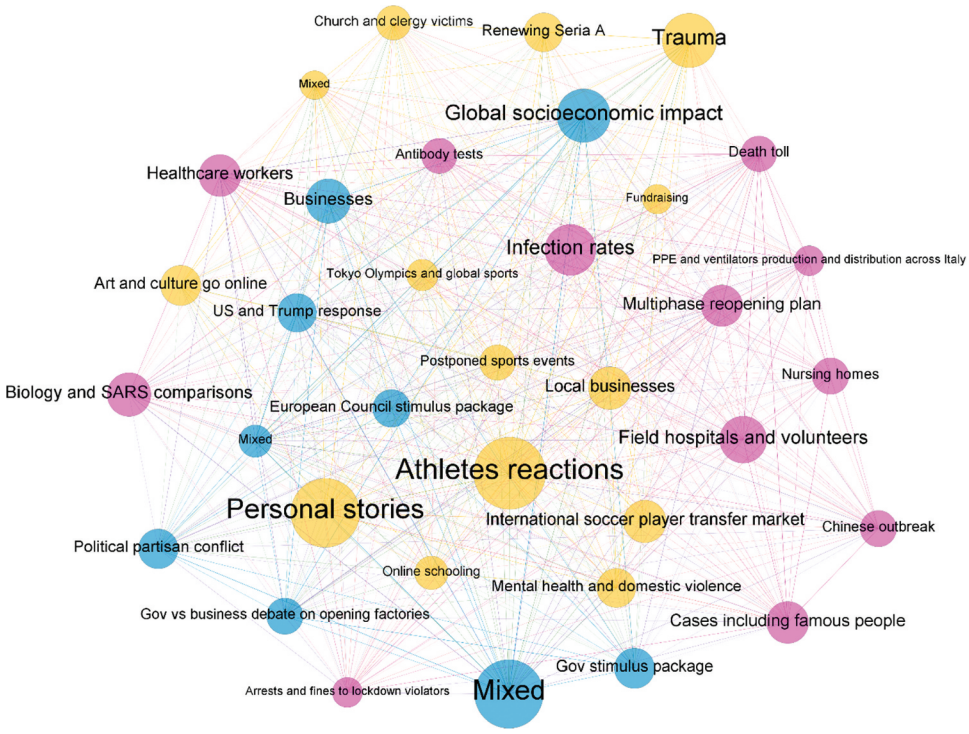

Figure 1. The topic network. Nodes represent topics; Edges represent the cosine similarity in document co-occurrence between topics; Size represents the prominence of each topic in the corpus; Node color represents community membership using the Louvain algorithm; Edge color represents the color of the community for intra-community edges, and gray for inter-community edges; Layout created using the Force Atlas algorithm. The network is fully connected, yet some edges may be too thin to see.

to as the "Louvain" algorithm for community detection. This procedure divided the network into clusters of nodes that maximized within-group links while minimizing between-group links. The resulting graph and communities can be seen in Figure 1. As detailed in the results section below, our community detection algorithm identified three media frames used to cover COVID-19 in Italian media. To examine the change in framing over time and its effects on mobility, for each news article in our corpus we calculated the share of language that was associated with each frame. We did so by summing the salience of each topic for each document (using theta values).

Analytic Approach for Time Series Analyses

We examined the association of the percentage of daily framing in national media on national-level mobility indicators. As a reminder, in ANTMN models, each news article is a mixture of all media frames. The cumulative daily percentage of the three frames always sums to 100% and thus the three could not be put together in a regression model due to multicollinearity. We, therefore, ran two separate models, one for the *social* and one for the *containment* frames. Our main outcome variable comes from the Google Community Mobility Reports, which includes six different types of mobility at the national level. These report the percent change in visits to places like grocery stores, parks, transit stations, retail and recreation, workplace, and time spent in places of residence. To serve as covariates in our models, we also collected additional data on daily deaths, and whether national restrictions were in place on any given day. We conducted Vector Autoregressive Models (VAR) using media frames as the independent variable, controlling for linear trends in the dependent variables, as well as for the number of deaths, the volume of coverage, and a binary restrictions factor to control for decree effects (starting March 12^{th,} 2020). The optimal number of lags for the VAR models was determined by an ADF test to be three days.

Results

We first examined which frames were used for the Italian media coverage of COVID-19 (RQ1). Figure 1 shows that the 35 topics could be coherently clustered into three frames. The first corresponded to the *scientific frame*, focusing on death tolls, infection rates, specific outbreaks and infections, and the virus's biological nature. This frame is congruent with the *scientific frame* identified by Ophir (2018) and the *medical frame* identified by Kott and Limaye (2016). The second frame we identified corresponded to the *social frame* (Ophir, 2018; Powers & Xiao, 2008), including topics such as businesses, global socioeconomic impact, the European council, political parties and conflicts, and governmental stimulus

packages. The third corresponded to the *pandemic* (Ophir, 2018) and *containment* (Ungar, 1998) frames, including topics such as quarantine, online schooling, suspension of sports events, and the move of art and cultural events online. While this frame is similar to the one Ophir (2018) named *pandemic*, in the Italian COVID-19 context the frame was more about ways to contain existing outbreaks and not about preventing the disease from entering the country, and thus, we renamed it the containment frame, a term consistent with prior findings from the study of media coverage of Ebola (Ungar, 1998). Importantly, topic modeling interpretation is complex and the nature and meaning of some topics could be fully understood only when read in context and in light of the full texts in which they appeared.

As for changes over time, Figure 2 shows that early on, while media coverage was still scarce, journalists largely focused on containment. With the introduction of Italian cases, the focus began shifting toward the scientific frame. After the first Italian death on February 22,nd 2020, the focus moved to discuss ways to contain the outbreak, and potential closures became the main topic of media coverage. Throughout the timeline of the disease, the social frame remained the least prominent frame among the three, though its use was substantial.

Next, we examined the relationship between media coverage and mobility (RQ2). Our main findings are illustrated below using the impulse response function (IRF). Panel 1 in Figure 3 shows the orthogonal impulse response (OIR) of the *social frame* on six categories of mobility. Substantively, these can be interpreted as the effect of a one standard deviation change within each media frame on the six measures of mobility. Note that the IRF only achieves statistical significance for the second and third lags in most models.

Panel 1 demonstrates the social frame was associated with a marked increase in mobility across all categories, except for time spent in residential areas which decrease in response to this frame. Panel 2, for the relationships between mobility and the *containment frame*, shows the converse relationship, as the prominence of the frame in media coverage was associated with decreased mobility across all mobility categories, except for time spent in residential areas which increased. Granger causality tests performed on the VAR models showed that there was instantaneous causality between the media frames and mobility in almost every model for the containment and social frames, and Granger causality in some. Table 1 details the coefficients in both models. Most associations were instantaneous ($p < .05$). The only ones where the data indicate a Granger causal direction ($p < .05$) are the effect of the *social frame* on mobility in public parks and residential areas, as well as the *containment frame's* effect on residential areas. Finally, the *scientific frame* was not associated with any of the mobility indicators ($p > .05$). The direction of association was similar to that of the containment frame, meaning associations were negative with mobility indicators, but these

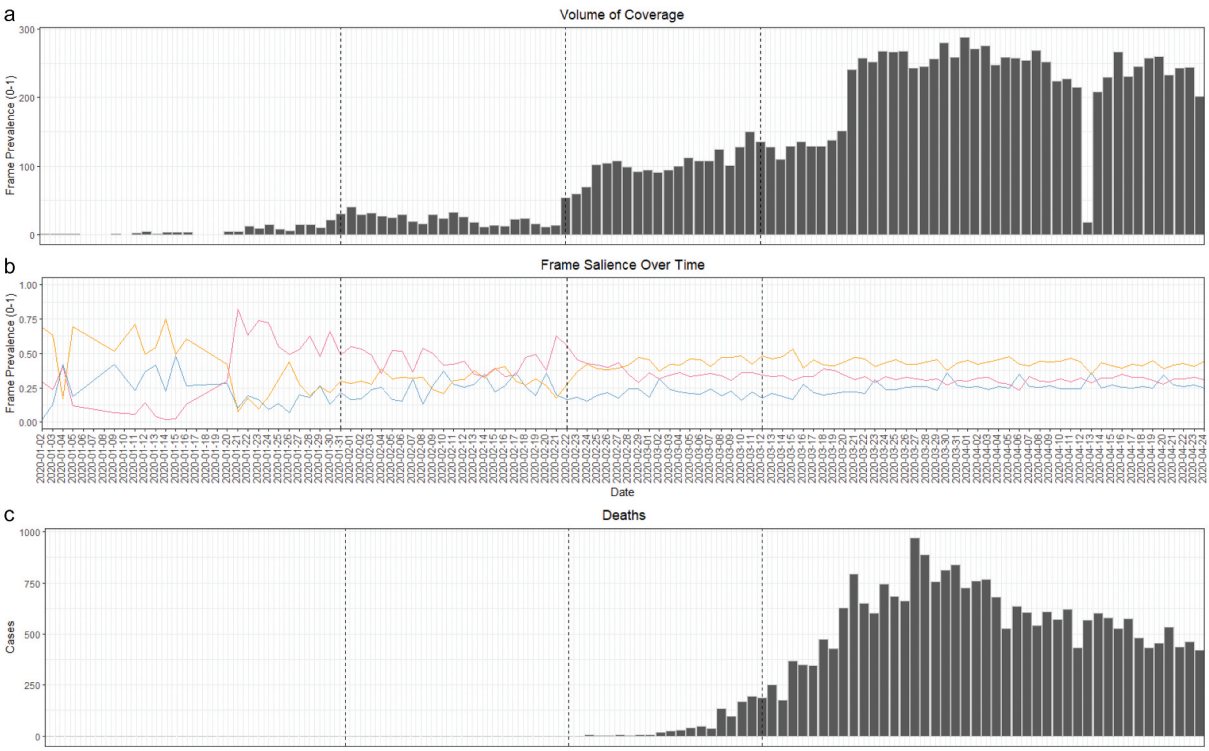

Figure 2. Change in the volume of coverage (panel A), frame salience (panel B), and the number of deaths (panel C) over time. The dip in volume corresponds to the Easter holiday. The colors of the frame correspond to Figure 1; purple for the scientific frame, blue for the social frame, and orange for the containment frame. Dashed lines represent the first cases in Italy (January 31), the first death in Italy (February 22), and national quarantine following the WHO's declaration of a pandemic (March 12). For convenience, dates are presented in the middle panel but correspond to all panels.

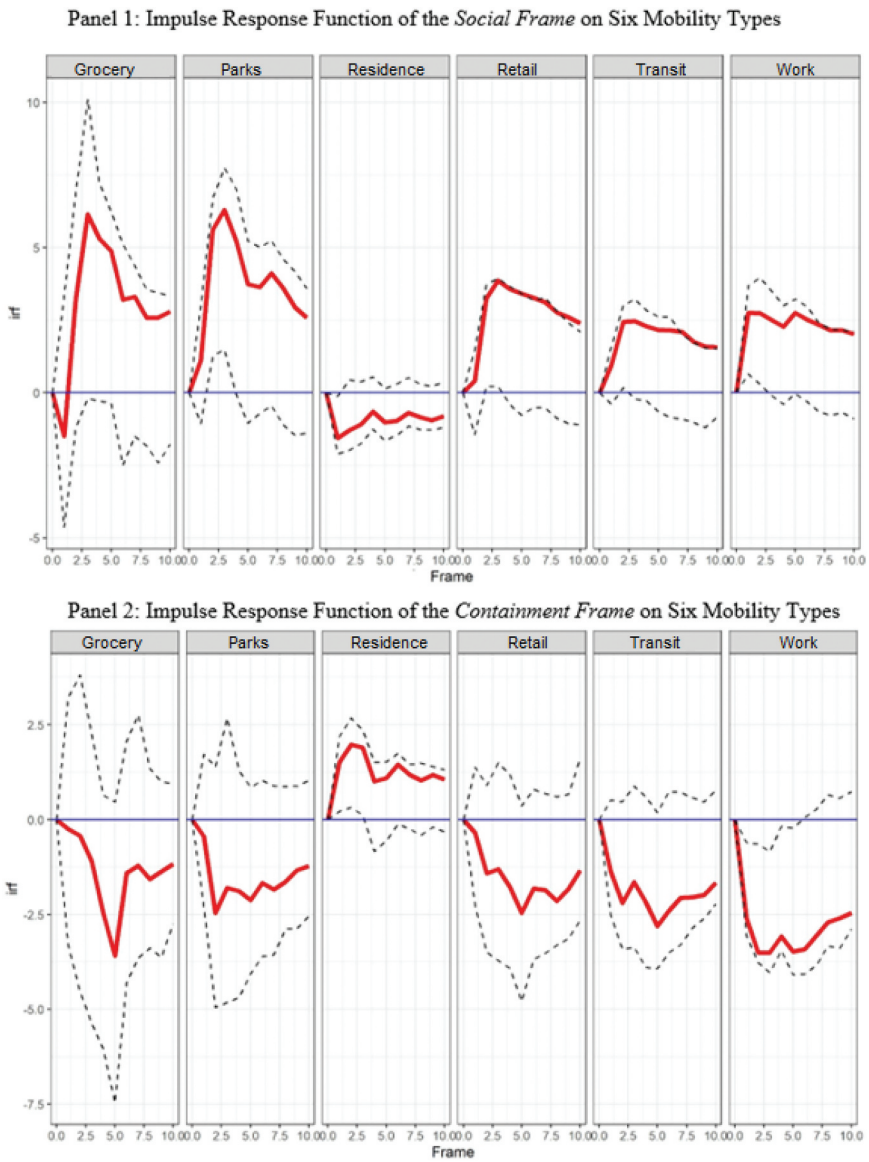

Figure 3. Impulse response function of two main frames on mobility. The red line represents the main IRF point estimates for each lag level and bootstrapped 95% confidence intervals are depicted with dashed lines around it.

were not statistically significant. Table 2 and Figure 4 corresponding to this frame could be found in the online appendix.

Discussion

Our study examined the thematic content of Italian media coverage of COVID-19 and its relationship with public mobility. We found that Italian coverage largely followed the framing strategies used by the American media during other outbreaks (Ophir, 2018; Powers & Xiao, 2008; Ungar, 1998). The social frame that was highly prominent in American coverage of H1N1, Ebola, and Zika (Ophir, 2018) and the coverage of SARS in Hong Kong (Powers & Xiao, 2008), was the least salient in Italian media coverage of COVID-19. This could be the result of differences in journalistic standards, but also the circumstances of the specific diseases. In Ophir's analysis (Ophir, 2018), discussion of sports and arts was associated with the *social frame*, while in our study topics about sports and arts were associated with the *containment frame*. The difference can be the result of H1N1, Ebola, and Zika only threatening to impact cultural industries, while COVID-19 effectively lead to the actual closures and suspensions of many events, and was thus associated more with discussions of containment than ones around the social-economic impact of the disease. Future comparative studies could further contribute to understanding the differences and similarities between journalistic practices in different countries (Hallin & Mancini, 2004) while looking at the coverage of the same, or different diseases, as well as the factors that shape them. Similarly, future triangulations with experimental and survey work could shed

Table 1. Main VAR model coefficients (social and contaminent frames)

	Dependent variable:					
	Retail	Grocery	Parks	Transit	Work	Residential
	(1)	(2)	(3)	(4)	(5)	(6)
Social Frame (lag 1)	−10.90	−89.75	25.55	16.04	61.44**	−44.63**
	(44.78)	(90.35)	(41.99)	(28.63)	(25.52)	(19.17)
Deaths per day (lag 1)	−0.02	−0.04*	−0.03**	−0.01	0.01	−0.01*
	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Social Frame (lag 2)	128.67***	90.40	157.07***	67.20**	26.13	−13.30
	(42.43)	(90.92)	(40.57)	(28.42)	(27.66)	(21.11)
Deaths per day (lag 2)	−0.01	−0.04	0.005	−0.0000	−0.01	0.01*
	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)
Trend	−0.22	−0.28	−0.38*	−0.14	−0.20	0.15
	(0.18)	(0.33)	(0.19)	(0.13)	(0.18)	(0.11)
Observations (days)	50	50	50	50	50	50
Adjusted R^2	0.95	0.72	0.94	0.96	0.94	0.90
F Statistic	65.00***	8.76***	45.49***	74.14***	51.84***	27.20***
Cont. Frame (lag 1)	11.20	8.69	−11.89	−38.58	−50.19*	34.25*
	(50.81)	(86.55)	(55.71)	(31.28)	(27.57)	(19.27)
Deaths per day (lag 1)	−0.02	−0.05*	−0.04**	−0.01	0.01	−0.02**
	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)
Cont. Frame (lag 2)	−38.39	−41.60	−114.23**	−36.01	−36.06	20.77
	(50.57)	(85.87)	(52.94)	(31.21)	(28.99)	(20.25)
Deaths per day (lag 2)	−0.01	−0.04	0.001	−0.002	−0.01	0.01*
	(0.02)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)
Trend	−0.02	−0.16	−0.16	−0.04	−0.04	0.05
Observations	50	50	50	50	50	50
Adjusted R^2	0.94	0.69	0.92	0.96	0.94	0.90
F Statistic	50.89***	7.86***	35.34***	69.07***	52.18***	27.60***

Note: Each coefficient is followed by standard error in parentheses below. The upper panel shows the first two lags of deaths per day and the social frame predicting mobility, across each of their different types. The lower panel shows the first two lags of deaths per day and the Containment frame. Volume of coverage and mobility restrictions were excluded from the table for brevity. The number of observations for mobility data represents the number of days collected, not the number of people participating, which is not released by Google. The models show that the social frame is associated with increased mobility in the following period of one or two days and is statistically significant. The Containment frame, on the other hand, is associated with decreased mobility in the following period. Models control trends in the data.

more light on the cognitive and psychological mechanisms behind the macro-level changes identified here.

Our study is the first to examine the relationship between media frames and public mobility. We find that it was not the coverage volume (Ophir & Jamieson, 2018; Tizzoni et al., 2020), but the specific frames that were associated with behavioral change during the pandemic. Specifically, the *social frame* that emphasized social and economic issues was associated with increased mobility and decreased time spent in residential areas (as the two variables are complementary and therefore tend to be opposite in direction). The *containment frame*, on the other hand, that emphasizes the seriousness of the disease and the required policies to mitigate risks led to a decrease in overall mobility and an increase in time spent at home. The pattern of effects for the *scientific frame* was similar to that of the *containment frame*, but the effects for this frame were not significant. While most associations were instantaneous (making it is impossible to determine the causal direction of effects), Granger causality tests suggested directional effects for the impact of the *social frame* on mobility in public parks and residential areas, as well as the effect of the *containment frame* on people's time at residential area. In both cases, our data suggest that it was more likely that the media influenced mobility and not vice a versa.

Importantly, like other media frames, such as episodic and thematic (Scheufele & Iyengar, 2014), the ones identified here are not necessarily associated with specific valence or arguments. A *social frame* could emphasize the importance of keeping the economy safe, but also the need to close businesses. Our study shows that the mere focus on social issues, at the expense of other topics of science and containment, yielded detrimental effects. Future research could further examine the specific arguments (e.g., pro- or anti-mobility restrictions) made by different media actors within each frame.

Four caveats should be noted. First, Google does not release information about the sample size and population distributions of mobility data. Additionally, the Google mobility data are

Table 2. Main VAR model coefficients (scientific frame)

Dependent variable:						
	Retail	Grocery	Parks	Transit	Work	Residential
	(1)	(2)	(3)	(4)	(5)	(6)
Scientific Frame (lag 1)	23.12	88.06	28.15	32.09	−23.03	11.06
	(39.24)	(81.46)	(51.62)	(27.61)	(34.83)	(22.19)
Deaths per day (lag 1)	−0.01	−0.04	−0.03	−0.01	0.02	−0.02**
	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)
Scientific Frame (lag 2)	−74.90*	−34.16	−102.11*	−31.10	41.07	−43.40*
(lag2)	(41.11)	(84.94)	(55.90)	(28.23)	(35.78)	(22.49)
Deaths per day (lag 2)	−0.01	−0.04	0.01	0.0003	−0.005	0.01
	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)
Trend	−0.06	−0.17	−0.15	−0.004	0.09	−0.07
	(0.15)	(0.30)	(0.19)	(0.11)	(0.18)	(0.09)
Observations	50	50	50	50	50	50
Adjusted R^2	0.95	0.70	0.92	0.96	0.93	0.89
F Statistic	55.74***	8.12***	34.08***	67.34***	44.86***	25.57***

Note: Each coefficient is followed by standard error in parentheses below. Models control trends in the data.

Table 3. Top 10 unique (FREX) words, and labels for each topic

Topic Label	Top 10 Words	Associated Frame
Chinese outbreak	cina, cinese, cinesi, coronavirus, wuhan, italia, virus, voli, italiani, stati (china, chinese, chinese, coronavirus, wuhan, italy, virus, flights, italian, states)	Scientific
Mixed	più, perché, solo, essere, può, molto, così, fatto, ancora, quando (more, why/because, only, to be, can, much, so, done, more, when)	Social
Mental health and domestic violence	più, persone, casa, bambini, famiglie, può, donne, anziani, possono, fare (more, people, house, kids, families, can, women, elders, can, to do)	Containment
Healthcare workers	salute, nazionale, misure, presidente, emergenza, sanitario, personale, essere, rischio, attività (health, national, measures, president, emergency, health, employees, to be, risk, activity)	Scientific
Local businesses	città, via, casa, più, solo, spesa, persone, giorni, due, qui (city, street, house, more, only, expense, people, days, two, here)	Containment
Renewing Serie A (Italian soccer league)	club, calcio, serie, presidente, stagione, campionato, lega, società, giocatori, giocare (club, soccer, league, president, season, championship, league, society, players, to play)	Containment
Gov stimulus package	euro, milioni, imprese, miliardi, mila, decreto, fino, cassa, lavoro, governo (euro, millions, businesses, billions, thousand, decree, until, cashier, work, government)	Social
Nursing homes	rsa, anziani, regione, ospiti, riposo, strutture, tamponi, case, stati, morti (nursing home, elderly, region, guests, rest, structures, covid tests, houses, states, deaths)	Scientific
European Council stimulus package	paesi, germania, europea, miliardi, europeo, crisi, debito, italia, europa, mes (countries, germany, european, billions, european, crisis, debt, italy, europe, esm)	Social
Art and culture go online	film, musica, mondo, teatro, cinema, cultura, serie, libro, coronavirus, anni (movie, music, world, theater, cinema, culture, series, book, coronavirus, years)	Containment
Infection rates	più, casi, ieri, numero, morti, contagi, decessi, dati, positivi, nuovi (more, cases, yesterday, number, deaths, infections, deaths, data, positive, new)	Scientific
Global socioeconomic impact	più, crisi, essere, sistema, paese, sociale, anni, politica, sarà, oggi (more, crisis, to be, system, country, social, years, politics, it will be, today)	Social

(*Continued*)

Table 3. (Continued)

Topic Label	Top 10 Words	Associated Frame
Multiphase reopening plan	misure, attività, sarà, governo, distanza, più, sicurezza, essere, persone, fino (measures, activities, it will be, government, distance, more, security, to be, people, until)	Scientific
Church and clergy victims	anni, stato, san, dopo, prima, sempre, via, coronavirus, papa, francesco (years, state, saint, after, before, always, street, coronavirus, pope, francis)	Containment
Trauma	più, vita, mondo, tempo, ogni, perché, oggi, senza, virus, solo (more, life, world, time, every, why/because, today, without, virus, only)	Containment
Personal victim stories	anni, quando, casa, più, poi, dopo, fatto, perché, giorno, prima (years, when, house, more, after, done, why/because, day, before)	Containment
Mixed	della, alla, una, dalla, emergenza, nella, italia, più, epidemia, poi (of the, to the, a, from the, emergency, in the, italy, more, pandemic, after)	Social
Postponed sports events	ieri, marzo, coronavirus, aprile, fino, sarà, già, domenica, dopo, giorni (yesterday, march, coronavirus, april, until, it will be, already, sunday, after, days)	Containment
US and Trump response	stati, new, trump, stato, uniti, york, più, presidente, usa, pandemia (states, new, trump, state, united, york, more, president, usa, pandemic)	Social
Tokyo Olympics and global sports	sport, più, mondo, giochi, mondiale, due, dopo, prima, tokyo, luglio (sport, more, world, games, worldwide, two, after, before, tokyo, july,	Containment
International soccer player transfer market	squadra, più, calcio, stagione, dopo, tempo, giocatori, due, club, campo (team, more, soccer, season, after, time, players, two, soccer club, field)	Containment
Mixed	social, video, facebook, coronavirus, instagram, foto, casa, messaggio, giorni, diretta (social, video, facebook, coronavirus, instagram, picture, house, message, days, live broadcast)	Containment
Fundraising	euro, mila, fondi, raccolta, fondazione, solidarietã, riservata, coronavirus, donazioni, riproduzione (euro, thousand, funds, fundraising, solidarity, reserved, coronavirus, donations, riproduction)	Containment
Arrests and fines to lockdown violators	roma, lazio, stato, polizia, due, riproduzione, coronavirus, riservata, carabinieri, stati (rome, lazio, state, police, two, riproduction, coronavirus, reserved, carabinieri, states)	Scientific
Political partisan conflict	governo, presidente, conte, ministro, premier, consiglio, stato, capo, italia, decreto (government, president, conte, minister, prime minister, council, state, head, italy, decree)	Social
PPE and ventilators production and distribution across Italy	mascherine, protezione, dispositivi, civile, guanti, medici, mascherina, produzione, giorno, ospedali (masks, protection, equipment, civil, glove, doctors, mask, production, day, hospitals)	Scientific
Online schooling	online, scuola, studenti, casa, lezioni, digitale, scuole, distanza, più, ragazzi (online, school, students, house, classes, digital, schools, distancing, more, guys)	Containment
Cases including famous people	stato, giorni, tampone, coronavirus, sintomi, dopo, positivo, due, febbre, quarantena (state, days, covid test, coronavirus, symptoms, after, positive, two, fever, quarantine)	Scientific
Antibody tests	test, tamponi, dati, essere, fase, sarà, virus, app, anticorpi, persone (test, covid test, data, to be, phase, it will be, virus, app, antibody, people)	Scientific
Athletes reactions	più, fare, perché, cosa, quando, molto, essere, sarà, dobbiamo, poi (more, to do, because, thing, when, more, to be, will be, we have to, then)	Containment
Field hospitals and volunteers	pazienti, medici, terapia, posti, ospedali, intensiva, infermieri, ospedale, covid, malati (patients, doctors, therapy, spots/hospital beds, hospitals, intensive, nurses, hospital, covid, sick patients)	Scientific
Death toll	bergamo, sindaco, milano, brescia, lombardia, zona, provincia, regione, città, più (bergamo, mayor, milan, brescia, lombardy, area, province, region, city, more)	Scientific
Businesses	milioni, più, mercato, euro, miliardi, società, crescita, calo, secondo, crisi (millions, more, market, euro, billions, society, growth, decrease, second, crisis)	Social
Biology and SARS comparisons	virus, coronavirus, più, malattie, ricerca, vaccino, malattia, essere, può, studio (virus, coronavirus, more, diseases, research, vaccine, disease, to be, can, study)	Scientific
Gov vs business debate on opening factories	aziende, imprese, settore, lavoro, dipendenti, attività, lavoratori, presidente, produzione, sicurezza (companies, sector, work, employees, asctivity, workers, president, production, security)	Social

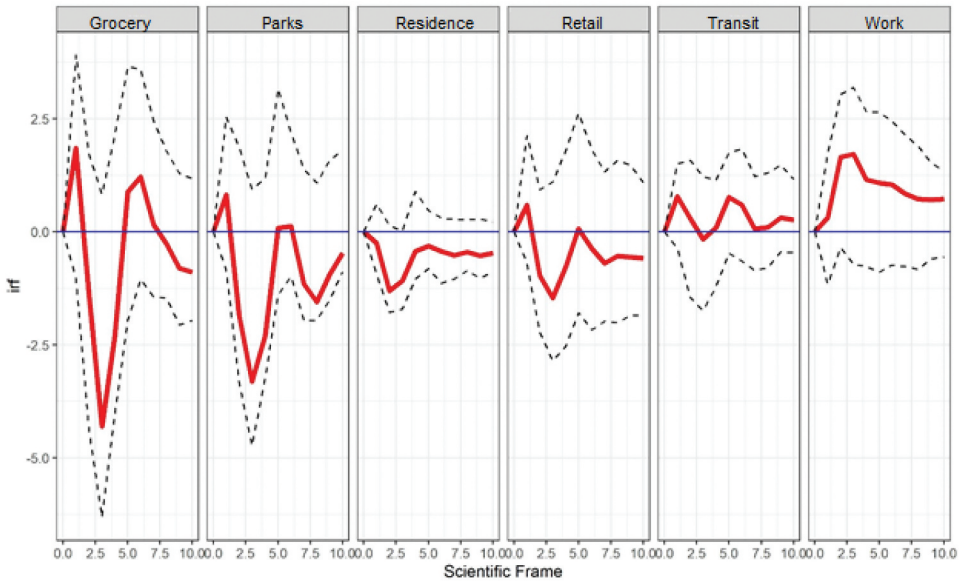

Figure 4. Impulse response function of the scientific frame on mobility.

limited to Android users with location history turned on. Despite these limitations, multiple scientific papers have employed the data recently and found it to be robust and effective for predicting social phenomena (e.g., Herren et al., 2020). Second, while the chosen method measures the amount of attention paid to frames, it does not account for all aspects of framing, including the use of visuals or the placement within physical or digital issues. We believe the method's benefits, such as the analysis of large-scale data, and the inductive nature of the frame identification step, offset such limitations. Third, although directionality was suggested for some variables via Graner tests, causality should be taken with caution, as we did not directly examine the effects of exposure to the articles analyzed on specific people's behaviors, nor did we examine the full information environment Italians were exposed to during the pandemic (e.g., their social media or discussions with family and friends). Fourth, our framing analysis relies on journalistic emphasis frames (D'Angelo, 2018) only. Future studies may look at the relationships between behavior and alternative types of frames, including gain and loss frames, or other equivalency frames (Kahneman & Tversky, 1984).

Despite those caveats, our results emphasize the role played by the media during public health crises. It demonstrates that Italian journalists used media frames similar to those employed in the coverage of other diseases in other countries, with some nuanced differences in frame elements and frame salience. Our results demonstrate the need to cover epidemics in responsible ways that emphasize scientific facts, risk information, and practical ways to alleviate risks. Focusing on social and economic aspects, while important for sensemaking during crises, could lead people to take the disease less seriously and harm compliance. As the focus on social and political aspects is often the result of work routines, commercial pressures, and editorial decisions, and thus is likely to remain stable in future crises (Van Gorp, 2007), we encourage public health communicators to try and emphasize the *scientific* and *containment* frames in their own communications to complement media coverage.

Data Availability Statement

The aggregated news data and the R code used for analysis will be available at https://www.yotamophir.com/covid19-italian-media.

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