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Abstract

There are substantial differences across regions regarding COVID–19 infections and deaths, which are partly explained by differences in practicing social distancing. In this paper, we argue that the portrayal of COVID–19 in regional media might be an important factor in explaining regional differences in social distancing. By using mobility as a proxy, and analyzing data on regional news coverage in Germany, we empirically investigate whether the geographical heterogeneity in COVID–19-related news reporting has translated into spatial variations in social distancing. Our results confirm that the frequency of and the element of fear in COVID–19 news has a significant albeit time-varying relationship with social distancing.

Keywords— COVID–19, coronavirus, news media, mobility, regional analysis

JEL Classification— R10, I12, D10, L82

1 Introduction

The coronavirus, COVID–19, has quickly become a global pandemic with seemingly inescapable consequences on daily life. Since its first appearance, COVID–19 has infected more than 600 million people. There is no doubt that both the disease and the measures taken against it changed the established patterns of people's daily lives suddenly and drastically. However, the response to the pandemic has not been the same everywhere. In some places, people changed their lives substantially while in others, they reacted rather modestly, and the determinants of such spatial variations are not fully clear. The present paper argues and empirically tests whether the presentation of COVID–19 in news media contributes to this spatial heterogeneity.

COVID–19 brought uncertainty to people's lives, which induced a strong demand for information regarding the virus and everything related to it. In most cases, people turn to the news media to update their knowledge of the disease and inform their behavioral responses. In many instances, the first information source from which people learned about the existence of the disease has been the news media. However, news media outlets are rarely identical in terms of selection and reporting of issues, and this is not any different for COVID–19-related news. Crucially, news reporting and consumption have a strong geographical dimension at the sub-national level (Althaus et al., 2009; Bogart, 1989; Ozgun and Broekel, 2021).

In this paper, we first explore the sub-national heterogeneity in COVID–19-related news coverage. Second, we assess if sub-national variations in the frequency and tone of news coverage of the pandemic translate into spatial variations in peoples' pandemic-related behavior. As several studies confirm the important role of news information on health behavior (Simonov et al., 2020; Bursztyn et al., 2020; Ash et al., 2020), our study focuses on the mobility of individuals as an observable expression of social distancing behavior. Using spatial panel regression models at the level of German districts and weekly observations, we identify a significant albeit time-varying relationship between COVID–19 news reporting and regional mobility patterns. In regions where COVID–19 was covered more frequently and presented in more fearful ways during the pandemic's early stage, we observe larger drops in weekly mobility. This negative relationship, however, becomes a positive one during "the good times", i.e., at low points of infection numbers in summer and when the first vaccines became available. Given that mobility is a critical determinant of COVID–19 infections and deaths (Glaeser et al., 2020; Nouvellet et al., 2021; Alessandretti, 2021), our study suggests that regional news media has played a role in the spreading of COVID–19, especially at the beginning of the pandemic. People in locations where the news media covered the virus with a lower frequency and communicated its risks in less dramatic ways were less likely to adapt their mobility behavior and, hence, put themselves and others in greater danger.

The remainder of the paper is organized as follows. Section 2 reviews the related literature and develops the research hypotheses. The utilized data sources are described in Section 3. Section 4 introduces the employed empirical approach and the results are presented and discussed in Section 5. Section 6 concludes the paper.

2 The link between the news media and health behavior

Although the COVID–19 pandemic was a global threat, there have been substantial differences across regions in the extent to which they were affected by the pandemic (White and Hébert-Dufresne, 2020; Bosa et al., 2021; Hoekman et al., 2020; Roelofs et al., 2022). Many studies show that preventive practices, such as social distancing, have been one of the main determinants of regional differences in the number of infections and deaths (Badr et al., 2020; Glaeser et al., 2020; Carteni et al., 2020; Engle et al., 2020; Nouvellet et al., 2021; Hadjidemetriou et al., 2020). Although national and regional policies including lock-downs and stay-at-home orders had significant impacts on social distancing behavior, i.e., on reducing the mobility of individuals (Courtemanche et al., 2020; Dave et al., 2021; Gupta et al., 2021; Bialek et al., 2020), compliance with orders and voluntary social distancing, i.e., individual choices, have been identified to have played a more important role (Goolsbee and Syverson, 2021; Eckert and Mikosch, 2020). That raises the question of what factors explain these differences. The literature on spatial differences in social distancing and accordingly infection rates, identifies a number of regional factors to have been decisive including population density (Allcott et al., 2020; Ehlert, 2021; Desmet and Wacziarg, 2021; Engle et al., 2020; Bialek et al., 2020), income level (Chiou and Tucker, 2020; Maiti et al., 2021; Desmet and Wacziarg, 2021), age composition (Bialek et al., 2020; Engle et al., 2020; Desmet and Wacziarg, 2021; Ehlert, 2021), political leanings (Engle et al., 2020; Desmet and Wacziarg, 2021; Painter and Qiu, 2021; Barrios and Hochberg, 2020), and share of foreigners and ethnicity (Egorov et al., 2021; Benitez et al., 2020; Maiti et al., 2021).

The media coverage of COVID–19 is argued to be another important factor affecting individuals' social distancing decisions. Individuals' dependence on media clearly intensifies during times of crises or uncertainty (Ball-Rokeach and DeFleur, 1976; Ball-Rokeach, 1985) since perceived risks garner attention (Burns and Slovic, 2013). It is confirmed that crisis situations such as natural disasters, terrorist attacks, and political turmoil are associated with increased news consumption (Lowrey, 2004; Althaus, 2002; Westlund and Ghersetti, 2015). The COVID–19 outbreak is undoubtedly a significant crisis that suddenly challenged established patterns of daily life. In particular, at its beginning, billions of people had no idea about the potential magnitude of the upcoming crisis, how it would impact them individually, and most importantly, how they could adapt their behavior to protect themselves. In line with what has been observed for other crises, the COVID–19 pandemic also led to an increase in information-seeking and news consumption all around the world (Bento et al., 2020; Lemenager et al., 2021; van Aelst et al., 2021; Hölig et al., 2020).

The well-established influence of news media on people's perceptions and the importance they attach to issues (McCombs and Shaw, 1972; Hester and Gibson, 2003) emerges from the frequency of coverage, the tone, and the framing (Entman, 1993; Doms and Morin, 2004; Booth, 1970; Bursztyn and Cantoni, 2016; Hollanders and Vliegenthart, 2011). Crucially, this influence also alters risk perceptions (Pidgeon et al., 2003). For instance, the frequency of media coverage tends to increase the sense of hazard and leads to changes in associated behaviors (Mazur, 1984; Gaskell et al., 1999; Mazur, 2006; Bauer, 2005; Holman et al., 2014). Given the magnitude, severity of health risks, and uncertainty regarding COVID–19, it can be expected that the presentation of COVID–19 in news media has a substantial impact on how people adapt their health behavior related to this new and highly dynamic threat. Several recent studies provide empirical support for this assumption. For example, by focusing on the time dimension, Ophir et al. (2021) identify that the framing of COVID–19 news has been associated with changes in peoples' mobility.

Of course, the news media is not one uniform entity but rather is comprised of a large set of various outlets. Even in the case of a global pandemic, news outlets select different events to report about, emphasize varying aspects, or express different stances and attitudes towards issues. These differences across news sources (primarily based on the political leaning of the news outlets) explain their audiences' health-related behaviors, including their compliance with stay-at-home orders, and their purchasing of goods necessary for protection (Jamieson and Albarracin, 2020; Andersen, 2020; Simonov et al., 2020; Ash et al., 2020). Bursztyn et al. (2020) even find that consuming particular shows within the same network, that communicate COVID–19-related risks in distinct ways, translates into variations in their audiences' COVID–19 infection rates. However, the extent to which differences in COVID–19-related reporting explain the spatial pattern of behavioral reactions to the pandemic and, ultimately to its spatial diffusion, is still unknown. This knowledge gap motivates the present paper.

A substantial portion of heterogeneity within news media is geographical in nature. That is, the available news sources, broadcasting channels, and consumption patterns differ systematically between places (Hutchins, 2004; Carpini et al., 1994; Dou et al., 2006; Young and Dugas, 2012). As a consequence, even individuals with similar individual traits and news preferences can be exposed to distinct sets of news information as well as the presentation thereof, only because they reside in different locations (Althaus et al., 2009; Bogart, 1989; Ozgun and Broekel, 2021). This applies to health-related news as well (Powell et al., 2016). Despite large geographical variations in COVID–19 exposure and responses as well as the easily observable heterogeneity in pandemic reporting across news outlets, little is known about the extent of sub-national variations in the news presentation of COVID–19.[1] These arguments and research gap lead to our first hypothesis.

H1: There exists substantial regional heterogeneity in news media reporting on COVID–19.

The existence of systematic sub-national heterogeneity in COVID–19 reporting becomes relevant when it results in systematic variations in peoples' behavioral responses to the pandemic. In light of the findings of previous studies, our second hypothesis is related to behavioral responses. We focus on social distancing as a health-related behavior because it is adaptable and can be empirically captured with the help of a proxy.

H2: Regional heterogeneity in news media reporting on COVID–19 translates into regional variations in social distancing.

We expect people to adapt their social distancing behavior in ways that reduce the risks associated with COVID–19 more strongly in regions where the news media reports COVID–19 more frequently and in a more alarming fashion than in regions where this is less the case. However, the effects of news media on health-related behavior, e.g., social distancing, might not be as straightforward as the hypothesis suggests. Increased media coverage of a risk does not always lead to behavioral changes. While the news media is frequently a trigger of abstract worries and risks, studies show that these do not necessarily translate into actions (Hawkes et al., 2009). For instance, when media over-dramatize issues, trust in the media declines, which lays the ground for counterproductive behaviors such as a higher reluctance to be vaccinated (Elledge et al., 2008; Taha et al., 2013). In addition to too little or too much coverage, contradictory and confusing news distorts the public's perceptions of health risks (Taha et al., 2014). While it can be expected that such over- and undershooting, as well as contradictory information, mediate the impact of the news media on behavior, they also imply that news media's influence is time-variant and fact-specific. The news media effect is greater when topics are new and people cannot rely on their own experiences (Zucker, 1978). This occurred during the beginning of the pandemic when individuals' knowledge about and experiences with the coronavirus were very limited. As, unfortunately, first-hand experiences gradually increased, the reliance on news as a crucial information source is likely to have decreased. Consequently, it can be expected that the relationship between news reporting and behavioral responses weakened over the course of the COVID–19 pandemic. Our third hypothesis reflects this progression:

H3: The influence of news media on social distancing diminishes over time.

[1] Although at a larger geographical scale, Liu et al. (2021) take an initial step towards this direction. By investigating the first month of the pandemic, authors find that media coverage is associated with a reduction in the number of COVID–19 cases.

The three hypotheses are tested by using information on German regions' exposure to COVID–19, COVID–19-related news reporting in (regional) newspapers, and by utilizing mobility as a proxy of social distancing behavior.

3 Data and variables

3.1 Units and time of observation

The empirical analysis focuses on Germany, as we have access to high-quality information on individuals' mobility and regional news coverage. The time period under consideration ranges from the beginning of March 2020 to the end of February 2022, which captures the early phase of the COVID pandemic in Germany (albeit not the very first infections in January 2020) and the subsequent development.

Ideally, analyses on COVID–19-related behavior and news media exposure would take place at the level of individuals. However, since this information is not available, we opt for a second-best approach and conduct the analysis at the regional level. The unit of observations is the 401 German NUTS-3 regions (districts), the smallest available spatial entity for which comprehensive data on mobility and news are available. Another aggregation is done in the time dimension. While the mobility and news information is available for individual days, we aggregate it to weekly averages since there is an unknown time lag between news exposure and mobility response, and there is significant heterogeneity in the COVID–19 testing and, accordingly, infection data, and in mobility patterns between the weekends and weekdays (Edsberg Møllgaard et al., 2021; Christidis et al., 2021). Weeks are defined as calendar weeks: January 1 – 5, 2020 is the first week, January 6 – 12, 2020 is the second, and so on.

Figure 1 shows the weekly number of new infections divided by the population. Each point corresponds to a district for the given week and dates indicate the first day of the given week. According to the Robert Koch Institute[2], the first wave started around the 10^{th} calendar week of 2020, i.e., at the beginning of March 2020, and ended around mid-May 2020. Following the first wave, there was a so-called interim period, during the summer, with few and mild cases (Schilling et al., 2021). The second wave was from the beginning of October 2020 until mid-February 2021, which was immediately followed by a third wave that ended in June 2021. After a summer plateau in mid-August 2021, the fourth wave, also known as the Delta wave, started. Immediately after the fourth wave, at the end of 2021, the fifth wave, the Omicron wave, started.[3]

[2]The Robert Koch Institute (RKI) is Germany's central scientific institution in the field of biomedicine and one of the most important bodies for the safeguarding of public health.

[3]Information on pandemic waves is taken from the epidemiological bulletin of RKI: `https://www.rki.de/DE/Content/Infekt/EpidBull/Archiv/2022/Ausgaben/10_22.pdf?__blob=publicationFile`.

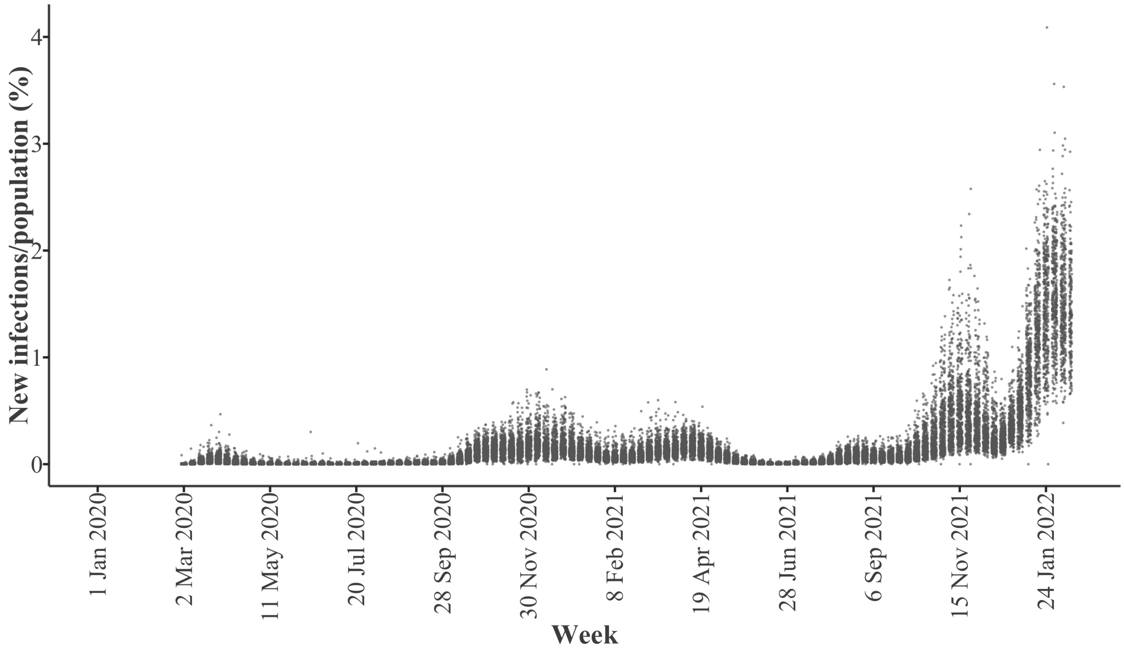


Figure 1: Share of population newly infected with COVID–19 in Germany, data taken from the Corona Data Platform

3.2 Mobility as an indicator of social distancing

As highlighted above, we focus on social distancing as a health-related behavior, because it is highly likely to be affected by news reporting about COVID–19 and is empirically observable. Several studies find and confirm that mobility, as a proxy for social distancing, is strongly related to infections and deaths (Glaeser et al., 2020; Carteni et al., 2020; Nouvellet et al., 2021). We follow the established practice and utilize the mobility indicator provided by the German Federal Statistical Office (Statistisches Bundesamt).[4] It is based on mobile network data, which are widely used to detect mobility patterns of individuals (Bwambale et al., 2019; Oliver et al., 2020; Pullano et al., 2020). The indicator denotes the change in the total number of mobile devices within a region carrying out a movement, i.e. switching from one radio cell to another, within a day, by comparing it to the same working day in 2019.[5] Crucially, the statistical office adjusts the indicator for public holidays.[6]

[4]For further details about data collection, see: `https://www.destatis.de/DE/Service/EXDAT/Datensaetze/mobilitaetsindikatoren-mobilfunkdaten.html`.

[5]Note that mobile phone data also have several shortcomings related to population sampling and market share of operators providing the data. However, since we do not have access to metadata due to privacy concerns, we are not able to assess and report potential issues here. The mobility indicator also does not differentiate between the distances traveled. Although not all movements indicate the same level of contact rate, mobility data is still the best proxy we have for social distancing.

[6]Public holidays refer to both national holidays and state-level religious holidays.

Figure 2 shows the average weekly mobility change in German districts from the beginning of January 2020 to the end of February 2022. The first waves of the pandemic are clearly visible in Figure 2, with significant drops in mobility. However, Figure 2 also shows that although individuals' mobility behavior always responded to the changes in the COVID–19 situation, the magnitude of response has diminished over time. While the number of confirmed cases is a lot higher in the last wave, mobility response is almost non-existent in many regions.

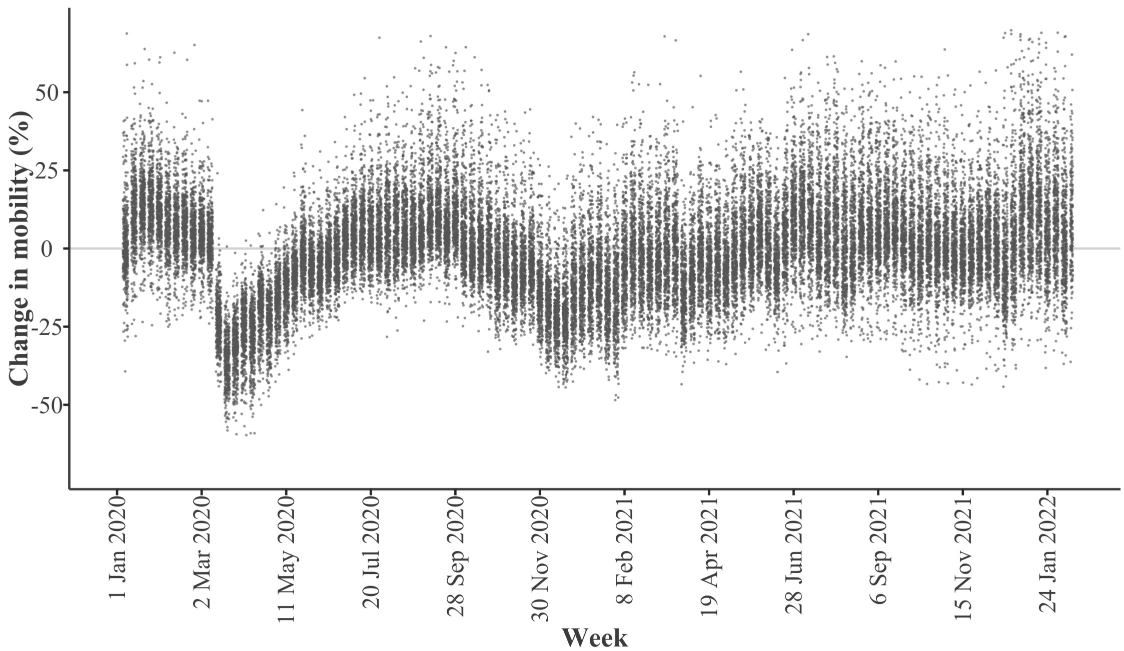


Figure 2: Weekly mobility change compared to 2019

3.3 Regional COVID–19 News

To explore to what extent the portrayal of COVID–19 in regional news explains behavioral responses in the form of decreased mobility, we construct a set of variables reflecting this dimension at the regional level. While the consumption of national newspapers shows considerable geographic variations, local and regional news, as well as regional sections of national newspapers, are the main drivers of inter-regional heterogeneity in news exposure. They, therefore, stand in the foreground of the subsequent analysis. In Germany, regional newspapers are an essential part of news consumption (Mangold et al., 2017; Humprecht and Esser, 2018; Newman et al., 2019; Hölig et al., 2020). Studies and surveys show that local and regional newspapers and their online offerings have been very important in informing the population in Germany during the pandemic (Maurer and Gutenberg, 2021), and general trust for media about COVID–19 information was about 85% (Viehmann et al., 2020). This importance of and reliance upon regional news media makes Germany an ideal case for testing the hypotheses in this study.

We obtain information on newspapers at the regional level from the RegNeS database. RegNeS provides a daily collection of news headlines and snippets of most newspapers circulating in Germany that are presented on newspapers' websites. Crucially, it differentiates between national and sub-national sections as well as versions of national newspapers implying that portions of their content can also be associated with specific localities. The cleaning and geo-locating procedure of news items are outlined in Appendix A.

To identify news items related to COVID–19, we use a rule-based classification method and pattern matching. More precisely, after pre-processing the text data, we identify news articles that contain words related to COVID–19 in the title or snippet. The list of search terms are: *COVID–19, coronavirus, Sars-Cov-2, pandemic, quarantine, lockdown, and virus-mutation.*[7,8]

The first variable constructed on the news information is the share of COVID news (*COVID_NEWS*). This variable is first constructed at the newspaper level implying that for each newspaper (or its regional section), the share of COVID-related news articles is calculated. Secondly, the average of this figure across all newspapers associated with a region is computed. The idea behind this method of calculation is that people usually read just one newspaper, so they are exposed to all articles dealing with COVID–19 featured in one newspaper and their combined (average) characteristics will determine the impact on the readers' mobility behavior. Lacking precise readership information on all newspapers, we are limited to assigning equal weights to all of them when aggregating this variable at the regional level. Consequently, the variable represents the average share of COVID-related news in newspapers read in a specific region.

Figure 3 shows *COVID_NEWS*, for each week and for all districts. The first COVID–19-related news in the RegNeS database appears on January 9, 2020, the day on which the World Health Organization published an online statement on a cluster of pneumonia cases in Wuhan, China.[9] Following this initial appearance, the virus was featured only in a few news articles. With the first announced case in Germany on 27 January 2020, attention for the topic increased and COVID–19-related news articles went up to 10% of all news before the share decreased again. In March 2020, news coverage of COVID–19 surged, which coincided with the first COVID–19-related deaths being reported in Germany, and with the World Health Organization declaring COVID–19 a pandemic on March 11.[10] At the end of March 2020, almost 60% of all news articles published in Germany were mentioning COVID–19 in one way or another. Although the temporal development of media attention generally matches the ups and downs of COVID–19 case numbers in the country, news coverage has never reached these levels in the subsequent waves. This shows that the newsworthiness of COVID–19 was mostly determined by the *unexpectedness*, and to some extent by the *magnitude*

[7]The exact search terms in German are: COVID–19, corona, SarsCov2, pandemie, quarantäne, ausgangssperre, virusmutation.

[8]Clearly, this list does not capture all news about COVID–19. For example, news stories with the phrase *vaccination center* almost exclusively refer to facilities for COVID–19 vaccine injections, however, the text might not mention the word COVID–19. Identifying all of those cases would introduce a lot of subjectivity and potentially many false-positive results. We, therefore, stick to the rather conservative approach, requiring any of the key tokens above to appear in the text.

[9]See: `https://www.who.int/china/news/detail/09-01-2020-who-statement-regarding-cluster-of-pneumoniacases-in-wuhan-china`.

[10]See: `https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020`.

of the threat. Note that the observed patterns in our dataset are in line with Maurer and Gutenberg (2021), who show that the peak of media coverage was in the first wave, although the infection rate was much more dramatic in the later waves.

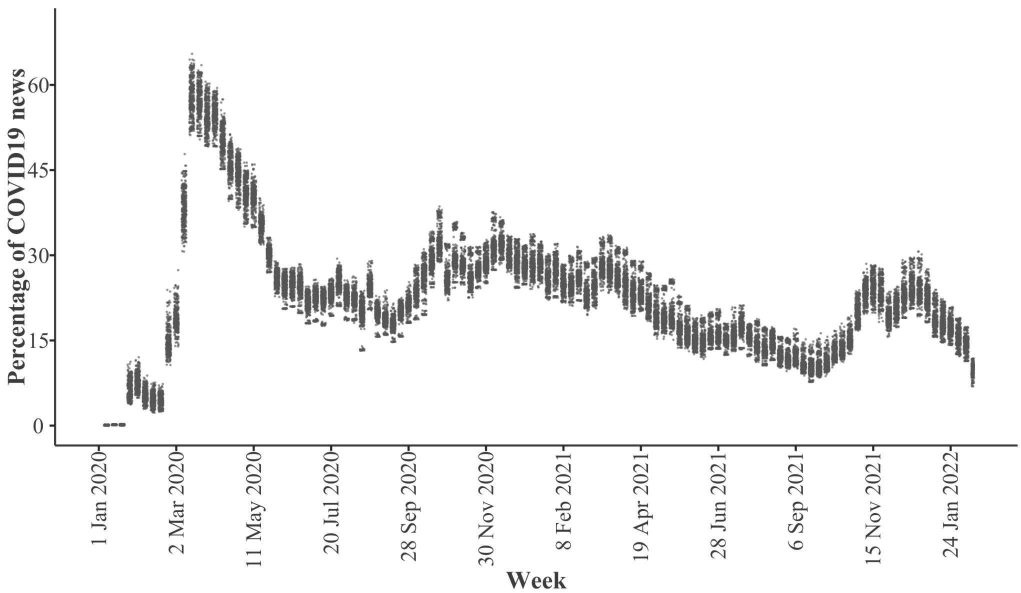


Figure 3: Weekly percentage of COVID–19 news

In addition to the intensity of reporting, we are interested in the ways COVID–19 is presented. Ideally, one can assign a sentiment polarity index to each piece of news, based on a sentiment lexicon. However, available sentiment dictionaries do not fit the specific needs of analysis for COVID–19 news since the list of sentiment-bearing words and their weights are misleading in this context.[11] We therefore rely on an emotions lexicon, i.e., NRC[12], which associates words with basic emotions such as *anger, fear, anticipation, trust, surprise, sadness, joy,* and *disgust* (Mohammad and Turney, 2013) and has been used to identify sentiments in text documents (Mohammad et al., 2013; Bose et al., 2019). Since the health risks conveyed by news articles have the most potential to influence peoples' related behavior, of these basic emotions, we use *fear*, to assess the degree to which newspapers covered COVID–19 in a dramatic way.[13]

[11]German sentiment dictionaries developed for general purpose or political texts fail to assign coherent sentiment scores to COVID–19-related texts. For example, the word *positive* has a positive association in all sentiment dictionaries (see e.g., Rauh, 2018; Remus et al., 2010), while in the context of COVID–19, the word is usually used for *testing positive* which is definitely not a positive development, on the contrary, a negative one. Since this and many other sentiment-bearing words predominantly imply the opposite sentiment in the COVID–19 context, conducting a sentiment analysis based on lexicons that are not specifically designed for COVID–19 generates not only useless but also misleading results.

[12]National Research Council Canada

[13]In the lexicon, there are 1454 fear-associated German words. Some examples that frequently show up in COVID–19-related news articles are (translated in English): *alarming, fatal, collapse, contagious, dead, harm, infectious, quarantine, risky, threatening, unsafe, worrying.*

To represent the degree of *fear* expressed in an article about COVID–19, we use the share of its words with a fear association in it; i.e., it is the total number of fear-associated words divided by the total number of words. Figure 4 shows the average share of fear words in the COVID–19 news. Aside from the sharp increase before the beginning of the pandemic, and an increase at the peak of the fourth wave, we see only a modest decreasing trend over the observed time period. This implies that on average, news articles reporting about COVID–19 used more or less the same wording in terms of inducing fear, and the fear element in news articles decreased over the course of the pandemic. For our analysis, this rather time-invariant character of the variable is positive, as it allows assessing inter-regional variations in this dimension with less concern about overall time trends. On this basis, we construct the region-level variable, the share of fear words in COVID–19 news (*COVID_FEAR*) in the same way as the *COVID_NEWS*, i.e., by first calculating the average at the newspaper level, before averaging it across all newspapers appearing in a region.

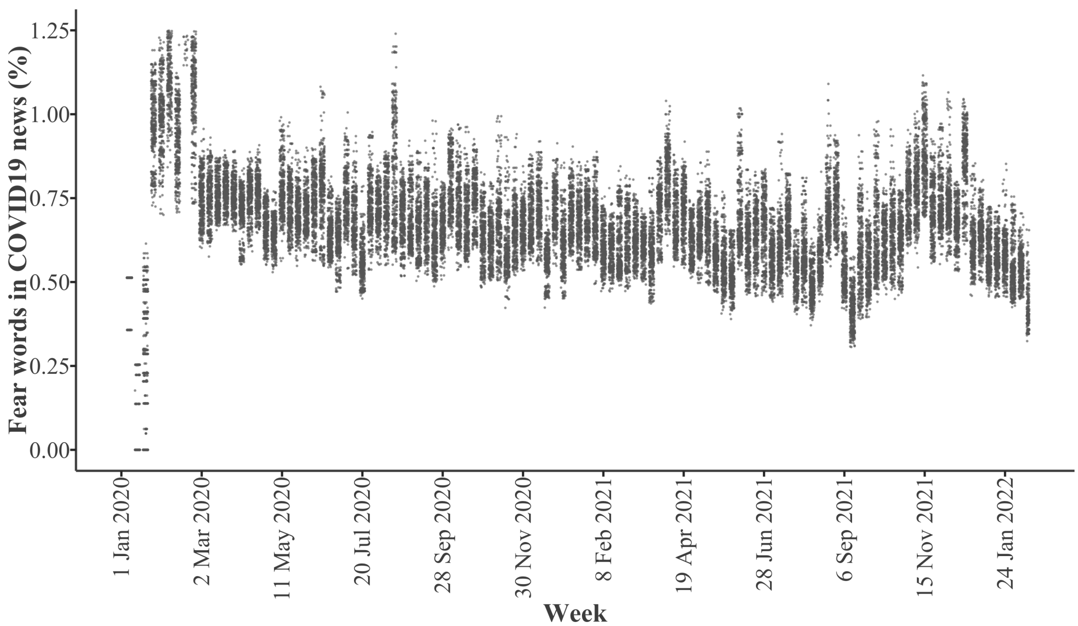


Figure 4: Weekly percentage of fear words in COVID–19 news

Crucially, newspapers are known to have certain writing styles. Consequently, articles published by one newspaper (in different regions), are likely to be more similar in this dimension than articles published by different newspapers. To account for this, we construct a variable that represents the average fear element in all non-COVID-related news items published by a newspaper and average this across all newspapers in a region (*NONCOVID_FEAR*).

3.4 Non-news related control variables

The two news-based variables are our main explanatory variables whose influence on mobility we seek to identify. This requires a set of controls (in addition to the *NONCOVID_FEAR*), to isolate news variables' effects from potentially confounding factors. The most important control variable in this respect is the number of COVID–19 cases, which we obtain from the Corona Data Platform database.[14] The variable *NEW_INFECT* denotes the sum of newly reported COVID–19 cases per week in a district divided by the district's population.

Another potential influence on mobility behavior is weather conditions. Studies show that mobility is closely related to temperature and precipitation (Cools et al., 2010; Keay and Simmonds, 2005; Spinney and Millward, 2011). We consider two weather variables to account for this: the average temperature (*TEMP*) and precipitation height (*PREC*) for each calendar week and district. The data collection process is outlined in Appendix B.

School holidays are another factor impacting the mobility of individuals. In Germany, school holidays are set by each federal state administration. Both the timing and the number of vacation days vary across states. To control for this, we include a school holiday binary variable (*H_DAY*) indicating if at least two days in a week were school holidays or not. Given that our dependent variable, *MOBIL*, already accounts for public holidays, each of which lasts for one or two days only, this variable is intended to capture regional differences in mobility and news reporting during school holidays.

4 Empirical approach

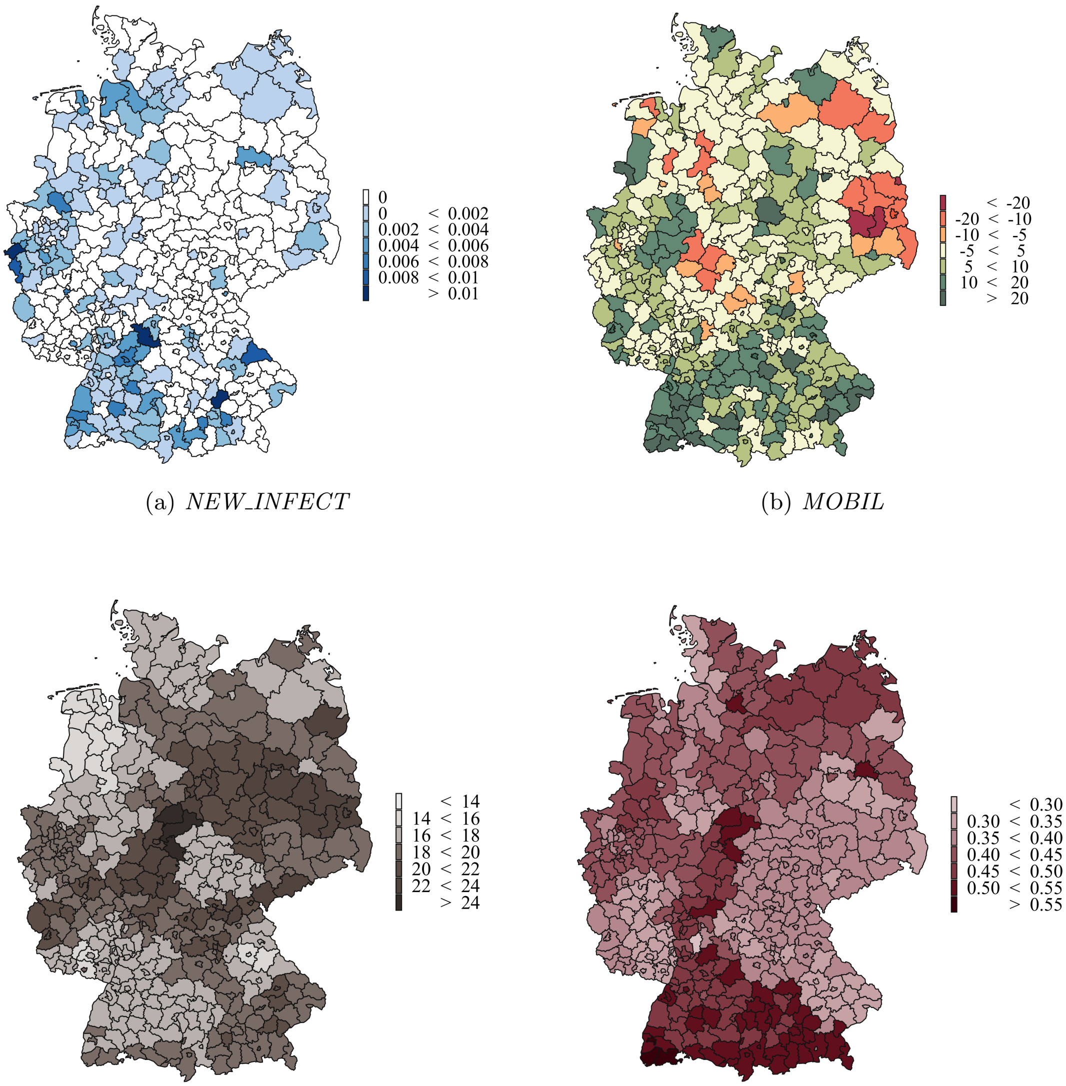
In total, our data include observations for 103 calendar weeks (from March 1, 2020 to February 28, 2022) and for 400 German NUTS–3 regions.[15] Summary statistics for the variables are given in Table 1.

Table 1: Summary statistics

	Obs.	**Min**	**Max**	**Median**	**Mean**	**Std.dev**
MOBIL	41,200	−59.701	90.511	−1.570	−1.220	16.229
NEW_INFECT	41,200	0	4.089	0.054	0.169	0.347
COVID_NEWS	41,200	6.937	65.487	22.973	24.175	10.085
COVID_FEAR	41,200	0.306	1.283	0.663	0.665	0.112
NONCOVID_FEAR	41,200	0.583	1.401	0.926	0.931	0.097
TEMP	41,200	−13.286	25.814	9.521	9.929	6.584
PREC	41,200	0	28.250	1.314	2.042	2.278

[14] Corona Datenplattform is commissioned by the German Federal Ministry for Economic Affairs and Energy and collects daily COVID–19 statistics at the district level. See: `https://www.corona-datenplattform.de`.

[15] We exclude the observations before the 10^{th} calendar week as we do not have infection numbers at the district level before that. Also, infection data is not available for the DEG0N region from August 2021 onward, so this region is removed from the analysis.



(a) *NEW_INFECT*

(b) *MOBIL*

(c) *COVID_NEWS*

(d) *COVID_FEAR*

Figure 5: Spatial distribution of selected variables on 10^{th} calendar week of 2020

The spatial variation in the core variables is illustrated by Figure 5 for the first week of the pandemic in Germany (10^{th} calendar week of 2020). At this time, 241 regions did not have any confirmed COVID–19 cases. The clustering of cases in the southern and western regions is clearly visible. Interestingly, changes in mobility during the same week do not show the same pattern (Figure 5b); regions in which mobility dropped the most are those with few or no cases at all. The share of COVID–19 news does not seem to correlate with the number of cases either (Figure 5c); regions with larger shares are not the ones with higher infection rates. In contrast, the share of fear-bearing words seems to correlate with the number of new cases. However, these are just cross-sectional correlations at one moment in time, which do not qualify for statistical inference.

Nevertheless, these highlight that the behavioral response may not be a one-to-one reaction to regional COVID–19 cases, which prompts the question of whether variations in news reporting about the pandemic act as a mediator.

Figure 5c and Figure 5d support our first hypothesis **H1**, as we see substantial differences in the frequency and ways of presenting COVID–19 in regional news at this moment in time. Clearly, some regions experience larger than average exposure to COVID–19 news, while others are below average. In addition, *COVID_NEWS* and *COVID_FEAR* are clustered in space indicating that substantial parts of this variation emerge from differences in reporting between newspapers as their distribution areas frequently cross district boundaries.

As shown in Section 3.1, the pandemic came in waves, which are also reflected in news reporting. Recent studies show that the determinants of the spread of COVID–19 varied in different phases of the pandemic (Roelofs et al., 2022). This implies that, with each new wave and growing scientific and experience-based insights, peoples' perceptions and behavioral reactions to the pandemic might have also changed. In other words, the relationship between news reporting on COVID–19 and changes in mobility are unlikely to be time-invariant. We take this into account by splitting our data set (103 weeks $\times$ 400 regions) into sub-samples of 3 months each. Subsequently, we run individual analyses for each 3-month sub-sample that is overlapping with the previous one by 2 months. In each of the 22 regressions, change in mobility (*MOBIL*) constitutes the dependent variable. We exploit the panel structure of the data to control for time-invariant unobserved factors by including region-specific fixed effects. Potential week-specific global events are accounted for by time (week) fixed effects.[16]

Our spatial units of observations are rather small, implying that our observations are likely characterized by spatial dependencies.[17] We, therefore, use spatial panel regression including the spatial lag of the dependent variable and a spatial error component (See e.g., Anselin et al., 2008). The spatial weight matrix is constructed on a binary basis, i.e., based on whether districts share a border or not.[18] Accordingly, our framework is a spatial panel regression model with two-way fixed effects.[19]

5 Results and discussion

Our first hypothesis (**H1**) concerning the existence of significant regional heterogeneity in COVID–19-related news reporting is tested with a simple two-way fixed effects (region and week) panel regression. The dependent variable is the share of COVID-related news that is related to the number of confirmed new COVID–19 cases, which is theoretically its primary determinant. Nevertheless, we find the regional-fixed effects to be statistically significant. A similar outcome is observed when doing the same estimations with the share of fear words in COVID news as the dependent variable, which is related to the number of cases and to the share of COVID-related news.[20] Consequently,

[16]Accordingly, what we aim to capture is the global associations between news exposure and social distancing by taking local variations into account.

[17]See the Lagrange multiplier test results in Appendix C.

[18]Note that the spatial weight matrix is row standardized.

[19]Estimations are done with *splm* library of *R* (Millo and Piras, 2012).

[20]F-statistic for *COVID_NEWS* and *COVID_FEAR* are 1.2163^{***}, and 7.2163^{***}, respectively.

there is additional systematic variance in both variables besides the reported COVID–19 cases at the regional level, which confirms our hypothesis.

Before we present the detailed results for the other two hypotheses, Figure 6 gives a first impression of the bivariate relationship between *COVID_NEWS* and *MOBIL* pooled over all periods. As both variables do not follow the same time trend (see Figures 1 and 2), the figure illustrates the existence of a negative relationship between the intensity of news reporting about COVID–19 and mobility, which motivates the following analysis.

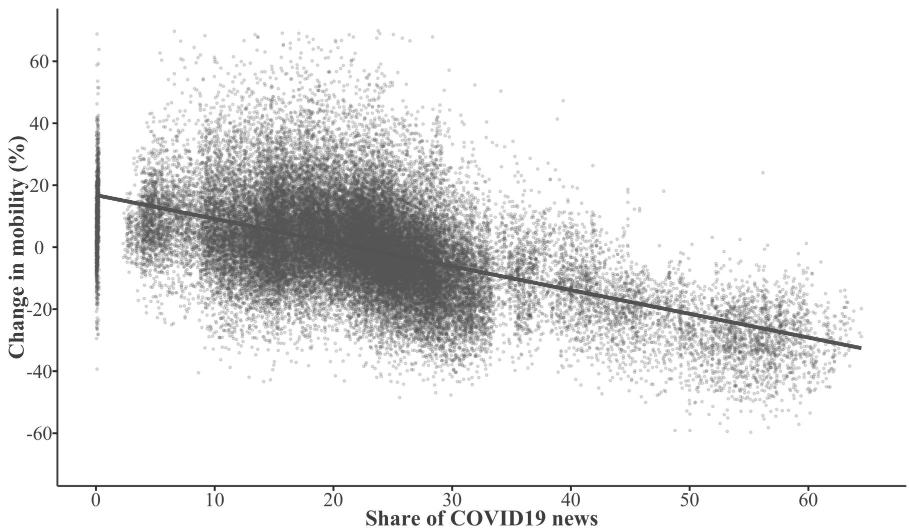


Figure 6: COVID–19 news frequency and change in mobility

Figure 7 illustrates the results of 22 spatial panel regressions with each regression representing a specific 3-month period: the first one includes all weeks in March, April, and May 2020; the second includes all weeks in April, May, and June 2020, and so forth. The figure features the coefficients of explanatory variables and their 99% coefficient intervals.[21]

The coefficient of *COVID_NEWS* is negative and mostly statistically significant for all periods from the beginning of the pandemic until November-December 2020 and January 2021 (Figure 7a). Hence, in the first 10 months of the pandemic, regions where newspapers covered COVID–19 more frequently experienced larger decreases in mobility. This provides clear empirical support for our second hypothesis (**H2**): A more intensive presentation of COVID–19 in the (regional) news discourages people to become less mobile in order not to get exposed to risks which are, in this context, potential COVID–19 sources. The figure also adds support for news media's effect not being constant over time, i.e., hypothesis **H3**. At the beginning of December 2020, the direction of the relationship reverses: the frequency of news coverage becomes positively related to mobility implying that more news about the virus translates into higher mobility levels. We suspect that this reversal is driven by the reporting about the arrival of effective COVID–19 vaccines. In November and December 2020, the share of vaccination news drastically increased and changed the content

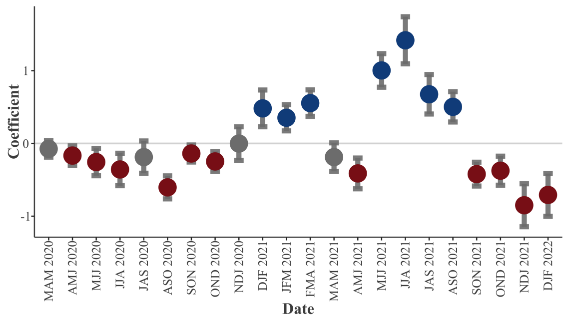
[21]Results are also provided in a table in the Appendix D.

of the COVID–19-related news in a positive way (See Figure A1 in Appendix E). The anticipation of vaccines is associated with less willingness to keep up social distancing (Andersson et al., 2021), which is confirmed by our results. The new information about the availability of vaccines in December 2020 is likely to have convinced people of the pandemic's approaching end. In anticipation of this, people in regions where COVID–19 was covered more frequently show higher levels of mobility in anticipation of this, i.e, low levels of social distancing. This pattern remains intact until the third wave starts around March 2021 when the relationship's direction flips again, which coincides with a fading optimism in the vaccines putting an end to the pandemic. In addition, it was around this time when the third wave peaked, which had severe consequences for people's lives. Consequently, the coefficient of the share of COVID–19 news in the April-May-June 2021 period is significantly negative. With the ending of the third wave and the generally positive developments during the summer plateau (rapidly increasing vaccination rates and fewer infections), the relationship between COVID–19 news coverage and mobility turns statistically significant and positive again. We suspect that people had learned from previous experiences and anticipated that the pandemic was not over yet. Consequently, they heavily utilized this window of opportunity to compensate for their lower mobility in the prior months. Very much in support of this explanation is the effect suddenly wearing off with the beginning of the fourth wave and new virus mutations looming on the horizon. The statistically significant and negative coefficient of the share of COVID–19 news in the most recent periods reflects this.

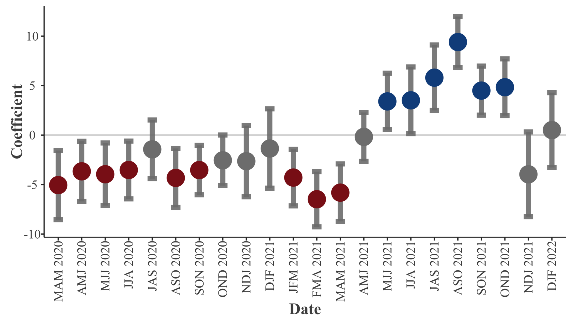
In sum, our findings on the share of COVID–19 news support our hypothesis **H2** and partly hypothesis **H3**. In addition, they highlight that the relationship between news and mobility behavior is complex and difficult to assess when looking at one dimension of news such as the frequency of reporting about a topic alone. Therefore, the second perspective, the emotionality of reporting (here with a focus on the fear emotion) complements the previous analysis. Figure 7b shows the coefficients obtained for *COVID_FEAR*.[22]

The negative and mostly statistically significant coefficient of *COVID_FEAR* during the first three waves of the pandemic support the above reasoning: higher levels of the fear element in COVID–19 news articles negatively related to mobility from the beginning of the pandemic until the end of the third wave. That is people in regions where the news media communicated the risks regarding COVID–19 in a more fearful way, decreased their mobility to a larger degree. The findings also support the argument that the positive relationship between the frequency of news and mobility during the second wave was related to the content of news being relatively more positive, which is likely due to reporting about effective vaccines.

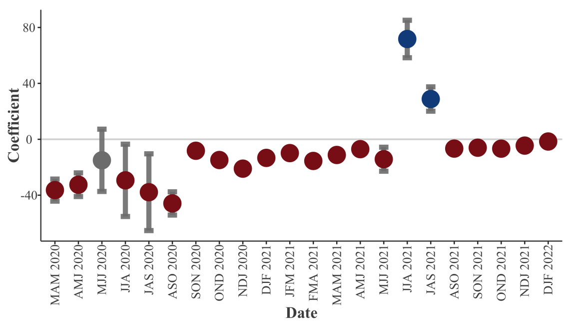
[22]Note that we also include a control for the general tendency of newspapers to use such words in the respective region and week (*NONCOVID_FEAR*), so that the variable captures to what extent the fear element in COVID–19 news articles diverge from the newspaper's general reporting style.



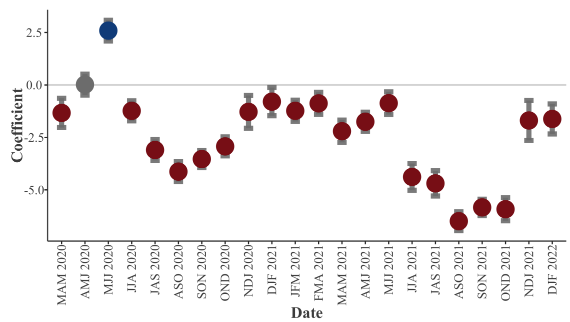
(a) *COVID_NEWS*



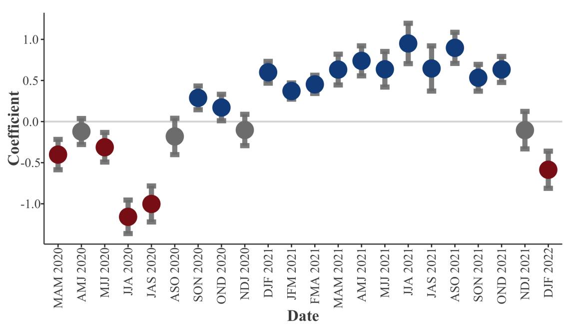
(b) *COVID_FEAR*



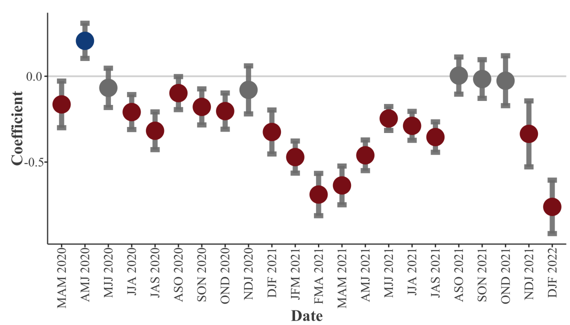
(c) *NEW_INFECT*



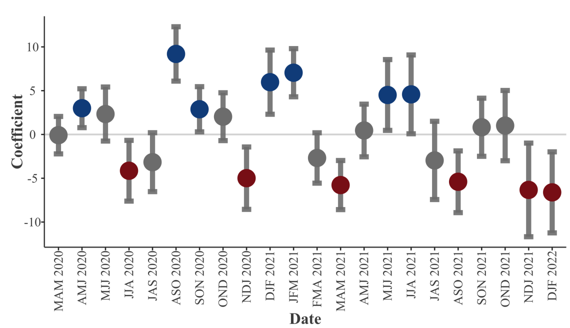
(d) *H_DAY*



(e) *TEMP*



(f) *PREC*



(g) *NONCOVID_FEAR*

Figure 7: Spatial panel regression results

Starting with the plateauing of infection numbers in the summer of 2021 and during the fourth wave, we obtain some counter-intuitive results that to a degree resemble some of which are observed for the frequency of COVID–19 coverage as well: A more fearful reporting is associated with higher levels of mobility. As the fifth wave started (the Omicron variant phase) and Germany reported unprecedented high numbers of COVID–19 infections, the positive relationship between the fear element in the COVID–19 news and mobility vanished again. Most likely, this changing relationship reflects a potential temporal mismatch between the intensity of a threat (i.e., as expressed in current infection rates) and its representation in the media. During the good times of the pandemic (e.g., interim periods), higher levels of the fear emotion in the news media are understood as a signal that bad times are still ahead (e.g., the next wave). In anticipation, people reacted by increasing their mobility - they seized the opportunity while they still could. Another explanation is that misalignment of what (and how) is reported in the news media and actual infection numbers translated into people perceiving the media as over-dramatizing issues. Consequently, they reacted opposite from what is expected based on the news. The latter process has been observed by Taha et al. (2014) for the H1N1 outbreak. Our research adds suggestive evidence as far as the coefficient of the fear emotion becomes negative, although insignificant, when the fifth wave started and the infection numbers became much more threatening. In any case, our results for the share of fear words add further evidence for the impact of regional news on social distancing behavior (**H2**) and that this impact is not time-invariant (**H3**). As for the frequency analysis, the relationship is time-invariant and complex in nature. Crucially, it is troubled by a so far unidentified and most likely time-variant time lag between the news and people's behavioral responses. In addition, an analysis at the regional level, such as ours, doesn't allow for considering the heterogeneity of individuals' experiences and what is reported on an aggregated level in the news.

Figures 7c–7g report the findings for the control variables. As expected, Figure 7c confirms that the percentage of the population infected with COVID–19 is negatively related to weekly mobility change except for two periods during the summer plateau of 2021 when the coefficient becomes positive. This is the period when vaccination surged and restrictions were lifted. However, a warning regarding a possible next wave was made . Increasing infection rates during this period (albeit at low levels) might have signaled to people that they should enjoy their mobility while they still can before the next wave starts. Thereby, the perception of a "window of opportunity" seems to have emerged. The coefficient of H_DAY is almost always negative (and significant), with the exception of one (summer) period in 2020. In a common manner, higher temperatures and lower rainfall are associated with higher mobility in the majority of our regressions (Figures 7f and 7e).[23] In sum, the control variables show the expected relations and thereby add confidence to the specification of the models. To further reduce the potential of our results being driven by misspecification, we present the results for two alternative specifications. In the first, we consider the effects of partial lock-downs and in the second, we apply a looser definition of which news are about COVID–19 (see Appendix F). The results confirm the findings of the baseline model.

[23] We refrain from interpreting the coefficients of $NONCOVID\_FEAR$, since we define COVID–19 news in a very conservative manner. Consequently, this variable may still be shaped by COVID–19 news. The variable is primarily designed to isolate the true effects of fear word usage in COVID–19 news.

In summary, our findings contribute to the literature on how the communication of health risks in the context of the COVID–19 pandemic via the news media shapes changes in social distancing behavior at the regional level, something that has not been explored so far (Andersen, 2020; Simonov et al., 2020; Ash et al., 2020; Bursztyn et al., 2020). The study shows that regional heterogeneity in news reporting explains differences in social distancing across regions (**H2**), except for those times during the pandemic when the overall situation appeared less threatening. The latter point underlines the time-varying influence of news, which is mediated by the situation during different phases of the pandemic (**H3**).

6 Conclusion

Although the COVID–19 pandemic was (and at the time of writing, remains) a global threat, its effects were not only specific to countries but also differed between regions (White and Hébert-Dufresne, 2020; Bosa et al., 2021; Hoekman et al., 2020). Preventive measure practices such as social distancing have been shown to be the main determinants of differences in infection and death rates across regions (Badr et al., 2020; Glaeser et al., 2020; Carteni et al., 2020; Engle et al., 2020; Nouvellet et al., 2021; Hadjidemetriou et al., 2020), and regional differences in social distancing are shown to be related to various factors including population density, income level, age composition, political leanings, etc. (Desmet and Wacziarg, 2021; Ehlert, 2021; Engle et al., 2020; Bialek et al., 2020; Barrios and Hochberg, 2020). Yet, the precise spatial diffusion of the pandemic is not fully understood and the present paper argues that the news media's reporting about it is a missing piece in the explanation. While existing research supports this view with studies comparing the situation in one country over time or comparing the audiences of different news organizations, there were hardly any insights into the sub-national dimension. That is, does the regional heterogeneity in the ways COVID–19 is presented in the media impact peoples' behavioral reactions, resulting in differences in the pandemics' spatial diffusion, was still unknown. The present paper addresses this question and explores how regional variations in COVID–19 coverage relate to peoples' social distancing decisions as expressed by their mobility behavior.

Empirically, we investigated whether regional differences in the mobility responses to the pandemic can be explained by variations in the frequency and tone of COVID–19-related news in Germany. Changes in mobility behavior have been approximated with mobile phone data and information on the news has been extracted from the RegNeS database. By estimating a range of spatial panel regression models, we find that regions where media covered COVID–19 more frequently and in more fearful ways experienced higher drops in mobility at the beginning of the pandemic. Crucially, we observed these relations to be time-variant with their effects being conditional on the general COVID–19 situation. That is, while the link was found to be negative at the beginning of the pandemic and during the times of high rates of infection, it was insignificant or even positive when the infection rates were low and when the first vaccines arrived. Accordingly, our results suggest that news media's effect on behavior is largest when their content (and tone) fits the situation as perceived by individuals. This conclusion is consistent with previous studies arguing that news exposure is more likely to reinforce actual experiences than completely change or create new perceptions (Klapper, 1960; Miller and Krosnick, 1996; Newton, 2006). In any case, our results provide further evidence that the news media plays a role in the spatial diffusion of the COVID–19 pandemic by shaping compliance with social distancing behavior (Andersen, 2020; Simonov et al., 2020; Ash et al., 2020; Bursztyn et al., 2020).

Our study has some limitations. Although the frequency and fear intensity of COVID–19 news give insights into how the news media communicates the risks related to the disease, we do not know the exact content of these news articles. Since the pandemic affects almost all parts of daily lives, news articles are likely to address a wide range of aspects related to COVID–19. For example, news can be about local cases or the national situation; they can contain announcements of event cancellations or re-openings; they may present new vaccines or new virus variants. Consequently, by using purely quantitative measures, our study just scratches the surface of what news articles contain, which gives a clear direction for future research. Another limitation concerns our focus on just one type of media, namely newspapers. There are some indications of COVID–19 having reduced print media consumption (Mihelj et al., 2021; Newman et al., 2021; Hölig et al., 2020). Individuals who used to read newspapers might have switched to online news outlets during this time. Social media may also have become a substantial substitute in this context. Future studies with access to other data sources should therefore consider this and shed additional light on the relative importance of different news channels and outlets. Another limitation is the unknown time-lag structure between news consumption and individual response. The aggregation in this study implies a relationship between weekly news exposure and subsequent behavioral change. Although alternative specifications (not reported here) and tested time lags ranging from one day up to one week, did not provide more conclusive results than the ones presented here, the nature of the temporal relationship between news exposure and behavior is not based on empirical grounds. Lastly, while the employed news database establishes a link between news data and the area of their most likely readership, it doesn't contain any information on the location of the events reported. This creates a discrepancy between how close the event, e.g., the health threat of COVID–19, is to a news article's readership. As our results suggest, considering this appears to be crucial for identifying the effect of news at the regional level. Notwithstanding these limitations, our study contributes to the growing literature stream on exploring variations in news and its effects at the sub-national level. Crucially, it highlights that this frequently overlooked (spatial) dimension of news matters and that it seems to have considerable implications for understanding socio-economic processes and (spatial) heterogeneity in developments.

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Appendix A Geolocating the news

The link between news articles and regions is established by two types of information. For about half of the newspapers, RegNeS has obtained data on readership shares from the German Audit Bureau of Circulation (IVW). This organization collects information on the number of print and digital subscriptions for most newspapers in each district. For the other half, regionalization is done on the basis of information provided by newspapers on their targeted geographical areas. That is, almost all newspapers organize their news articles according to geographical areas for which they are believed to be of relevance. Some of these articles are assigned to multiple locations while others are exclusive to specific locations. RegNeS utilizes this information in combination with the readership shares to assign news articles to regions in the following way: If a newspaper featuring an article has a positive readership share in a NUTS3 region, the article is assigned to that region. If no readership information is available, RegNeS relies on the location extracted from the newspaper's website for which this article was featured. Since newspapers that are linked to almost all regions in Germany (truly national newspapers) and that do not have dedicated regional sections do not add to regional variation, they are excluded from the analysis. We exclude all newspapers that are associated with more than 50 % of the regions in our sample. Note that although some newspapers might be read by more people in a district compared to other available newspapers, all newspapers circulating in a district are considered equal in the analysis.[24] Accordingly, the COVID–19 news exposure in this study should be seen as the probability of being exposed to COVID–19-related information, picking a newspaper randomly, among the newspapers circulating in the region.

After the cleaning and geolocation process of the news articles, there are $9,083,623$ unique news articles, from January 1, 2020 to February 28, 2022. The dataset covers 224 different newspapers of which 46 circulates in only one NUTS3 region. Each news item in the dataset is assigned a unique ID based on the title and first few sentences so that no double counting can occur at the newspaper level. However, when a news article is published by multiple newspapers in the region (for example, when provided by a press agency), we take this information into account as this increases the likelihood of people in a region coming across that news article.

Appendix B Data on temperature and precipitation

Data on weather-related variables are obtained from the climate data center (CDC) of Germany's national meteorological service, DWD.[25] Temperature and precipitation variables are constructed on the basis of weather station observations; the daily observations are obtained on precipitation height and mean temperature at the station level. Based on the geographical coordinates of the weather stations, regional weekly averages of all observations falling into their area are calculated. For daily precipitation, there are 5,599 weather stations. Of 401 districts, 70 have a single station, 277 have more than one, and 54 have none. For daily temperature, there are 1,106 weather stations and of 401 districts, 183 have one, 108 have multiple stations, and 110 have none. If a district has

[24]For further details regarding the geolocation of news articles and calculation of readership shares, see Ozgun and Broekel (2021).

[25]The Deutscher Wetterdienst. Accessed on 2 March 2022 at `https://cdc.dwd.de/portal/`.

no weather station within its borders, the observations of the closest weather station are assigned to the district.

Appendix C Spatial diagnostics

Tables A1 and A2 show the results of Lagrange multiplier tests (Anselin et al., 1996) for spatial dependence. Note that the within transformation is applied to the baseline model before the tests are performed. In the tables, *LML* and *LME* refer to LM test statistics for spatial lag dependence and error dependence, respectively. *RLML* and *RLME* are the locally robust test statistics for spatial lag, allowing for a spatial error; and for error, allowing for a spatial lag, respectively. As seen in the tables, although spatial dependence structure differs from one analysis period to another, the vast majority of the periods are characterized by spatial lag and error dependence. Accordingly, we use spatial panel regression including the spatial lag of the dependent variable and a spatial error component.

Table A1: Spatial diagnostics 1

	MAM2020	AMJ2020	MJJ2020	JJA2020	JAS2020	ASO2020	SON2020	OND2020	NDJ2020	DJF2021	JFM2021
LML	2089.94***	2034.81***	1529.47***	1747.37***	2017.58***	2667.18***	2894.05***	2919.87***	1724.60***	1510.97***	1438.13***
LME	2092.18***	2027.11***	1496.13***	1736.96***	2017.08***	2712.97***	2863.22***	2896.61***	1733.68***	1496.95***	1361.47***
RLML	0.28	7.83**	44.78***	10.65**	7.98**	1.16	37.05***	27.84***	0.04	14.48***	86.55***
RLME	2.53	0.13	11.43***	0.24	7.49**	46.94***	6.21*	4.58*	9.12**	0.46	9.89**

Note: *p<0.05; **p<0.01; ***p<0.001

Table A2: Spatial diagnostics 2

	FMA2021	MAM2021	AMJ2021	MJJ2021	JJA2021	JAS2021	ASO2021	SON2021	OND2021	NDJ2021	DJF2022
LML	1867.27***	1743.17***	1670.94***	2999.06***	3510.97***	3223.64***	1629.86***	911.20***	868.69***	1639.62***	1778.12***
LME	1755.3***	1737.87***	1668.69***	2949.72***	3533.96***	3242.55***	1694.80***	939.39***	876.38***	1618.91***	1740.06***
RLML	115.32***	17.33***	10.22**	49.62***	14.5***	8.87**	0.41	0.19	2.21	20.73***	40.6***
RLME	3.35	12.02***	7.97**	0.28	37.48***	27.77***	65.34***	28.38***	9.91**	0.01	2.55

Note: *p<0.05; **p<0.01; ***p<0.001

Appendix D Regression results for the baseline model

Tables A3, A4, A5, and A6 show the results of the baseline model. Numbers in the parentheses depict 99% confidence intervals.

Table A3: Regression results 1

	Dependent variable: *MOBIL*				
	MAM 2020	AMJ 2020	MJJ 2020	JJA 2020	JAS 2020
COVID_NEWS	-0.074	-0.167	-0.256	-0.358	-0.188
	$[-0.188; 0.039]$	$[-0.300; -0.034]$	$[-0.444; -0.068]$	$[-0.581; -0.135]$	$[-0.410; 0.034]$
COVID_FEAR	-5.054	-3.661	-3.956	-3.525	-1.438
	$[-8.548; -1.560]$	$[-6.700; -0.622]$	$[-7.119; -0.794]$	$[-6.443; -0.607]$	$[-4.402; 1.527]$
NEW_INFECT	-36.362	-32.493	-15.043	-29.370	-37.859
	$[-44.257; -28.467]$	$[-40.946; -24.040]$	$[-37.321; 7.236]$	$[-55.239; -3.501]$	$[-65.320; -10.398]$
TEMP	-0.401	-0.121	-0.312	-1.159	-1.002
	$[-0.586; -0.217]$	$[-0.279; 0.037]$	$[-0.492; -0.133]$	$[-1.362; -0.955]$	$[-1.221; -0.783]$
PREC	-0.164	0.206	-0.068	-0.209	-0.318
	$[-0.300; -0.028]$	$[0.104; 0.309]$	$[-0.182; 0.047]$	$[-0.310; -0.107]$	$[-0.428; -0.208]$
H_DAY	-1.331	0.018	2.590	-1.233	-3.098
	$[-2.029; -0.633]$	$[-0.481; 0.517]$	$[2.097; 3.083]$	$[-1.709; -0.756]$	$[-3.596; -2.600]$
NONCOVID_FEAR	-0.079	2.999	2.333	-4.142	-3.164
	$[-2.215; 2.057]$	$[0.779; 5.220]$	$[-0.753; 5.420]$	$[-7.611; -0.674]$	$[-6.527; 0.199]$
λ	-0.356^{***}	-0.41^{***}	-0.113	0.17^{*}	0.075
ρ	0.405^{***}	0.424^{***}	0.104	-0.148	-0.018
Observations	5200	5200	5200	5200	5200

Table A4: Regression results 2

	Dependent variable: *MOBIL*				
	ASO 2020	SON 2020	OND 2020	NDJ 2020	DJF 2021
COVID_NEWS	-0.604	-0.138	-0.248	-0.002	0.482
	$[-0.762; -0.446]$	$[-0.255; -0.021]$	$[-0.385; -0.110]$	$[-0.232; 0.229]$	$[0.229; 0.735]$
COVID_FEAR	-4.326	-3.533	-2.547	-2.636	-1.354
	$[-7.304; -1.348]$	$[-6.030; -1.036]$	$[-5.104; 0.010]$	$[-6.233; 0.960]$	$[-5.363; 2.655]$
NEW_INFECT	-45.897	-8.205	-14.834	-21.015	-13.318
	$[-54.221; -37.572]$	$[-11.771; -4.639]$	$[-17.259; -12.409]$	$[-23.960; -18.071]$	$[-16.589; -10.047]$
TEMP	-0.181	0.288	0.171	-0.102	0.600
	$[-0.402; 0.040]$	$[0.144; 0.433]$	$[0.010; 0.332]$	$[-0.293; 0.088]$	$[0.467; 0.732]$
PREC	-0.098	-0.178	-0.203	-0.079	-0.325
	$[-0.194; -0.002]$	$[-0.283; -0.073]$	$[-0.309; -0.098]$	$[-0.219; 0.061]$	$[-0.453; -0.197]$
emphH_DAY	-4.129	-3.531	-2.927	-1.281	-0.794
	$[-4.607; -3.652]$	$[-3.939; -3.122]$	$[-3.379; -2.475]$	$[-2.060; -0.501]$	$[-1.467; -0.122]$
NONCOVID_FEAR	9.196	2.879	2.031	-4.989	5.972
	$[6.091; 12.301]$	$[0.300; 5.458]$	$[-0.701; 4.763]$	$[-8.551; -1.427]$	$[2.308; 9.637]$
λ	-0.042	-0.288^{***}	-0.325^{***}	0.055	-0.006
ρ	0.109	0.292^{***}	0.337^{***}	-0.009	0.029
Observations	5200	5600	5200	5200	5200

Table A5: Regression results 3

	Dependent variable: *MOBIL*					
	JFM 2021	FMA 2021	MAM 2021	AMJ 2021	MJJ 2021	JJA 2021
COVID_NEWS	0.353	0.554	−0.188	−0.412	1.004	1.418
	[0.173; 0.534]	[0.373; 0.736]	[−0.383; 0.008]	[−0.624; −0.201]	[0.773; 1.234]	[1.095; 1.742]
COVID_FEAR	−4.292	−6.480	−5.814	−0.182	3.404	3.513
	[−7.152; −1.433]	[−9.269; −3.692]	[−8.717; −2.910]	[−2.650; 2.287]	[0.554; 6.254]	[0.140; 6.886]
NEW_INFECT	−9.880	−15.502	−11.220	−7.061	−14.257	71.751
	[−12.718; −7.043]	[−18.924; −12.079]	[−14.715; −7.725]	[−10.779; −3.344]	[−22.837; −5.677]	[58.350; 85.152]
TEMP	0.372	0.453	0.633	0.739	0.636	0.950
	[0.273; 0.470]	[0.342; 0.564]	[0.446; 0.820]	[0.556; 0.921]	[0.420; 0.853]	[0.705; 1.196]
PREC	−0.471	−0.689	−0.636	−0.460	−0.246	−0.289
	[−0.564; −0.377]	[−0.812; −0.566]	[−0.749; −0.523]	[−0.550; −0.371]	[−0.316; −0.176]	[−0.373; −0.205]
H_DAY	−1.231	−0.877	−2.204	−1.752	−0.868	−4.381
	[−1.739; −0.723]	[−1.403; −0.350]	[−2.735; −1.673]	[−2.208; −1.296]	[−1.409; −0.327]	[−5.016; −3.745]
NONCOVID_FEAR	7.052	−2.684	−5.778	0.456	4.509	4.581
	[4.303; 9.801]	[−5.560; 0.193]	[−8.582; −2.974]	[−2.550; 3.461]	[0.467; 8.551]	[0.080; 9.081]
λ	−0.003	−0.093	0.316***	0.397***	0.468***	0.349***
ρ	−0.033	0.089	−0.324***	−0.423***	−0.503***	−0.343***
Observations	4800	5200	5200	5200	5200	5200

Table A6: Regression results 4

	Dependent variable: *MOBIL*					
	JAS 2021	ASO 2021	SON 2021	OND 2021	NDJ 2021	DJF 2022
COVID_NEWS	0.676	0.503	−0.422	−0.375	−0.850	−0.708
	[0.405; 0.947]	[0.295; 0.711]	[−0.585; −0.258]	[−0.574; −0.175]	[−1.145; −0.554]	[−1.002; −0.413]
COVID_FEAR	5.802	9.401	4.496	4.837	−3.961	0.506
	[2.497; 9.107]	[6.821; 11.982]	[2.018; 6.974]	[1.972; 7.703]	[−8.242; 0.319]	[−3.273; 4.285]
NEW_INFECT	28.809	−6.660	−6.019	−6.706	−4.520	−1.586
	[20.098; 37.521]	[−10.403; −2.917]	[−7.026; −5.011]	[−7.774; −5.639]	[−5.536; −3.504]	[−2.287; −0.885]
TEMP	0.646	0.897	0.533	0.634	−0.104	−0.586
	[0.371; 0.921]	[0.708; 1.086]	[0.370; 0.696]	[0.476; 0.792]	[−0.332; 0.124]	[−0.812; −0.360]
PREC	−0.354	0.004	−0.016	−0.026	−0.336	−0.761
	[−0.443; −0.266]	[−0.104; 0.112]	[−0.129; 0.097]	[−0.171; 0.119]	[−0.528; −0.144]	[−0.917; −0.605]
H_DAY	−4.691	−6.491	−5.835	−5.921	−1.692	−1.619
	[−5.292; −4.089]	[−6.939; −6.043]	[−6.224; −5.445]	[−6.472; −5.370]	[−2.642; −0.742]	[−2.334; −0.903]
NONCOVID_FEAR	−2.963	−5.401	0.824	1.012	−6.331	−6.610
	[−7.430; 1.503]	[−8.926; −1.875]	[−2.494; 4.142]	[−2.998; 5.022]	[−11.677; −0.985]	[−11.237; −1.983]
λ	0.31***	−0.01	−0.032	0.046	−0.193*	0.28***
ρ	−0.285***	0.04	0.09	−0.01	0.237**	−0.281***
Observations	5600	5200	5200	5200	5200	5200

Appendix E Share of vaccination news

Figure A1 shows the share of COVID–19-related news that refer to vaccination. We identify vaccination-related news using a pattern matching approach with the pattern *vaccine* while excluding news related to non-COVID vaccines (e.g., influenza). The exact (German) patterns used are *impfung, impfen, impfstoff, impfzentrum.* We exclude patterns in which *impf* is preceded by any of the following strings: *grippe, influenza, malaria, masern, polio, pocken, staupe, krebs, zecke, schweinepest.* News about vaccines was below 2% in all COVID–19-related news until November 2020. On 9 November 2020, Pfizer-BioNTech announced that their vaccine candidate against COVID–19 achieved success in a first phase 3 study.[26] In December 2020, many countries gave emergency-use authorization to Pfizer-BioNTech, and shortly after, the Moderna vaccine received approval as well. During the same month, in Germany, the first vaccination doses were given to a select group of people. The introduction of vaccines meant that COVID–19 lost some of its threat, implying different mobility responses. In addition, it changed the discussions in the news, which became increasingly centered around vaccination and everything related to it. By January 2021, more than 20% of all COVID–19-related news already included the mentioning of vaccines and this figure has remained at high levels since.

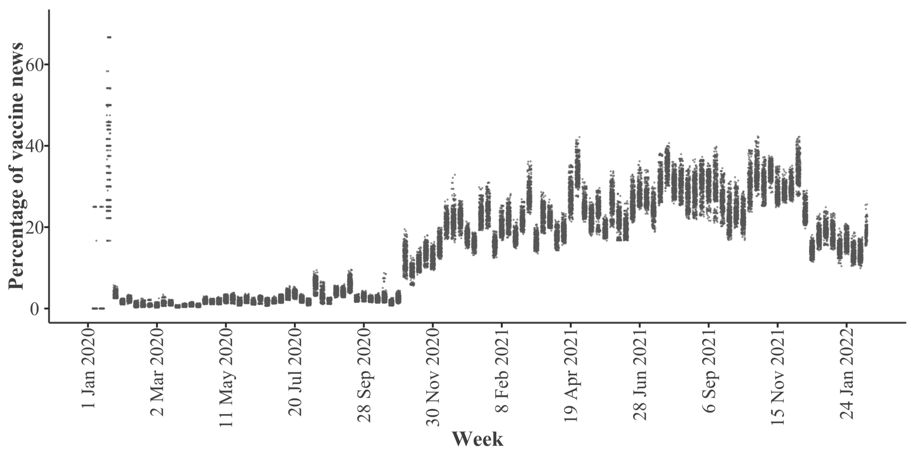


Figure A1: Weekly share of vaccination news in COVID–19-related news

Appendix F Results for alternative specifications

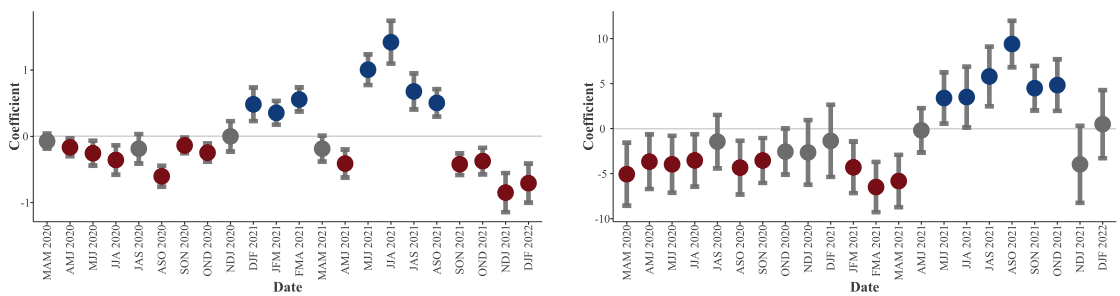
In the following, we assess the validity of our results under different model specifications. The specifications are analogous to our baseline, except for the given deviation in each case. We only show the results for the focal explanatory variables, i.e., the share of COVID–19 news and share of fear-associated words in COVID–19 news, but all of the variables in our baseline are also controlled for and full regression result tables are available upon request.

In Germany, restrictions are subject to a rule, based on the number of new infections per $100,000$ inhabitants, in each municipality. The seven-day incidence rate being above or below certain thresholds such as 35, 50, 100, and 165 specifies which activities are allowed and which are not. Incidence rate 100, for example, is a significant threshold which is called *emergency break*. In the event this threshold is reached, all leisure facilities close, restaurants can only offer takeaways, shops can only offer click-and-collect service, and accommodation in tourist facilities is not allowed. Accordingly, this specific number of new infections is expected to limit the mobility of individuals significantly. Similarly, if the incidence rate exceeds 165, schools and similar education and training

[26]See: https://www.pfizer.com/news/press-release/press-release-detail/pfizer-and-biontech-announce-vaccine-candidate-against.

facilities are not allowed to offer in-classroom teaching, which means a further reduction in mobility. Since the incidence rate is a function of the weekly number of COVID–19 infections which we already control for, including both measures causes multicollinearity. This is why we do not include this incidence rate variable in our baseline model. In this specification, we drop the new COVID–19 infections and, in addition to the other controls in the baseline, we include a dummy variable based on the incidence rate that takes 5 different values: *below 35*, *between 35 and 50*, *between 50 and 100*, *between 100 and 165*, and *above 165*.

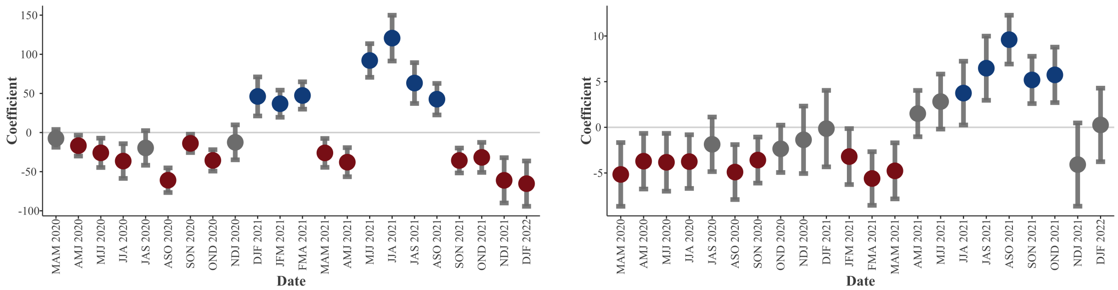
Figure A2 shows the coefficients of news-related explanatory variables when the specific intervals for the incidence rate are controlled. The coefficients only slightly change and the statistical significance of results stays the same in all regressions, accordingly, our results hold under this specification as well.



(a) *COVID_NEWS* (b) *COVID_FEAR*

Figure A2: Spatial panel regression results: Restrictions are controlled for by including the thresholds of incidence rate, instead of the number of confirmed cases

Figure A3 shows the results for the case when COVID–19 news are defined in a more general manner. In our baseline, news articles categorized under COVID–19 were only the ones explicitly mentioning the name of the virus and the disease. In the following case, we also include COVID–19 vaccine-related news, which does not necessarily mention COVID–19 but mentions phrases such as *vaccination center* so that we know for sure the news article is about COVID–19, although it does not explicitly mention it. The coefficients of frequency and fear intensity of COVID–19 news are nearly identical to our baseline results, showing that the results are not sensitive to the exact choice of search terms used in pattern matching.



(a) *COVID_NEWS*

(b) *COVID_FEAR*

Figure A3: Spatial panel regression results: A more general COVID–19 news definition