When War Crowds Out the Pandemic: Health and Political Effects of Media Shifts*

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Abstract

This paper explores the unintended effects of a sudden media shift from pandemic health-crisis coverage to the Russo-Ukrainian war. Using a dynamic Difference-in-Differences, we first examine how increased media focus on the war impacted contagion across Italian municipalities, with proximity to U.S. military bases serving as our treatment and proxy for heightened fear. Our findings reveal a temporary spike in infections, particularly in areas closer to bases, driven by increased mobility and a rise in "bunker" Google searches. Secondly, we show that politicians, especially from right-wing parties, gained electoral advantages in subsequent unexpected elections by leveraging war-related fears at the onset of the conflict. Voters in districts near bases responded more to the emotional tone of war-related messaging than its volume, underscoring fear's influence on political outcomes. In contrast, left-wing parties benefited from the war's media prominence, as their supporters responded more to issue salience than to emotional tone.

Keywords— Media attention, Issue salience, Health outcomes, Electoral outcomes, Political communication, COVID-19, Russo-Ukrainian War, Fear of war.
JEL Numbers— D01, H8, D91, I12, D74, I31.

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1 Introduction

The relevance of political issues can rapidly shift in response to changing circumstances (Aytaç and Çarkoğlu, 2021; Bordalo et al., 2020), and shape socio-economic and political decisions (DellaVigna and Gentzkow, 2010; Durante and Zhuravskaya, 2018; Jetter, 2017). This paper provides causal evidence on how media attention can shape citizens' behavior, specifically focusing on the consequences of a health crisis suddenly coming out of the spotlight.

There is no doubt that the COVID-19 pandemic has dominated public discourse since the first case emerged, prompting citizens to reassess their priorities and perceptions of political issues (Casero-Ripollés, 2020). Yet, as for many other salient issues of the past, also COVID-19 lost centrality. This occurred rather suddenly, as soon as another unexpected and threatening event hit the press: the Russo-Ukrainian war. Since the first day of the war and for many weeks afterward, all media sources extensively prioritized the war over the pandemic.

How does a sudden shift in media attention affect both contagion dynamics and political preferences? To our knowledge, this is the first study to offer an empirical analysis of this issue. We focus on the Italian context, which presents two distinctive elements.

First, Italy experienced a notable contagion dynamic at the onset of the Russia-Ukraine conflict. In February 2022, as COVID-19 cases were steadily declining, the trend reversed following the surge in media coverage of the war. This shift in public attention, from domestic health concerns (COVID-19) to international geopolitical events, suggests a potential link between media focus and health outcomes. Second, Italy held unanticipated early political elections just seven months after the invasion of Ukraine. This unique timing enables us to examine how politicians may have electorally benefited from war-related messaging during the early stages of the conflict, despite not anticipating upcoming elections at the time.

By examining both the contagion effects and the electoral consequences of the war suddenly coming to the forefront, we tackle the broader question of whether and how a sudden, media-driven shift in public attention can significantly influence citizens' behavior.

In the first part of the paper, we provide causal estimates of the effects on health outcomes of the sudden shift in media attention from pandemic to war. We carry out a differences-in-differences (DID) event study in the specific context of the Russo-Ukrainian conflict that occurred during the COVID-19 pandemic, and examine how the trend in contagion across Italian municipalities was affected by the (news of the) war.

We construct a counterfactual trend that proxies for how contagion would have evolved had the war never happened, relying on an exogenous geographical feature of Italian municipalities: proximity to the closest U.S. military bases. We posit that the closer citizens are to a U.S. military base, the higher the perceived threat and/or salience of the war. The rationale for using U.S. rather than Italian military bases is twofold. First, media discourse—both during the Russia-Ukraine war and in peacetime—more frequently and explicitly associates NATO's military presence with U.S. bases, rather than Italian ones. This stronger narrative link may enhance the salience of the conflict for citizens living near U.S. military installations. Second, as we will show later in the paper, this distinction is empirically meaningful: proximity to Italian bases does not yield significant effects on contagion dynamics. Based on this logic, we use proximity to U.S. bases to construct an index of indirect war exposure, which is plausibly exogenous to both the war and the spread of COVID-19. We then compare the trend in contagion between more vs. less exposed municipalities (between-difference) in the weeks before and after the outbreak of the war (within-difference).

Results show positive treatment effects of the sudden coverage of the war on the spread of contagion, with a larger magnitude reached in the second week after the beginning of the war. During the first week after the event, municipalities closer to the U.S. bases observed a higher (near 10%) increase in new COVID-19 cases than those farther away. This effect is even more pronounced (17%) during the second week after the event. This effect, however, seems to be temporary, as contagion trends across municipalities at varying distances from U.S. bases begin to converge by the third week. This convergence likely reflects a waning perception of global conflict risk over time, as seen in media discussions highlighting countries' reluctance to become directly involved in the conflict.

Moreover, we address critiques concerning the comparability of treatment and control units. U.S. military bases, predominantly located along coastlines, might lead to confounding factors when comparing nearby and distant municipalities. To mitigate this, we refine our approach by comparing municipalities with U.S. bases to their closer neighboring municipalities, ensuring greater similarity and reducing potential bias, as confirmed by balance tests. Again similar results are obtained. Additionally, we run placebo tests using the distance from TripAdvisor's top-rated beaches, the distance to the nearest Italian Army regiments, and an in-time placebo shifting the event window to 2021. The findings show no significant effects, reinforcing our main argument that the observed impacts are attributable to the presence of U.S. bases rather than other geo-economic or temporal factors.

Furthermore, our estimates show that treatment effects are more pronounced among young and young adult citizens. These groups are typically more exposed to social media, where the shift in issue salience was particularly noticeable at the beginning of the conflict, in contrast to more traditional media outlets. Consistent with this, our findings reveal that treatment effects are driven by municipalities where most households have better access to broadband services. These results underscore the significant role of social media in shaping public perception, which can potentially translate into shallow behaviors.

In addressing the underlying mechanisms, our analysis of Google mobility and search data reveals a marked increase in mobility and in online activity linked to concerns about global conflict within the treatment group. This suggests that the anticipation—and fear—of a potential new international crisis, coupled with declining attention to the ongoing pandemic, drove the observed, temporary rise in contagion. We identify two distinct behavioral responses: a reduction in COVID-related risk salience, which led to more relaxed attitudes toward mobility, and a wave of anticipatory consumption, with people—especially those living closer to U.S. military bases—visiting grocery stores and pharmacies in response to fears of supply disruptions. These shifts reflect a broader redirection of public anxiety from the pandemic to the threat of war, echoed in a rise in fear-driven online searches, such as those for "bunker."

The second part of this paper hinges on the analysis of the political consequences of shifts in media attention, particularly in the context of the 2022 Italian national elections. Held a few months after the outbreak of the Russo-Ukrainian war, these elections saw significant changes in the political landscape, with the right-wing coalition, led by Giorgia Meloni, securing a majority of votes.

To estimate the effects of political communication during the conflict on voter preferences in unexpected elections that occurred months later, we apply the same identification strategy used in our analysis of contagion dynamics. We examine how the volume and emotional tone of war-related tweets posted by political candidates soon after the Russian invasion of Ukraine influenced their electoral outcomes. This analysis is particularly relevant in electoral districts where the salience of war exceeded that of COVID-19, i.e., those closest to U.S. military bases, where—as shown in the first part of the paper—the perceived threat of war was higher. Notably, and as expected given the unexpected nature of the national elections, additional empirical findings confirm the hypothesis that candidates' volume and sentiment regarding the war did not systematically vary based on their electoral districts' proximity to U.S. military bases. This suggests that their communication strategies were not strategically tailored to geographic location.

Our results indicate that proximity to U.S. military bases significantly moderated the impact of war-related political communication. Voters in electoral districts closer to the bases—where the perceived threat of war was higher—were more responsive to the emotional content of political messaging than to the overall volume of war-related discourse. Notably, this effect varied by political leaning. Right-wing parties, using fear-based messaging, capitalized on the heightened sense of threat in areas closer to U.S. military bases, gaining electoral advantages in subsequent elections. In contrast, left-wing parties benefited more from the overall salience of the war, as their voters were swayed by the prominence of war-related issues in the media, regardless of the emotional tone. These findings highlight the critical role of fear in shaping outcomes for right-wing parties, while left-wing parties leveraged the broader visibility of the conflict.

Overall, our findings highlight how issue salience influences citizen behavior, resulting in significant health costs for society. The shift in political discourse from domestic concerns like COVID-19 to foreign policy issues, such as the unexpected war, played a temporary yet crucial role in the rebound of COVID-19 cases. This exogenous shock diminished the prominence of the pandemic while heightening fears of global conflict, leading citizens to become less vigilant about COVID-19 and reduce adherence to health-protective behaviors. Simultaneously, this shift in public attention also impacted political preferences, favoring politicians whose messaging resonated with the dominant public sentiment. Thus, media shifts affect not only health outcomes but also have broader electoral implications, highlighting the intersection between public sentiment and political strategy during times of overlapping crises.

Related literature This paper contributes to the growing literature on media attention in three ways. First, while existing studies have extensively explored the political consequences of media shifts, our paper uniquely focuses on the impact of a singular, unexpected event—the Russia-Ukraine war—rather than a series of ongoing issues or gradual media trends. Previous research has examined how changes in media coverage influence voter behavior, particularly during election campaigns (Strömberg, 2004a; Gentzkow, 2006; Snyder Jr and Strömberg, 2010; Drago et al., 2014) or in response to shifts in the media environment caused by new media technologies (George and Waldfogel, 2008; Campante et al., 2018; Gavazza et al., 2019). For example, Caprini (2023) investigates the sudden reduction in political coverage caused by the resignation of Pope Benedict XVI, showing how this disruption negatively affected Berlusconi's vote share in the 2013 Italian election. Similarly, Durante et al. (2019) document the long-term effects of early exposure to entertainment television in Italy, showing that individuals with access to commercial TV were more likely to support Berlusconi's party over multiple elections. In contrast, our study isolates the media shift to an unexpected international conflict, providing novel evidence on how such a sudden reallocation of media attention can reshape broader political preferences. By focusing on a single, highly salient and unexpected event, we are able to isolate the immediate effect of this media shift within an exogenous context, thereby minimizing the potential confounding effects associated with ongoing issues or gradual media trends.

Second, we contribute to the literature by examining the effects of media attention not only on political behavior but also on public health. While the political economy literature has extensively studied the role of media in shaping political outcomes (DellaVigna and Kaplan, 2007; Adena et al., 2015; Barone et al., 2015; Miner, 2015; Strömberg, 2004b; Drago et al., 2014; Gentzkow et al., 2011), and how media access affects public good allocation and political participation (Gavazza et al., 2019; Campante et al., 2018), few studies have addressed how media shifts can influence behaviors related to public health–an area that remains underexplored despite its importance in times of crisis. Expanding upon prior studies that show how media campaigns can be effective in changing health-risk behaviors (Wakefield et al., 2010), our paper provides causal evidence on how a sudden reallocation of media attention—away from a public health crisis, such as the COVID-19 pandemic, to an international conflict—affects adherence to health-protective behaviors.

Finally, our study adds to the understanding of how emotional content in media coverage, particularly fear, amplifies the effects of media shifts, distinct from the mere volume of coverage. Prior work has largely focused on the role of media salience in shaping political preferences, often conflating the quantity of media coverage with its effects (Gentzkow and Shapiro, 2010; Larcinese et al., 2011; Sobbrio, 2014). Additionally, recent studies have highlighted how digital platforms and social media, through algorithmic ranking systems, contribute to the spread of emotionally charged content, intensifying polarization and influencing public perceptions (Bakshy et al., 2015; Guess et al., 2023; Flaxman et al., 2016; Enikolopov et al., 2020; Allcott et al., 2020). Our paper disentangles the role of emotional tone, showing that fear-based narratives—especially in the context of social media—can act as powerful amplifiers of public behavior, influencing both political preferences and health-related decisions. This contributes to the broader literature on the interaction between emotions and media effects, particularly in environments where digital platforms play an increasingly prominent role in shaping public discourse.

Roadmap The remainder of the article is organized as follows: In the second section, we describe the data used in the empirical analyses and show trends in issue salience on the Twitter platform. The third section investigates the impact of shifting media attention from the pandemic to the war on contagion dynamics. In the fourth section, we discuss the potential mechanisms underlying these effects. Section five explores the electoral gains associated with politicians' messaging volume and tone during the early stages of the conflict. Finally, the sixth section presents our concluding remarks.

2 Data and trends in issue salience

2.1 Data on COVID-19 cases and distance to U.S. bases

The trend in the number of COVID-19 cases at the municipal level in Italy is obtained from the "Istituto Superiore della Sanità" (ISS). The records span from February 2020 to May 2022 and include daily counts of confirmed COVID-19 cases at the municipality level in Italy[1].

The second dataset is the municipal distance to U.S. bases[2]. Since there is no official list of U.S. bases in Italy, we relied on an article[3] published in a reputable Italian weekly journal (L'Espresso) to obtain a list of U.S. bases in Italy. This article categorizes U.S. bases in Italy into nine types: NATO, Army, Navy, Setaf, Usaf, Shooting Ranges, Depots, Radar, and Other bases. We excluded Radar stations and depot bases for our analysis and focused on the distance to all other bases. This is because we assume that the population may not be aware of the exact locations of the radars, which are often represented by antennas, and the depot bases, which are typically underground. Figure A.1 depicts the spatial distribution of all U.S. bases in Italy (including radar stations and depots) and the spatial distribution of those included in the analysis. Notably, the positions of the radar bases and depots do not differ significantly from those of the other bases. We then use Google Maps to extract the exact locations of these bases and calculate the distance between each municipality and the nearest U.S. base. Figure 1 shows how we computed the shortest distance

[1]The institute uses the label "< 4" for counts within the range of "less than 4 but greater than 0", without specifying the exact number of cases. To tackle this ambiguity, we create three distinct variables by interpreting instances originally marked as "< 4" as 1, 3, or as a randomly selected value from a uniform distribution between 1-3.

[2]See Section A.1 in Appendix for further details on the U.S. presence in Italy.

[3]See https://espresso.repubblica.it/attualita/cronaca/2012/05/02/news/l-elenco-delle-servitu-militari-1.42767

between Italian municipalities (centroids) and the nearest U.S. base. Lastly, Figure 2 plots the spatial distribution of the treatment based on proximity to U.S. bases. This dataset provides valuable information on the proximity of each municipality to U.S. bases. It enables us to examine the relationship between the presence of U.S. bases and the heightened media coverage of war-related issues.

Figure 1: Minimum Distance from U.S. bases

(a) U.S. bases - Italian Centroids

(b) Minimum Distance

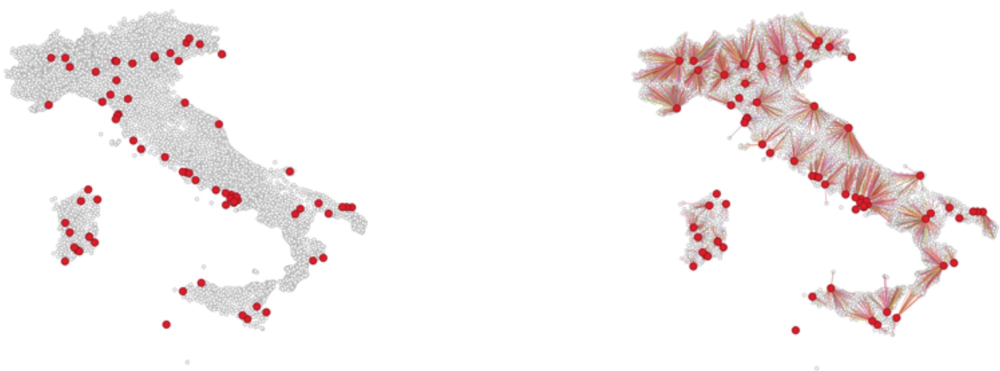
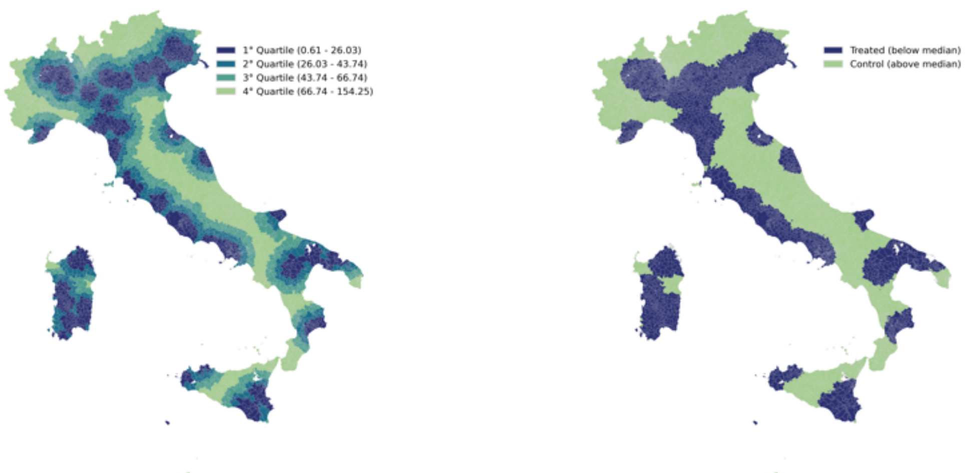


Figure 2: Treatment

(a) Index of proximity to U.S. bases

(b) Treatment



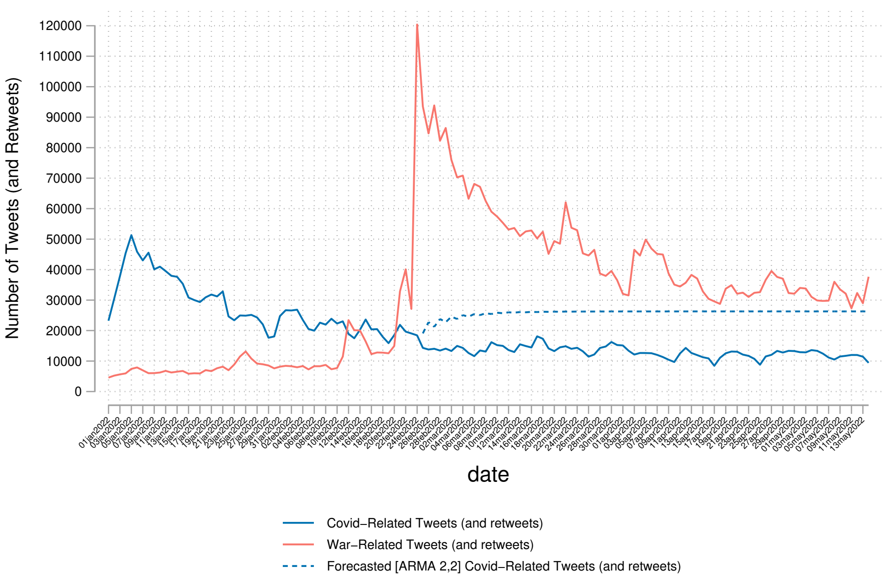
2.2 Salience of pandemic vs. salience of war

Social Media - Twitter

To analyze trends in issue salience on social media, we collected Italian Twitter data, using the Twitter API for Academic Research[4]. We used a query of COVID-19 and Ukraine and Russia war-related terms to retrieve both the content of each tweet and publicly available information about the respective tweet authors (Table A.1)[5]. Figure 3 shows the daily trend of war-related and COVID-related tweets (including retweets) in our sample of tweets.

In Figure 3 we plot three distinct curves. The red curve shows the total number of

Figure 3: Number of War-related and Covid-related Tweets and Retweets



tweets (and retweets) related to the war, the blue curve represents the total number of tweets (and retweets) related to COVID-19, and the blue dotted curve plots the

[4]See https://developer.twitter.com/en/products/twitter-api/academic-research.
Note that we pulled the total sample of tweets before Twitter changed its policy for research, removing the possibility of extracting tweets for academic studies.

[5]Our analysis covers the period from 1 January 2022 to 14 May 2022, which includes more than five weeks before and after Russia's invasion of Ukraine (i.e., the event we exploit in our analysis). Each tweet retrieved includes plain text, along with unique identification details such as tweet ID, creation date, and engagement metrics (replies, likes, mentions, retweets, hashtags, and multimedia content). If available, additional information about tweet-specific location and user details like user ID, Twitter handle, display name, bio, verification status, Twitter join date, and specific User metrics (i.e., number of friends, followers, and tweets posted) were also collected.

forecast of tweets (and retweets) related to COVID-19 with an ARMA (2,2)[6] following the exogenous event of the war.

These descriptive results offer valuable insights into the historical context. First, the war-related tweets outperformed the trend of COVID-related tweets only two days before the outbreak of war, on 24 February 2022. This fact suggests a lack of anticipatory effect in the public debate, indicating that the salience of war as an issue only becomes significant with the sudden onset of war.

Secondly, if we analyze the difference between the curve representing the actual tweets on COVID-19 and those predicted by the ARMA(2,2) model, we observe that from the day the relevance shifts to the war, the trajectory of COVID-19-related tweets substantially diverges from the predicted pattern. This suggests that the onset of the war not only leads to an escalation in the significance of war-related content but also results in an automatic decrease in the relevance of COVID-19 tweets.

Traditional media (online newspapers)

To verify that the reallocation of attention observed on Twitter is mirrored in legacy news outlets, we exploit the *Italy–National and Italy-State & Local* corpus of the MEDIA CLOUD ONLINE NEWS ARCHIVE, which continuously ingests the full text of the main national dailies and digital-only newspapers.[7] For each day between 1 January and 13 May 2022 we construct two series: the number of articles containing any COVID-19 keyword and the number containing any Russia–Ukraine-war keyword[8]. Dividing each series by the total number of stories published that day yields two salience shares that are directly comparable across time.

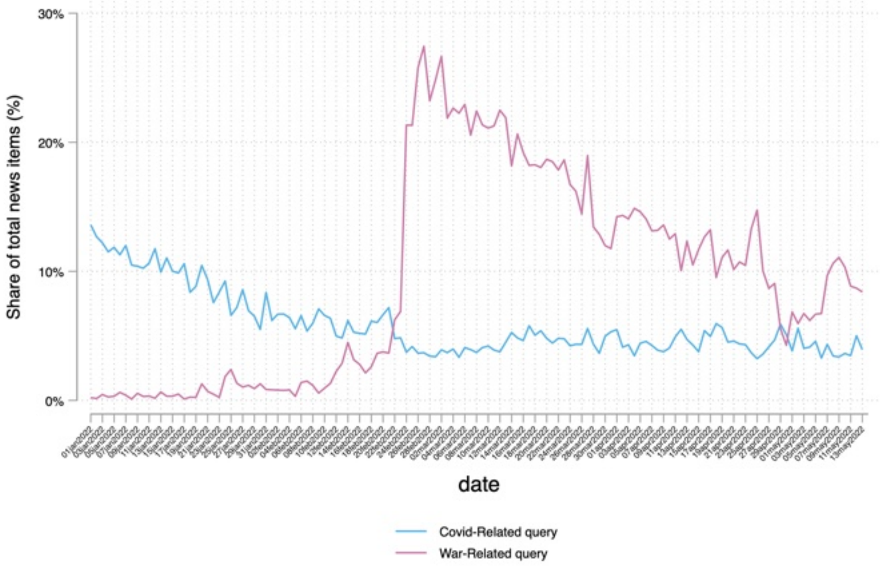
Figure 4 traces the daily share of news stories that mention the war or the pandemic in the main Italian online newspapers. Up to 23 February the war line is practically flat, while COVID–19 still attracts the lion's share of coverage: the press, like

[6]The selection of ARMA (2,2) for forecast value of COVID-19-related tweets, underscores the use of a predictive modeling approach involving a cycle to choose autoregressive (AR) and moving average (MA) values. This selection process is guided by minimizing the Bayesian Information Criterion (BIC). Further details on this modeling procedure and the related results can be provided upon request.

[7]See https://www.mediacloud.org

[8]We deliberately keep the war query minimal to avoid noise from peripheral topics such as energy or inflation that often co-occur with a longer keyword list. The precise Boolean string is `("ucrain*" OR "russi*") AND ("guerra" OR "conflitto" OR "invasione")`. The COVID query is `("covid_19" OR "covid" OR "coronavirus" OR "pandemia")`.

Figure 4: Salience of war and pandemic in Italian online newspapers



Twitter, shows *no sign of anticipating* the Russian attack. The picture flips overnight on 24 February. War-related items suddenly account for more than one story in five, and the pandemic drops into the background. From the third week of March the war curve starts to drift downward, yet it never falls back to the pre-invasion baseline and it never lets COVID reclaim the top spot. In short, Italian newspapers replicate the same sharp and persistent reallocation of attention that we observed on social media, reinforcing the idea that 24 February 2022 marks a genuine break in the information environment.

2.3 Metrics of salience and emotional tone in politicians' tweets

To evaluate politicians' sentiments on war-related issues, we analyze their statements on social media, particularly Twitter. Focusing on the same tweet sample from Section 2.2, we restrict our analysis to tweets from politicians[9] who later became candidates in the September 2022 national elections[11].

[9]We retrieved the names of all candidates for each district in both the uninominal and proportional systems from the Italian Ministry of the Interior's website. Using Google, we then scraped the Twitter account names (preceded by @) for each politician. However, since the Twitter API for Academic Research only provides user IDs (numeric codes) rather than the visible account names, we used the website twiteridfinder.com[10] to automate the retrieval of each candidate's numeric user ID and corresponding profile description, which helped verify the accuracy of the profiles of the identified politicians.

[11]See Section A.1 in Appendix for further details on the Italian electoral system and the context of the 2022 national elections.

First, we classified the tweets into positive, negative, or neutral categories. Next, we conducted a more detailed analysis of the specific emotions conveyed in the tweets. For this purpose, we used the "FEEL-IT: Emotion and Sentiment Classification for the Italian Language" model developed by Bianchi et al. (2021), which assigns each tweet one of the following emotions: anger, fear, joy, or sadness.

We focus on two key aspects of political communications on Twitter: salience and emotional tone. Salience refers to the relative prominence of the war in politicians' discourse compared to the pandemic. We quantify this by calculating the proportion of tweets focused on the war relative to those discussing COVID-19. This share provides insight into how much attention the war received over the pandemic in the political debate. A higher salience score indicates that the war dominated political messaging compared to COVID-19, suggesting that candidates were prioritizing the war in their narratives.

$$\text{Salience} = \frac{\text{\# of War Tweets}}{\text{\# of War Tweets + \# of COVID-19 Tweets}}$$

Emotional tone, on the other hand, refers to the specific emotions conveyed in war-related tweets. By classifying tweets into emotional categories—such as fear, anger, joy, or sadness—we measure the intensity and type of emotions linked to the war. The tone of these emotions is crucial because it can shape public perception and potentially influence voter behavior. For instance, a high prevalence of fear or anger in war-related tweets might mobilize voters in areas where war anxiety is heightened, such as near military bases, while joy or sadness may trigger different responses.

$$\text{Emotional Tone}_j = \frac{\text{\# of War Tweets (for emotion } j\text{)}}{\text{\# of War Tweets + \# of COVID-19 Tweets}}$$

While salience captures the amount of attention given to the war relative to COVID-19, emotional tone reveals the underlying emotional content of this attention, providing a nuanced understanding of how political rhetoric might sway voter preferences in municipalities with higher war concerns.

3 Impact of media shifts on disease transmission

3.1 Media framing of NATO-related bases in Italy

A necessary pre-test for our empirical strategy is to show that the Italian press tends to describe the NATO-related military installations in Italy as primarily *American*. To that end, we query the *Italy–National and Italy-State & Local* collection in MEDIA CLOUD. An article enters the dataset if (a) it contains a base keyword (`base*`, `basi*`, `installaz*`), (b) it mentions the string `NATO`, (c) it refers to Italy either explicitly ("Italia/Italian*"). Within that set we label the text *NATO+USA* when it also cites the United States (`american*`, `statunitens*`, ``USA'', ``U.S.''); otherwise it is classified as *NATO+Italy*. For each period we compute

$$\text{USShare} = \frac{\#\,\text{NATO+USA articles}}{\#\,\text{NATO+USA} + \#\,\text{NATO+Italy}},$$

so that values above 0.5 indicate a predominance of the American frame.

Figure 5: Share of NATO–base articles that explicitly mention the United States

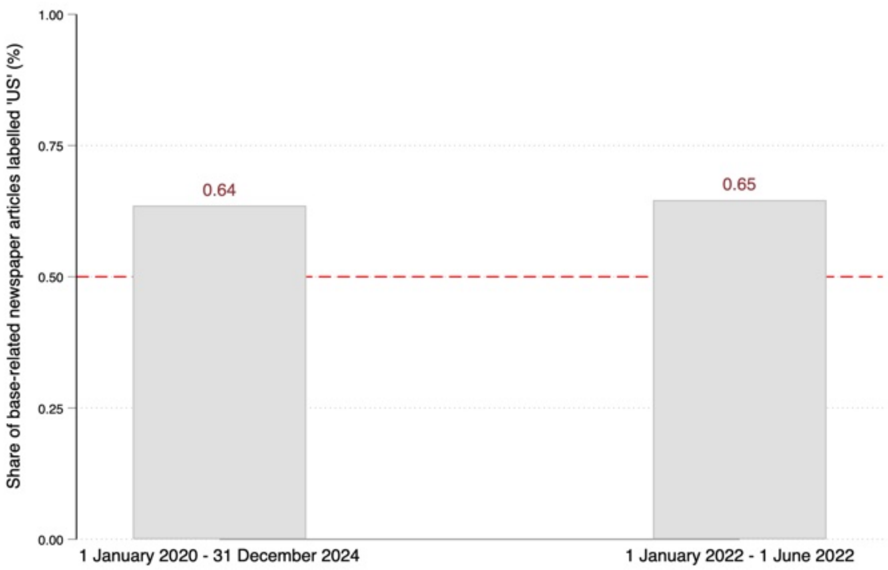


Figure 5 summarises the evidence. Over the entire 2020–2024 window—war months excluded—the statistic settles at 0.65; it remains essentially unchanged in the first one-hundred days of the Russian invasion. A value of 0.65 is far from marginal: it means that nearly *two out of every three* stories frame a military installation related to NATO as "American", leaving barely one third to the pure "Italian-NATO" (i.e., no American) perspective. Put differently, the American label enjoys a thirty-percentage-point lead over the national one, a gap large enough to speak of a *structural* framing. Because this imbalance persists even when NATO dominates the headline agenda, by focusing on *U.S. bases* we capture the way Italian media—and by implication the Italian public—conceive the country's foreign military footprint, and in particular the involvement of NATO in the country.

3.2 Econometric strategy

First, we rely on a dynamic differences-in-differences framework to assess the influence of the decreased prominence of the pandemic due to the Ukraine-Russia conflict on the count of COVID-19 cases in Italian municipalities. This methodology entails a comparison of fluctuations in the count of new COVID-19 cases before and after the onset of the conflict in municipalities categorized as "treated" and those categorized as "untreated" or "less treated". To determine the treatment status at the municipality level, we consider the distance from a U.S. military base, specifically whether it falls below or above the median distance. This treatment indicator serves as a proxy for the salience of the conflict and/or the perceived threat associated with it. Our estimating equation is as follows:

$$\textit{New Cases}_{m,w} = \beta_0 + \sum_{k=-5,\, k\neq -1}^{k=5} \beta_k \cdot \mathbf{Treat}^{(k)}_{m,w} + X'_m \cdot \textit{Post} + \theta_m + \gamma_w + \phi_{r,w} + \epsilon_{m,w} \tag{1}$$

We estimate this equation using a municipality-level fixed effects regression model, with standard errors clustered at the municipal level. The dependent variable is the number of new COVID-19 cases in municipality m in week w. We use the inverse hyperbolic sine (IHS) transformation for the outcome variable due to its logarithmic characteristics (similar to those of a standard natural logarithm) (Burbidge et al., 1988; MacKinnon and Magee, 1990). Its unique feature of retaining zero and negative values is essential to avoid biased estimates in our analysis. The treatment variable, i.e., the minimum distance from a U.S. base, is an indicator variable that takes a value of one if the municipality's distance from the U.S. base is below the sample median. We include a battery of baseline controls (X') at municipal level interacted with dummy Post (Baker et al., 2025) and control for municipality (θ), week (γ), and region-by-week (ϕ) fixed effects.

3.3 Results

Figure 6 plots the marginal effects from the differences-in-difference estimates[12]. Results show that municipalities that are closer (less distant) to U.S. bases experienced a surge in COVID-19 cases during the initial two weeks compared to municipalities that are further away from U.S. bases. The lack of statistically different pre-trends suggests that the parallel trend assumption holds. Figure A.4 presents two distinct graphs to support this assumption. The left plot displays observed means for each treatment group at various time points, while the right plot is based on an additional model outlined in the Appendix A.2, employed for the parallel-trends test. This model incorporates two variables indicating pre-treatment and post-treatment periods. Additionally, we conduct a Wald test to assess whether linear trends are parallel before treatment. The null hypothesis posits that linear trends are parallel, and our findings indicate no rejection of this hypothesis (Prob > F = 0.9173).

Figure 7 plots results from the dynamic differences-in-differences regression model. Again, no significant differences in the pre-trends are found.

WIn Figure A.2, we present the event-study estimates at the intensive margin, where municipalities are grouped into four distance-based quartiles (Q1 = closest, Q4 = farthest) relative to the nearest U.S. military base. We observe a clear, monotonic attenuation of the treatment effect as distance increases: the largest spike in new COVID-19 cases occurs in Q1 at the second weekend post-event (approximately +30 percent relative to the pre-treatment baseline), with progressively smaller and less precise effects in Q2 and Q3, and a null—statistically insignificant—estimate in Q4. Importantly, the absence of any systematic differences in the pre-treatment period across all quartiles supports the validity of the parallel-trends assumption.

We contrast municipalities that are close to a U.S. base with those located at a sig-

[12] More specifically, we estimate the following equation:

$$New\ Cases_{m,w} = \beta_0 + \beta_1 \cdot \mathbf{Treat}_m \cdot \gamma_w + X'_m \cdot Post + \theta_m + \gamma_w + \phi_{r,w} + \epsilon_{m,w} \quad (2)$$

Figure 6: Differences-in-Differences Event Study Estimates

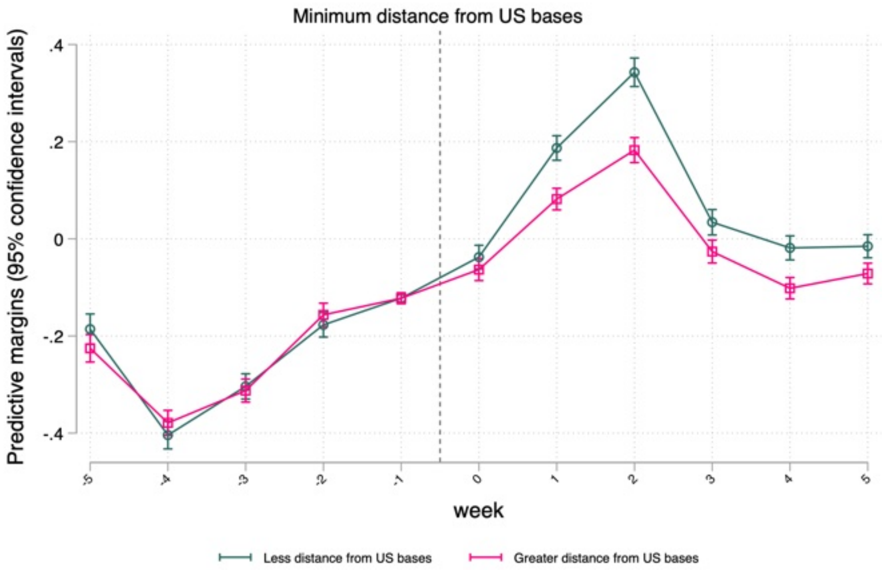
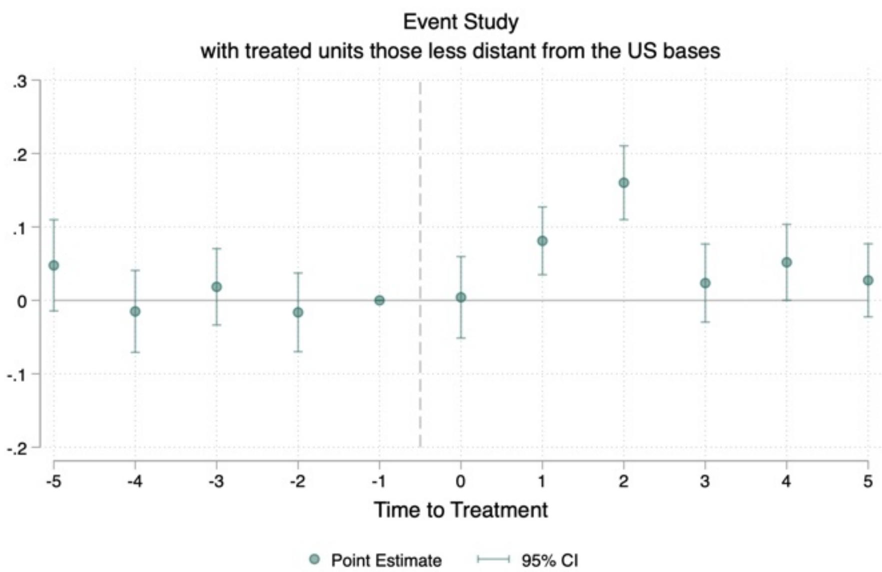


Figure 7: Panel Event Study



nificant distance from it. In this case, our treated units include municipalities falling in the first quartile/decile of proximity to U.S. bases, while the comparison group comprises municipalities falling in the last quartile/decile, representing those farthest from U.S. bases. Our results in Figure A.3 reveal a larger treatment effect when treated units include municipalities falling in the first decile. The treatment effect turns out to be greater also when treated units include municipalities falling in the first quartile compared when treated units include municipalities falling in the below median. In particular, in the initial week following the event, municipalities that are very close to U.S. bases experienced a larger increase (20%) of new COVID-19 cases than those located further away. This effect became even more pronounced (near 30%) during the second week following the event.

Our estimates are confirmed when we replace the number of COVID-19 cases originally marked as "< 4" by ISS with a value of 3 or 1 (Figures A.5-A.6-A.7-A.8). Our results are also robust to the exclusion from the sample of cities that host a U.S. base (Figures A.9)[13]. Furthermore, our findings are confirmed if we interact our municipal-level baseline controls with year fixed effects instead of with the post-treatment dummy.

3.4 Treatment refinement

One potential concern in our analysis is the comparison between treatment and control units that are too different from each other. U.S. bases are predominantly located along coastlines, and comparing units that are close to U.S. bases (below median distance) with those that are farther away (above median distance) might reveal a response to the event that is not directly related to the presence of U.S. bases. While the DiD strategy allows for differences among groups at the baseline provided they pre-trend similarly, treatment effects may arise from unobserved characteristics that account for the differential dynamic reactions to the war announcement.

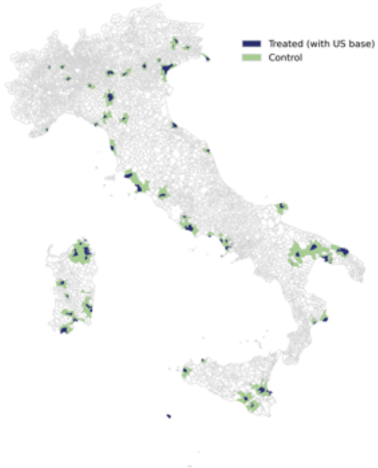
To address this potential issue, we refine our treatment by selecting control units that are closer, and hence most likely similar to the treated ones. More specifically, we compare treated units, those hosting a U.S. base, with a subset of control units composed by municipalities bordering those hosting a U.S. base. Figure 8 shows the new spatial distribution of the treated and control units. This new treatment approach partly solves the problem of different responses to events, as treated and control units appear to be more similar to each other, as confirmed by the balance test (upon request).

The findings reported in Figures A.10 and A.11 are consistent with previous

[13] More specifically, we exclude municipalities with a distance to the nearest U.S. base that is less than 10 kilometers.

results, reassuring us that the driver of the evolving concerns among Italian citizens does not hinge on differences in some intrinsic characteristics between treated and control municipalities.

Figure 8: Treatment refinement



3.5 Falsification tests

Distance from TripAdvisor 'Top Rated Beaches'

In this subsection, we conduct a 'placebo' test using the distance from the top-rated beaches on TripAdvisor as a metric to construct our treatment variable. We opt for these seaside locations since most U.S. bases are located along the coast. Hence, we expect no treatment effect of the war announcement on contagion as proximity to top rated beaches is completely irrelevant to the conflict.

Hence, we downloaded data on the top-rated beaches in Italy from TripAdvisor[14] and re-run the analysis performed in our main treatment (as in section 2.1). The spatial distribution of the treatment is reported in figure A.12, showing that top-rated beaches are concentrated on the Italian Islands. We focus on beaches along the coastlines (no lakes), and our results show no significant effects in either the pre-treatment or post-treatment periods (Figure A.13). This suggests that our analysis does not merely reflect the impact of being 'coastal municipalities', but rather indicates that the presence of a U.S. base itself affects the health outcomes.

[14]The ranking is updated regularly; data were downloaded on 16 July 2024. The ranking is available here.

Distance from Italian Military Regiments

In this subsection, we conduct a falsification test using the minimum distance from each municipality to the nearest Italian Army regiment as the treatment variable. Italian regiments represent domestic military installations, which are not expected to influence citizens' perceptions of an international conflict in the same way as proximity to U.S. bases in Italy. As demonstrated in Section 3.1, when discussing military bases and NATO, the Italian press predominantly associates the latter with the U.S. military presence in Italy. Thus, we anticipate no impact of the war's onset on COVID-19 contagion when employing proximity to Italian regiments as treatment.

To implement this analysis, we collected geographic coordinates for major Italian Army regiments (including Infantry, Bersaglieri, Alpini, Armored units, etc.) from publicly available Ministry of Defence registries, cross-validating their locations via OpenStreetMap. For each municipality, we computed the shortest road distance to the nearest regiment and defined a binary treatment indicator equal to one for municipalities below the national median distance. We then re-estimated our baseline differences-in-differences event-study specification described in Section 3, substituting distance to U.S. bases with distance to Italian regiments.

Figure A.14 shows the spatial distribution of this placebo treatment, highlighting that Italian regiments are dispersed throughout both inland and coastal areas. Figure A.15 reports the event-study coefficients, which indicate no statistically significant differences in COVID-19 contagion for municipalities near Italian regiments in either the pre-treatment or post-treatment periods.

These null results underscore that mere proximity to military infrastructure is insufficient to explain the temporary increase in COVID-19 cases. Rather, the observed contagion spike appears specifically tied to the salience and perceived threat associated with U.S. military installations. Moreover, this falsification test implicitly verifies that citizens distinguish between domestic and foreign military presences. The absence of significant effects suggests that behavioral responses were specifically triggered by perceptions of international conflict risk linked to U.S. bases, rather than reflecting a generalized response to military infrastructure.

In-time placebo test using a fake treatment year (2021)

To further verify that the observed effects on COVID-19 contagion are specifically due to the outbreak of the Russo-Ukrainian war in 2022, we conduct an additional in-time placebo test. Specifically, we artificially shift our event window back by exactly one year, treating the corresponding weeks in 2021 as if the war had occurred then. If our findings were driven by seasonal factors, annual trends, or other recurring phenomena, we would expect to see similar results in this placebo scenario.

To implement this placebo test, we define the treatment and control groups identically to our baseline analysis in Section 3, based on municipalities' proximity to U.S. military bases. We then apply the same differences-in-differences event-study specification, treating the corresponding weeks of 2021 as our placebo event period.

Figure A.16 displays the event-study coefficients obtained from this placebo analysis. The estimates clearly indicate no significant differences between treated and control municipalities, neither in the pre-treatment nor in the placebo post-treatment periods. This lack of significant effects confirms that our main findings for 2022 cannot be attributed to recurring annual trends or seasonality.

3.6 Heterogeneity

We conduct several tests to explore heterogeneous treatment effects to examine potential mechanisms explaining our results. The initial heterogeneity analysis is based on age groups, leveraging the breakdown of COVID-19 cases into categories (0-19, 20-39, 40-59, 60-79, 80+) as provided by ISS. These age groups are known to rely on and be exposed to different types of media as their main sources of information. Results from the dynamic differences-in-differences regression based on eq. 1 are reported in Table 1.

First, the causal effect observed during the second week for the entire sample also holds across different age groups. However, the treatment effect tends to follow a non-linear pattern by age, peaking for the age group 40-59. As hypothesized, this result can be due to varying information-seeking behaviors across different age groups. As supported by previous studies (Helsper et al., 2015; Hunsaker and Hargittai, 2018; Taipale et al., 2021), older individuals tend to rely more on tra-

Table 1: Heteregenous Effects by Age group

	Age Group				
	0-19	20-39	40-59	60-79	80+
Lag -5	0.0804***	-0.00183	-0.00267	0.00568	-0.0132
	(0.0212)	(0.0181)	(0.0187)	(0.0132)	(0.0105)
Lag -4	0.0180	-0.0251	-0.0159	-0.00173	0.00429
	(0.0192)	(0.0162)	(0.0174)	(0.0118)	(0.00909)
Lag -3	0.00714	-0.00186	0.00963	0.0160	0.0114
	(0.0172)	(0.0146)	(0.0147)	(0.0114)	(0.00914)
Lag -2	0.0190	-0.00461	0.00264	-0.00295	-0.00748
	(0.0176)	(0.0155)	(0.0160)	(0.0121)	(0.0100)
Lead 0	0.0211	0.000221	-0.0193	8.44e-05	-0.00666
	(0.0175)	(0.0156)	(0.0159)	(0.0121)	(0.00954)
Lead +1	0.0478***	0.0241*	0.0366***	0.00460	-0.00399
	(0.0145)	(0.0129)	(0.0134)	(0.00979)	(0.00776)
Lead +2	0.0736***	0.0559***	0.0503***	0.0347***	0.00332
	(0.0159)	(0.0135)	(0.0141)	(0.0107)	(0.00833)
Lead +3	0.0196	0.00253	-0.000194	-0.00104	0.00144
	(0.0156)	(0.0154)	(0.0154)	(0.0120)	(0.00876)
Lead +4	0.0336**	0.00679	0.00155	-0.00830	-0.00321
	(0.0159)	(0.0146)	(0.0159)	(0.0115)	(0.00896)
Lead +5	0.0269*	-0.00737	0.0118	0.0132	-0.00542
	(0.0145)	(0.0142)	(0.0148)	(0.0122)	(0.00885)
Municipality FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Region X Time FE	✓	✓	✓	✓	✓
Observations	63316	63382	63668	63107	60962

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at municipal level in parentheses. This table presents the estimated coefficients from a differences-in-differences event study model assessing the impact of age groups on the treatment effect. The dependent variable is the inverse hyperbolic sine (IHS) transformation of the weekly count of new COVID-19 cases. The main independent variable is an interaction term between the treatment indicator (whether the municipality is below the median distance from a US military base) and week dummies (Lead and Lag indicators, where "Lag -5" refers to five weeks before treatment, and "Lead +5" refers to five weeks after treatment). The coefficients represent the effect of the treatment relative to the reference period, which is "Lag -1" (one week before the treatment).

ditional media sources, such as newspapers and television, for their information, while younger individuals heavily depend on social media platforms. Given that news regarding COVID-19 cases in 2022 primarily circulated through newspapers and TV broadcasts, typically in a report format, it is unsurprising to see a smaller treatment effect among older individuals. These individuals predominantly rely on information sources that may have been less influenced by the substantial shift in media coverage compared to the more dynamic and interactive nature of social media platforms.

One concern is that the larger treatment effect observed among younger cohorts might be driven by differential Covid-19 risk across age groups rather than by differences in media-diet. Because we estimated separately for each age bracket and includes municipality fixed effects, any time-invariant Covid vulnerability is already absorbed. To address residual worries about time-varying Covid shocks, we add the log Covid-19 incidence recorded in each municipality during the month preceding the invasion (weeks –5 to –1) and interact it with the post dummy. Table A.2 shows that the interaction term (log Incidence_pre × Post) is small and statistically not significant, while the Treatment × Young coefficient remains unchanged.

Building upon the observed heterogeneous effect among age groups, primarily driven by the increased exposure of younger individuals to non-traditional media sources such as social media, we now investigate whether this effect is more pronounced in municipalities with faster internet speeds. To address this question, we employ publicly available municipal data sourced from AGOM[15]. We construct an index that encompasses the number of households with theoretically anticipated speeds greater than 30 Mbps range, relative to the total households within the municipality. Then, we compare municipalities based on the number of households below or above the median broadband speed[16]. Results from this heterogeneity analysis are shown in Table 2.

Results suggest that the main treatment effect is not statistically significant for municipalities characterized by an underserved or poorly established internet infrastructure, considering the total number of households within the municipality.

[15]Available at https://maps.agcom.it

[16]In this case, "above the median" implies a higher number of households covered by slow or no broadband

Table 2: Heteregenous Effects by Broadband Connection

	Broadband Connection	
	Slower broadband	*Faster broadband*
Lag -5	-0.000502	0.0993*
	(0.0310)	(0.0513)
Lag -4	-0.0468*	0.0391
	(0.0264)	(0.0446)
Lag -3	-0.00152	0.0729*
	(0.0229)	(0.0431)
Lag -2	-0.00878	-0.0114
	(0.0261)	(0.0447)
Lead 0	-0.0181	0.0400
	(0.0242)	(0.0464)
Lead +1	-0.0234	0.122***
	(0.0208)	(0.0378)
Lead +2	0.0223	0.185***
	(0.0221)	(0.0408)
Lead +3	0.00975	0.0329
	(0.0222)	(0.0440)
Lead +4	0.0182	0.100**
	(0.0220)	(0.0428)
Lead +5	-0.0262	0.107***
	(0.0211)	(0.0412)
Municipality FE	✓	✓
Time FE	✓	✓
Region X Time FE	✓	✓
Observations	28303	34166

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at municipal level in parentheses. This table presents the estimated coefficients from a differences-in-differences event study model assessing the impact of municipalities' broadband connection on the treatment effect. The dependent variable is the inverse hyperbolic sine (IHS) transformation of the weekly count of new COVID-19 cases. The main independent variable is an interaction term between the treatment indicator (whether the municipality is below the median distance from a US military base) and week dummies (Lead and Lag indicators, where "Lag -5" refers to five weeks before treatment, and "Lead +5" refers to five weeks after treatment). The coefficients represent the effect of the treatment relative to the reference period, which is "Lag -1" (one week before the treatment).

Conversely, for municipalities benefiting from more robust internet connectivity, the outcomes correspond with those obtained in the primary analysis. The initial week shows a positive and statistically significant treatment effect, while the second week exhibits an effect of even greater magnitude. This evidence further suggests the health effects of media attention shifts are amplified by exposure to social media and the use of the internet as the primary source of information.

4 Mechanisms

The two shocks we study—the pandemic and the war—tap into qualitatively different forms of fear. Illness-related fear hinges on personal vulnerability and contagion (Finucane et al., 2000; Slovic et al., 2013), whereas war-related fear is linked to sudden violence, economic disruption and collective security concerns (Lerner and Keltner, 2001; Huddy et al., 2008). These threats resonate with different social groups: older or clinically fragile citizens react primarily to health risks, while younger cohorts— relatively protected from severe COVID-19 symptoms—are more exposed to the economic fallout of an international conflict.

Both literatures converge on the idea that individuals manage a limited *budget of fear*. When a new, focal danger captures the news cycle, cognitive resources may shift away from the previous concern—a mechanism also related to moral licensing in the ethical domain (Monin and Miller, 2001). The media evidence in Sections 2.2 and 2.2 fits this pattern: war coverage surges on 24 February 2022 and pandemic coverage collapses, suggesting that the invasion absorbed the available "fear slots" in public debate. The empirical tests that follow exploit this reallocation of attention to study how health outcomes and electoral preferences respond when the dominant source of anxiety flips from illness to war.

4.1 Mobility patterns

We posit that shifts in media coverage influence real health-related behaviors primarily by affecting mobility patterns. Specifically, we propose two distinct mechanisms through which the sudden shift in media attention—from COVID-19 to the Russia-Ukraine conflict—may have influenced citizens' mobility.

Risk-salience attenuation

First, we argue that the rapid media shift toward war-related coverage reduced the perceived relevance of COVID-19, diminishing individuals' perceptions of pandemic threat. In the context of the COVID-19 pandemic, media attention played a central role in shaping precautionary and restrictive behaviors. However, our study suggests that a sudden shift in media attention, triggered by the escalating situation in Russia and Ukraine, may have diminished the perceived relevance of the COVID-19 threat. Consequently, this shift might have led to a decrease in the citizens' adoption of stringent health-related behaviors.

To investigate this hypothesis, we explore mobility patterns across municipalities, assuming that individuals might be more likely to change their movements if the concern about COVID-19 is perceived as less relevant due to the heightened focus on war-related events. The analysis of mobility data aims to identify behavioral shifts that suggest a reduced adherence to public health guidelines, particularly in areas where the media-driven shift in attention was most pronounced. Following DellaVigna and Kaplan (2007), we expect this increase in mobility to represent a persistent behavioral shift, reflecting a lasting reduction in perceived pandemic threat.

To obtain a measure of weekly mobility, we use Google mobility data as a proxy[17]. We analyze weekly mobility averages across various categories, encompassing leisure and entertainment venues, essential services, outdoor recreational areas, public transportation hubs, and residential areas.

We run the same specification as in eq. 1 using now mobility at the province level as our dependent variable and controlling for province and week fixed effects which absorb time-invariant local characteristics and common shocks. Results in column 2 of Table 3 reveal a significant correlation between the media-driven attention shift and increased mobility, especially in municipalities closer to military bases after the onset of the war. Importantly, also in this case, the pre-trends are not statistically different for treated and control units, whereas, after the Russian

[17] These data are available at the provincial level only. Despite this limitation, the provincial-level data can still provide valuable insights into local mobility trends, allowing us to draw meaningful conclusions about the relationship between the media-driven attention shift and changes in mobility patterns.

invasion of Ukraine, there is a positive effect for the municipalities closest to U.S. bases (i.e., our treated units). These findings confirm a lasting behavioral response to diminished COVID-19 risk perception.

Consumption anticipation

Second, we propose that the expectation of a catastrophic event—a sudden world war—prompted households to engage in short-term stockpiling, or "anticipatory consumption," as they rushed to secure food, medicine, fuel, and other essentials against potential supply disruptions. Under heightened uncertainty, theory predicts that individuals tend to mimic one another's behavior, creating informational cascades that generate a rapid—but transient—spike in visits to grocery stores and pharmacies (Bikhchandani et al., 1992).

To evaluate this channel, we use again Google mobility data at the provincial level, this time isolating the "Grocery & Pharmacy" category. We implement the same specification as in eq. 1 from Section 3, substituting weekly percent-change in grocery-and-pharmacy mobility for our COVID-19 outcome. Treatment is defined by provinces below the median distance to U.S. military bases, and province and week fixed effects absorb time-invariant local characteristics and common shocks.

Our estimates reveal a sharp, statistically significant increase in grocery-and-pharmacy visits in treated provinces during the first week following the invasion—consistent with a hoarding response driven by fear of imminent crisis. By the second week, however, treated and control provinces converge back to their pre-invasion mobility paths, confirming that this surge reflects short-lived anticipatory consumption rather than a sustained change in shopping behavior.

4.2 Increased fear of the war

Another important mechanism by which shifts in media coverage could translate into changes in real health-related behaviors is through their influence on people's fear. In the weeks following the war, media attention focused heavily on the clash in Ukraine, sometimes raising public debate about the potential involvement of other states in the conflict. This may have developed in individuals a significant increase in fear of an impending conflict.

Our study suggests that a sudden shift in media attention, triggered by the escalation of the situation in Russia and Ukraine, may have decreased the perceived relevance of the COVID-19 threat. A plausible catalyst for the reduced prominence of the pandemic, particularly in areas near military bases, could stem from the heightened sense of fear induced by the new focal point in media coverage.

In particular, we hypothesize that the shifted media attention resulting from the evolution of events in Russia and Ukraine influences the emotional states of citizens, particularly in terms of increased fear and apprehension. To empirically assess this hypothesis, we employ Google Trends data as a proxy measure of public sentiment. We conduct a comparative analysis between municipalities in close proximity to U.S. military bases and those situated at a distance, examining variations in the population's fear levels.

More specifically, using Google Trends data, which offer an unfiltered sample of search queries sent to Google (Brodeur et al., 2021), we aim to capture variations in the intensity of searches related to fear-inducing topics during the period of increased media attention to the war. The data provide an index of search intensity per topic over the specified time period in a given geographical area. The number of daily searches for the designated topic is normalized by dividing it by the maximum number of daily searches for that topic over the period analyzed in the respective geographical area.

For our analysis, we select the search term "bunker," chosen for its connotation with fear and instability at the onset of the war. This term is considered as a representative query to capture the overall sentiment of fear within the population[18].

The rationale behind this approach lies in the assumption that an increase in searches for fear-related terms such as "bunker" would indicate a heightened sense of fear and concern among the public. We analyze the fluctuations in search volume for this specific term before and after the Russian invasion of Ukraine and across municipalities situated at varying distances from U.S. military installations.

We run the same specification as in eq. 1 using now the daily Google trend

[18] In addition, we rely on this word given the prevailing media rhetoric in our context. Newspaper articles, such as the one from Huffington Post, often described how the Italian population was in search of bomb shelters to 'prevent' a probable outbreak of conflict. The use of terms like "bunker" in media reports not only reflects public concerns but also contributes to shaping the narrative surrounding the perceived threat.

searches as our dependent variable. Results in Table 3 reveal a significant correlation between the media-driven attention shift and an increase in the perception of war-related fear in the first week following the events, especially in municipalities closer to military bases after the onset of the conflict.

Notably, the effect seems to be more pronounced only after the initial week. Our explanation for this result is that the fear of a potential war may be a transient rather than a long-term effect. This idea could be supported by the evolving nature of the conflict and statements from countries not directly involved, which denied their potential involvement in the conflict.

5 Electoral consequences of shifting media attention

In this section, we investigate the political impact of emphasizing war-related issues at a time when the focus on COVID-19 had waned. Can politicians who tap into the heightened salience of the war and the public's sentiments gain an electoral advantage?

Italy experienced a notable political event a few months after the outbreak of the Russo-Ukrainian war: national elections. On Sunday, September 25, 2022, Italy held elections to renew both branches of its Parliament—the Senate of the Republic and the Chamber of Deputies—following President Sergio Mattarella's early dissolution of the Chambers on July 21, triggered by the Draghi government crisis. The elections resulted in a victory for the right-wing coalition, led by Giorgia Meloni, which secured about 44% of the vote and an absolute majority in both chambers[19]. The war significantly shaped the campaign, as parties differed on Italy's role in supporting Ukraine, including the provision of arms and aid to a NATO ally.

To measure the impact of war-related focus and sentiment on voting behavior in municipalities where the war overshadowed COVID-19, we use the identification strategy described in Section 3. We analyze how votes in the national elections—held seven months after the conflict's onset—were influenced by the volume and tone of candidates' war-related tweets following the Russian invasion of Ukraine. Specifically, we assess whether candidates' emphasis on the war,

[19] See Section A.1 in Appendix for further details.

Table 3: Mechanisms: Mobility Patterns and Fear of the war

	Mechanism Tested		
	Consumption Anticipation	Risk-Salience Attenuation	Google Searches on fear
Lag -5	0.566	0.140	0.000312
	(0.515)	(0.648)	(0.00129)
Lag -4	0.410	0.554	-0.00211
	(0.394)	(0.466)	(0.00134)
Lag -3	0.0929	0.189	0.000241
	(0.310)	(0.415)	(0.00152)
Lag -2	0.181	0.122	0.000806
	(0.291)	(0.462)	(0.00149)
Lead 0	0.559	3.975***	0.00259
	(0.379)	(0.905)	(0.00193)
Lead +1	0.997**	2.921***	0.00349**
	(0.412)	(0.836)	(0.00162)
Lead +2	0.311	0.325	0.00104
	(0.548)	(0.879)	(0.00178)
Lead +3	0.384	1.885**	0.000856
	(0.501)	(0.863)	(0.00165)
Lead +4	0.338	2.201**	-0.00110
	(0.561)	(0.877)	(0.00159)
Lead +5	0.693	2.691**	0.00104
	(0.709)	(1.043)	(0.00149)
Province FE	✓	✓	✗
Municipality FE	✗	✗	✓
Time FE	✓	✓	✓
Region X Time FE	✗	✗	✓
Observations	1166	1166	63954

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at municipal/province level in parentheses. This table presents the estimated coefficients from a differences-in-differences event study approach to examine two potential mechanisms through which the shift in media attention following Russia's invasion of Ukraine influenced public health behavior in Italian municipalities. The "Consumption Anticipation" column uses grocery and pharmacy mobility at the provincial level, derived from Google data, as the dependent variable; The "Risk-Salience Attenuation" column uses a composite index of mobility at the provincial level, derived from Google data; the "Google Trend" column uses the frequency of searches for the term "bunker," indicative of increased fear of war, as the dependent variable. The main independent variable is an interaction term between the treatment indicator (whether the municipality is below the median distance from a US military base) and week dummies (Lead and Lag indicators, where "Lag -5" refers to five weeks before treatment, and "Lead +5" refers to five weeks after treatment). The coefficients represent the effect of the treatment relative to the reference period, which is "Lag -1" (one week before the treatment).

along with their sentiment, provided an electoral advantage, particularly in districts where perceived threats were higher during the initial weeks, such as those near U.S. military bases.

Given the unexpected nature of the national elections, we hypothesize (and confirm) that the volume and sentiment of war-related tweets by candidates did not vary significantly based on the proximity of their districts to U.S. bases, suggesting an absence of targeted electoral campaigning by location.

5.1 Dynamics of salience and fear

To analyze how politicians' communication strategies shifted after the outbreak of the Russo-Ukrainian war, we rely on the metrics of salience and emotional tone in politicians war- and COVID-19-related tweets, as outlined in Section 2.3. This allows us to identify any changes in communication patterns across different political groups.

Politicians are categorized into three distinct groups based on their party affiliations during the 2022 Italian national elections: left-wing parties[20], right-wing parties[21], and other lists[22].

Results in Figure A.17 from the analysis of fear and salience show a clear shift in focus after the outbreak of the war. For fear, only right-wing parties show a significant change in the emotional tone, with a noticeable spike in war-related tweets immediately after the war began. On the other hand, left-wing parties and other lists do not exhibit any significant shifts in fear, with both groups maintaining stable communication patterns for both war and COVID-19-related tweets. This suggests that fear as a rhetorical tool was strategically leveraged by right-wing politicians during the conflict, whereas other groups maintained a more consistent tone.

Regarding salience, the data reveal a substantial shift in attention from COVID-19 to war-related topics across all political groups immediately after the war's onset. Right-wing parties show the most pronounced increase in war-related salience, accompanied by a marked reduction in COVID-19-related tweets. Left-wing parties

[20] Partito Democratico - Italia Democratica e Progressista, +Europa, Alleanza Verdi e Sinistra, and Impegno Civico Luigi Di Maio - Centro Democratico.

[21] Forza Italia, Fratelli d'Italia con Giorgia Meloni, Lega per Salvini Premier, and Noi Moderati/Lupi - Toti - Brugnaro - UDC.

[22] all remaining candidates not classified in the right-wing and left-wing parties categories.

and other lists also demonstrate an increased focus on war-related issues, but the shift is less pronounced compared to right-wing parties.

First, to test the exogeneity of politicians' communication to the distance of electoral districts from U.S. military bases (our treatment), we analyze whether candidates tweet more (indicating salience) or adopt a specific emotional tone (fear) in municipalities where they will later run. We employ an event difference-in-differences approach, defining the treatment based on the proximity of each electoral district to the nearest U.S. military base. Specifically, we examine how this proximity influences the volume of war-related tweets (salience) and the emotional tone expressed (fear).

Results in Figure A.18 highlight no significant relationship between proximity to U.S. military bases and changes in politicians' communication strategies regarding salience or fear. Across all political groups, the estimates remain close to zero, and the 95% confidence intervals include zero. This suggests that there is no systematic shift in communication behaviors associated with proximity to military bases. These findings support our hypothesis that, given the unexpected nature of the 2022 elections, politicians' communication is random concerning their future candidacy in districts near military bases.

5.2 Econometric approach

Having confirmed the exogeneity of politicians' messaging strategies to our treatment, we can now estimate the effect of salience and emotional tone on voting outcomes, as moderated by proximity of electoral districts to U.S. bases. The estimating equation is as follows:

$$\begin{aligned} \#\, Votes_{i,c} = \beta_0 + \beta_1 \cdot \mathbf{Treat}_c + \beta_2 \cdot \text{Salience}_i + \sum_j \beta_{3j} \cdot \text{Emotion}_{i,j} \\ + \beta_4 \cdot \mathbf{Treat}_c \cdot \text{Salience}_i + \sum_j \beta_{5j} \cdot \mathbf{Treat}_c \cdot \text{Emotion}_{i,j} + \delta_r + \theta_i + \zeta_c + \epsilon_{i,c} \end{aligned} \tag{3}$$

We estimate this equation using a fixed-effects regression model with standard errors double-clustered at the electoral district and municipality levels[23]. This ap-

[23]The double clustering at the electoral district and municipality levels is crucial due to the structure of the data: in large municipalities, there are multiple smaller electoral subsections, which could

proach accounts for the hierarchical structure of the data, as the dependent variable is the number of votes received by each candidate i in electoral district c, and larger municipalities include multiple electoral subsections. The dependent variable is the number of votes received by each candidate in their electoral district. We use the inverse hyperbolic sine (IHS) transformation for the outcome variable, as in the previous estimates, due to its logarithmic characteristics (similar to those of a standard natural logarithm), which allows us to effectively model complex relationships (Burbidge et al., 1988; MacKinnon and Magee, 1990).

The estimates include salience, which captures the relative attention given to war-related topics compared to COVID-19 by each candidate, and emotional tone, which categorizes the tone of each candidate's tweets into emotions such as joy, sadness, anxiety, and fear (constructed as described in Section 2.3). The tweets considered for salience and emotional tone are those made during the three-week period following the start of the war, reflecting the same causal effect window used in our analysis. The treatment variable is an indicator that equals one if the electoral district's distance from the nearest U.S. military base is below the sample median.

We include interaction terms to assess whether proximity to a U.S. military base—reflecting citizens' attention to (and fear of) war—modifies the impact of salience and emotional tone on voting outcomes. Additionally, we control for several candidate-specific characteristics, including age, gender (θ_i), type of election (e.g., single-member district or proportional representation for the Camera and Senato), and affiliation with a major party (ζ_c). Region fixed effects are included to account for unobserved heterogeneity across different geographical areas (δ_r).

5.3 Results and robustness checks

The results presented in Table 4 show that proximity to U.S. military bases, by itself, tends not have a significant direct impact on election outcomes. However, the interaction between proximity to military bases and the emotional tone of candidates' tweets reveals a significant effect on voting outcomes.

Specifically, we find that the interaction between fear and proximity to a U.S.

introduce intra-cluster correlations. This clustering approach ensures that our standard errors are robust to these correlations.

military base has a positive and a significant effect. Electoral districts near military bases experience around 1% increase in votes for candidates who express this sentiment.

Anger also shows a negative and significant effect on votes in two specifications (Column 3), though it is smaller than that of fear. The interaction with proximity to military bases has a positive and significant impact, suggesting that candidates who express anger manage to offset its adverse electoral effects in areas that are distant from a military base (0.1% effect size).

Importantly, the salience of war-related tweets is not significant, either directly or through its interaction with proximity to military bases. This suggests that, on average, it is not the volume of tweets that impacts voting outcomes, but rather the emotional tone conveyed by candidates. In other terms, in a period when it was not strategic to actively campaign for elections, voters responded more to the emotional content of communication rather than the "quantity" of war-related discourse.

We test the robustness of our results by using the distance from the top-rated beaches on TripAdvisor as a placebo, instead of proximity to U.S. military bases, as detailed in Section 3.5. Results in Table A.3 show no/mild significant effects for Treatment (proximity to U.S. bases), Salience, Emotional tone, or the interactions between Treatment and Salience or Emotional tone. [24]. This further reinforces our argument that proximity to U.S. bases plays a specific role in influencing electoral outcomes, while general geographic factors, such as proximity to popular beaches, do not account for the observed results. We also perform robustness checks using the treatment refinement described in Section 3.4. In this approach, the treatment is defined more strictly, i.e., by comparing municipalities hosting a U.S. base with those most adjacent to them. Results presented in Table A.4 are consistent with our main findings.

5.4 Heterogeneity by political parties

We further test whether the effect of emotional tone and salience on electoral outcomes is driven by a particular group of political parties. We estimate the column

[24] Where we find significant effects, they move in the opposite direction of those observed in the main estimates.

Table 4: Impact of Salience and Emotions on Election Outcomes

	(1)	(2)	(3)	(4)
	Votes (IHS)	*Votes (IHS)*	*Votes (IHS)*	*Votes (IHS)*
Treatment	0.221	0.257**	-0.167	0.230
	(0.277)	(0.128)	(0.228)	(0.284)
Salience	0.151			0.195
	(0.269)			(0.265)
Treatment#Salience	0.141			0.0387
	(0.315)			(0.319)
Fear		-1.340	-1.487*	-1.383
		(0.931)	(0.870)	(0.941)
Treatment#Fear		2.025**	2.307***	2.009**
		(0.801)	(0.758)	(0.789)
Sadness			0.430	
			(0.313)	
Treatment#Sadness			-0.315	
			(0.392)	
Joy			0.0752	
			(0.566)	
Treatment#Joy			0.634	
			(0.566)	
Anger			-0.701**	
			(0.297)	
Treatment#Anger			1.358***	
			(0.320)	
Constant	4.755***	4.875***	4.833***	4.756***
	(0.518)	(0.504)	(0.516)	(0.523)
Region FE	✓	✓	✓	✓
Election Controls	✓	✓	✓	✓
Candidate controls	✓	✓	✓	✓
Observations	77,757	77,757	77,757	77,757
R-squared	0.210	0.212	0.224	0.213

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at electoral district and municipal level in parentheses. The dependent variable in all columns is the number of votes received by each candidate, transformed using the inverse hyperbolic sine (IHS). "Treatment" refers to whether the electoral district's distance from the nearest U.S. military base is below the sample median. "Salience" captures the proportion of war-related tweets relative to other topics. Emotional tone variables ("Fear," "Sadness," "Joy," and "Anger") refer to the emotional classification of candidates' tweets. Interaction terms indicate how proximity to military bases influences the effect of emotional tone and salience on voting outcomes. Robust standard errors are double-clustered at the electoral district and municipality levels. All models include region fixed effects, election controls (e.g., type of election), and candidate controls (e.g., age, gender, party affiliation).

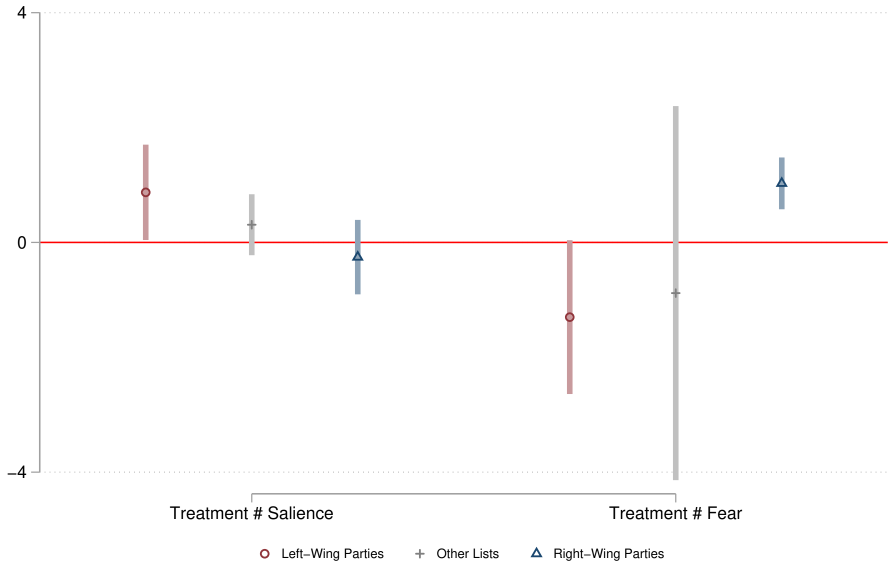
(4) of Table 4 separately for each group.

The results in figure 9 show that the interaction between treatment and salience significantly impacted the vote share only for candidates belonging to left-wing parties, with no significant effects for those belonging to right-wing parties or other groups. This suggests that the prominence of war-related communications, regardless of their emotional tone, influenced voter behavior for left-wing parties. In other words, voters in districts near U.S. bases tend to respond more favorably to candidates from left-wing parties due to the overall attention given to war-related topics rather than the specific emotional content of the messages (0.6% effect size).

In contrast, the interaction between treatment and fear shows a significant positive effect for right-wing parties, while it remains insignificant for left-wing parties and other lists. Thus, the influence of proximity to U.S. military bases on fear-based messaging is stronger for right-wing candidates. Voters in districts close to U.S. bases seem to respond positively to candidates from right-wing parties who express fear in their war-related communications (0.7%).

These results suggest that right-wing parties gained a significant voting advantage by using a communication strategy centered around fear (and, to a lesser extent, anger) when discussing war-related issues, especially in districts near U.S. military bases. Given the lack of evidence that politicians strategically targeted fear-related messaging to districts closer to military bases, they suggest that voters in these areas may have been more receptive to narratives emphasizing the emotional aspects of fear in the context of the war, which aligned more closely with the messaging of right-wing parties. In contrast, left-wing parties appeared to benefit more from the salience of war-related issues in the media, as the significant effect of treatment and salience suggests that their voters were more influenced by the visibility of the war itself rather than the emotional intensity of the messages. Left-wing parties likely capitalized on the heightened visibility of war-related topics to resonate with voters' broader concerns, without relying on fear-based messaging. Therefore, while right-wing parties leveraged fear to gain electoral advantages in districts more exposed to the perceived threat of conflict, left-wing parties benefited from the overall prominence of the war in the media.

Figure 9: Panel Event Study



6 Conclusions

The significance of political issues can swiftly transform in response to evolving events, subsequently influencing socio-economic and political decisions. This study explores the interplay between media attention, issue salience, and individual behaviors within a rapidly evolving global context.

With a specific focus on the media shift from the COVID-19 pandemic to the Russian-Ukrainian war, this research examines the consequences of a health crisis rapidly losing its central position in the public spotlight. Our differences-in-differences event study provides causal evidence on how a sudden shift in media attention substantially influences the dynamics of contagion and generates (unintended) electoral consequences.

Regarding the health consequences of shifting media attention, the rise in contagion we observed is particularly pronounced among younger citizens and in regions with better broadband access, highlighting the crucial role of social media in shaping public concerns. Additionally, we identify a mechanism through which reduced concerns about COVID-19 translate into less protective health behaviors: municipalities with higher exposure, such as those near U.S. military bases, experienced increased mobility soon after the Russian invasion of Ukraine. Thus, the heightened media salience of the war affected mobility patterns, potentially contributing to the observed temporary increase in COVID-19 cases. Furthermore, municipalities with higher exposure also exhibited increased fear of the war—measured by web searches for the term "bunker"—shortly after the invasion.

Concerning the electoral impact of changing media focus, we show how changes in issue salience can reshape political landscapes. Our analysis reveals that right-wing parties skillfully exploited the growing fear of war to gain an electoral advantage, particularly in municipalities near U.S. military bases. In these areas, where the threat of geopolitical conflict was most pronounced, the prominence of war significantly influenced voter sentiment. Residents near U.S. military bases tended to support candidates who addressed war-related anxieties, shifting their backing away from those focused on pandemic concerns. On the contrary, left-wing parties benefited significantly from the increased salience of war-related issues in municipalities close to U.S. military bases. This suggests that voters aligned with left-wing parties were more responsive to the visibility and prominence of the war itself, regardless of the emotional tone of the messaging.

A placebo test using distance from the top-rated beaches on TripAdvisor highlights that mere geographical location around the coasts of the U.S. bases is insufficient to explain the observed health and political outcomes. The lack of significant effects in this test reinforces our main findings: it was the proximity to U.S. military bases—rather than other geo-economic factors—that drove the notable changes in voting behavior and contagion patterns. This proximity heightened the sense of urgency around the war, shaping public and political reactions beyond other geographical features.

Concluding, our findings underscore the pivotal role of issue salience in shaping individual behaviors, which, in this context, results not only in non-negligible health costs to society, but also in significant political consequences. On the one hand, the shift from domestic to foreign policy issues, exemplified by the transition from the COVID-19 pandemic to the Russian-Ukrainian war, played a decisive role in the spread of COVID-19, primarily due to reduced public attention to health protective behaviors and increased fear of a new global conflict. On the other hand, this change has also profoundly influenced political preferences. When war-related concerns eclipsed anxieties about the pandemic, right-wing political parties skilfully exploited these new fears, particularly in the municipalities closest to U.S. military bases, where the importance of the war was most strongly perceived. Voters in these areas gravitated towards candidates who emphasized geopolitical threats over the health crisis, revealing how fear of conflict can quickly reshape electoral preferences. At the same time, left-wing parties benefited from the overall prominence of the war, as voters aligned with them appeared more responsive to the visibility of the conflict in the media, rather than the emotional tone of the messaging.

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A Online Appendix

A.1 Institutional context

U.S. presence in Italy

U.S. military bases in Italy represent a crucial component of the U.S. military presence in Europe and reflect the strategic relationship between the two countries within NATO. Their origin dates back to the end of World War II and the beginning of the Cold War, when Italy and the United States established close military and political cooperation to counter Soviet influence in Europe.

The agreement to establish the bases was formalised with the Treaty of Paris in 1947 and later reinforced by Italy's accession to NATO in 1949. American bases in Italy were initially conceived as a deterrent against a possible Soviet attack, providing logistical and operational support to NATO forces deployed in the European theatre.

Over the years, the number and importance of U.S. bases in Italy have varied in response to global geopolitical dynamics. In 2013, U.S. military personnel stationed in Italy numbered approximately 13,000, spread across several strategic installations.

In addition to their strategic function, U.S. military bases in Italy have a significant impact on local economies and surrounding communities. The military presence has led to infrastructure investments, job creation, and the development of cultural and social relations between U.S. military personnel and the Italian population.

Over the years, the presence of the bases has been debated both politically and among the Italian public. Some sectors criticise the limited sovereignty implicit in the presence of foreign troops, while others emphasise the economic and security benefits of cooperation with the United States. An example of this complex relationship is Sardinia, where the extensive presence of military installations has aroused both local opposition and economic dependence.

Sardinia is a special case but can show how salient the issue of U.S. bases in Italy is. The region hosts several important US and NATO military installations, including the bases at Decimomannu and the Capo Teulada training range. These bases are an integral part of NATO operations in the Mediterranean and provide essential training grounds for air and naval forces. However, the presence of these bases has also led to significant local opposition, mainly due to environmental concerns, health risks and the impact on local communities [25]. Protests and calls for the reduction or removal of military activities have been continuous, reflecting a broader feeling of frustration and resistance among Sardinians.

On the other hand, the economic benefits of the military presence cannot be ignored. Bases contribute to local economies through direct and indirect employment, contracts with local businesses and infrastructure development. This economic dependence creates a complex dynamic in which local communities must balance the tangible economic benefits with the perceived disadvantages of hosting foreign military installations.

All these elements make the issue of U.S. bases particularly relevant for local communities, where people not only recognise the presence of bases as an element of historical interest, but are also influenced by their advantageous/disadvantageous role in the present.

The electoral system and context of the 2022 Italian national elections

The 2022 Italian general elections, held on September 25, were called unexpectedly following the resignation of Prime Minister Mario Draghi in July 2022. Draghi's government, a broad coalition formed to stabilize the country amid political and economic crises, collapsed after key parties withdrew their support during a confidence vote. This led to the early dissolution of Parliament and elections being called several months ahead of the original schedule. The sudden nature of the elections underscored the volatility of Italian politics, where coalition instability frequently disrupts governance.

These elections were the first held after the 2020 constitutional reform, which significantly reduced the number of seats in both chambers of Parliament. The Chamber of Deputies was cut from 630 to 400 members, and the Senate from 315 to 200. This reduction reshaped the electoral landscape by concentrating competi-

[25]See this article as a direct example.

tion into fewer seats and requiring a redrawing of electoral districts (circoscrizioni) across the country.

The electoral system, known as the "Rosatellum-bis", is a mixed system combining both majoritarian and proportional components. 37% of the seats in both the Chamber and the Senate were allocated through a first-past-the-post system in single-member constituencies. For the Chamber of Deputies, this included 147 seats, while the Senate allocated 74 seats in this manner. In each constituency, the candidate who received the most votes was elected. The remaining 61% of the seats were distributed through proportional representation, where voters cast their votes for party lists in multi-member constituencies. This component allocated 245 seats in the Chamber and 122 seats in the Senate. Additionally, 2% of seats in both houses were reserved for Italians living abroad, with 8 seats in the Chamber and 4 in the Senate.

The structure of electoral districts reflects the varying population densities across Italy. In large urban centers such as Rome, Milan, and Naples, constituencies are smaller in geographic size but have more seats due to the higher concentration of voters. In contrast, rural areas and smaller towns are grouped into larger constituencies that cover wider areas but elect fewer representatives. This design aims to ensure balanced representation across different regions, from densely populated cities to sparsely populated rural areas.

The voting process in 2022 involved a single ballot for each chamber, allowing voters to select both a candidate in the single-member constituency (majoritarian component) and a party list (proportional component). Importantly, the electoral system does not allow for split-ticket voting, meaning voters could not choose a candidate from one coalition and a party list from another. Votes cast for a candidate in the majoritarian race were automatically linked to the proportional vote for the party list supporting that candidate.

To reduce the fragmentation of Parliament, the system introduced electoral thresholds. Parties had to secure at least 3% of the national vote to qualify for proportional representation seats, while coalitions needed to reach 10%. Within coalitions, individual parties still had to meet the 3% threshold for their votes to contribute to the coalition's total seat distribution.

A.2 Test for parallel trends

The following model is taken by Luedicke (2022).

Let $d_{w,0} = 1(d_w = 0)$ be a variable indicating pretreatment time periods, and let $d_{w,1} = 1(d_w = 1)$ be a variable indicating posttreatment time periods. Also, let η_m be a variable that is 1 if the individual belongs to a treated group and is 0 otherwise. The augmentation terms then consist of two 3-way interactions between $d_{w,0}$, δ_m, and w, and $d_{w,1}$, δ_m, and w.

$$y_{mw} = DID_{mw} + \eta_m d_{w,0} w \zeta_1 + \eta_m d_{w,1} w \zeta_2 + \epsilon_{mw}$$

The DID_{mw} is defined in equation 2. In this particular specification, the coefficient ζ_1 provides the difference in slopes between the treatment group and the control group during pretreatment periods, while ζ_2 captures the difference in slopes during posttreatment periods. A value of ζ_1 equal to 0 indicates that the linear trends in the outcome are parallel during pretreatment periods. The same principle applies to ζ_2 concerning the posttreatment period. However, differences in posttreatment trends do not hold significance in the evaluation of the parallel-trends assumption.

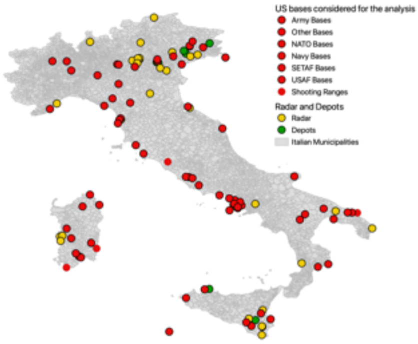
Table A.1: Query List for Twitter API

```
query_War='Ucraina Russia Guerra Conflitto Invasione Donetsk Luhansk Crimea Crisi Militare Tensione
↪  Separatisti Rifugiati Cessateilfuoco Donbas Frontiera Aggiornamenti Ribelli Occupazione Sanzioni
↪  Putin Zelensky Lukashenko Nato US Biden Bielorussia'

query_COVID19='COVID Covid-19 Vaccino Pandemia Coronavirus Varianti Contagio Lockdown Mascherine
↪  Vaccinazione Immunizzazione Isolamento Quarantena Sintomi Trattamenti Epidemia Test PCR Anticorpi
↪  Delta Vaccinato Immunità Passaporto Green Pass Effetti collaterali Dosi Somministrazione Variante
↪  Efficacia Omicron'
```

Figure A.1: Spatial Distribution of U.S. bases

(a) U.S. bases in Italy



(b) U.S. bases for the analysis

Figure A.2: Panel Event Study - Intensive margin

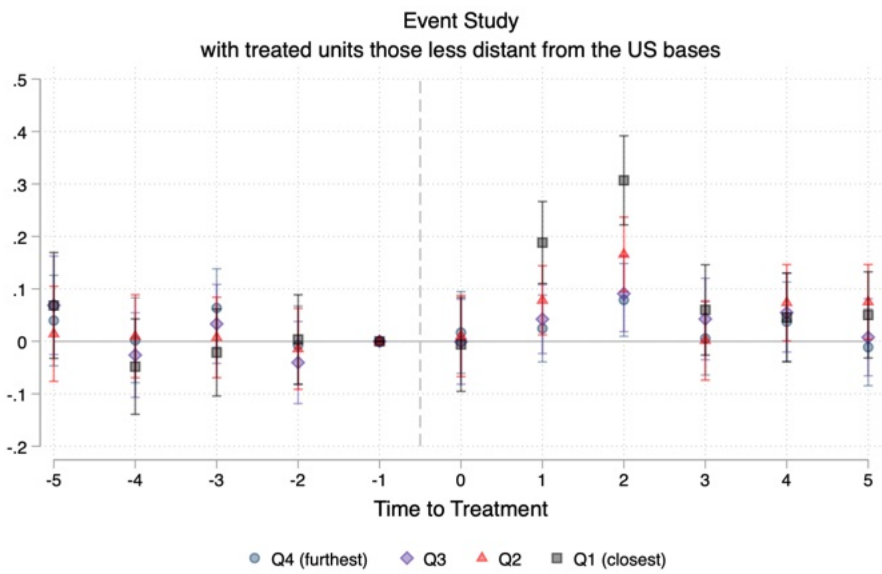


Table A.2: Heteregenous Effects by Age group - Robustness controlling for Log Incidence Pre x Post

	Age Group				
	0-19	20-39	40-59	60-79	80+
Lag -5	0.0804***	-0.00183	-0.00267	0.00568	-0.0132
	(0.0212)	(0.0181)	(0.0187)	(0.0132)	(0.0105)
Lag -4	0.0180	-0.0251	-0.0159	-0.00173	0.00429
	(0.0192)	(0.0162)	(0.0174)	(0.0118)	(0.00909)
Lag -3	0.00714	-0.00186	0.00963	0.0160	0.0114
	(0.0172)	(0.0146)	(0.0147)	(0.0114)	(0.00914)
Lag -2	0.0190	-0.00461	0.00264	-0.00295	-0.00748
	(0.0176)	(0.0155)	(0.0160)	(0.0121)	(0.0100)
Lead 0	0.0210	-5.87e-06	-0.0193	8.88e-05	-0.00664
	(0.0175)	(0.0156)	(0.0159)	(0.0121)	(0.00954)
Lead +1	0.0477***	0.0239*	0.0366***	0.00460	-0.00397
	(0.0145)	(0.0129)	(0.0134)	(0.00979)	(0.00776)
Lead +2	0.0735***	0.0557***	0.0502***	0.0347***	0.00333
	(0.0159)	(0.0135)	(0.0141)	(0.0107)	(0.00833)
Lead +3	0.0195	0.00231	-0.000204	-0.00103	0.00145
	(0.0156)	(0.0154)	(0.0154)	(0.0120)	(0.00876)
Lead +4	0.0335**	0.00656	0.00154	-0.00830	-0.00320
	(0.0160)	(0.0146)	(0.0159)	(0.0115)	(0.00896)
Lead +5	0.0268*	-0.00760	0.0118	0.0132	-0.00541
	(0.0145)	(0.0143)	(0.0148)	(0.0122)	(0.00884)
Log(Incidence)	0.00168	0.00429*	0.000124	-0.000183	-0.000673
× Post	(0.00265)	(0.00233)	(0.00268)	(0.00131)	(0.00139)
Municipality FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Region X Time FE	✓	✓	✓	✓	✓
Observations	63316	63382	63668	63107	60962

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at municipal level in parentheses. This table presents the estimated coefficients from a differences-in-differences event study model assessing the impact of age groups on the treatment effect. The dependent variable is the inverse hyperbolic sine (IHS) transformation of the weekly count of new COVID-19 cases. The main independent variable is an interaction term between the treatment indicator (whether the municipality is below the median distance from a US military base) and week dummies (Lead and Lag indicators, where "Lag -5" refers to five weeks before treatment, and "Lead +5" refers to five weeks after treatment). The coefficients represent the effect of the treatment relative to the reference period, which is "Lag -1" (one week before the treatment).

Table A.3: Impact of Salience and Emotions on Election Outcomes - Placebo using distance from 'Top Rated Beaches' on TripAdvisor

	(1)	(2)	(3)	(4)
	Votes (IHS)	*Votes (IHS)*	*Votes (IHS)*	*Votes (IHS)*
Distance from TripAdvisor	-0.290	0.177	0.307	-0.337
	(0.640)	(0.185)	(0.547)	(0.648)
Salience	0.143			0.0721
	(0.525)			(0.535)
Distance from TripAdvisor#Salience	0.511			0.631
	(0.795)			(0.804)
Fear		1.217	1.518	1.202
		(0.889)	(1.173)	(0.890)
Distance from TripAdvisor#Fear		-3.159*	-2.804	-3.502*
		(1.889)	(1.951)	(1.885)
Sadness			0.494	
			(0.913)	
Distance from TripAdvisor#Sadness			1.184	
			(1.038)	
Joy			-1.203	
			(0.953)	
Distance from TripAdvisor#Joy			2.524**	
			(1.151)	
Anger			0.450	
			(0.732)	
Distance from TripAdvisor#Anger			-1.937**	
			(0.843)	
Constant	8.241***	8.137***	7.596***	8.179***
	(1.381)	(1.263)	(1.404)	(1.386)
Province FE	✓	✓	✓	✓
Election Controls	✓	✓	✓	✓
Candidate controls	✓	✓	✓	✓
Observations	16,772	16,772	16,772	16,772
R-squared	0.292	0.292	0.324	0.294

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at electoral district and municipal level in parentheses. The dependent variable in all columns is the number of votes received by each candidate, transformed using the inverse hyperbolic sine (IHS). "Distance from TripAdvisor" refers to the electoral district's proximity to the top-rated beaches listed on TripAdvisor, used as a placebo for the treatment variable in this analysis. "Salience" captures the proportion of war-related tweets relative to other topics, and the emotional tone variables ("Fear," "Sadness," "Joy," and "Anger") refer to the emotional content of candidates' tweets. Interaction terms show how proximity to top-rated beaches interacts with salience and emotional tone. All models include province fixed effects, election controls (e.g., type of election), and candidate controls (e.g., age, gender, party affiliation).

Table A.4: Impact of Salience and Emotions on Election Outcomes - Treatment refinement

	(1)	(2)	(3)	(4)
	Votes (IHS)	*Votes (IHS)*	*Votes (IHS)*	*Votes (IHS)*
Municipalities with US base	0.722*	0.896***	0.870**	0.736*
	(0.387)	(0.151)	(0.333)	(0.381)
Salience	-1.297***			-1.379***
	(0.433)			(0.428)
Municipalities with US base#Salience	0.321			0.247
	(0.485)			(0.492)
Fear		2.147***	0.610	2.339***
		(0.312)	(0.952)	(0.325)
Municipalities with US base#Fear		0.835	0.884	0.724
		(0.770)	(0.942)	(0.806)
Sadness			-1.977	
			(1.301)	
Municipalities with US base#Sadness			0.664	
			(0.555)	
Joy			-0.223	
			(0.662)	
Municipalities with US base#Joy			-0.797	
			(0.792)	
Anger			-0.0754	
			(0.880)	
Municipalities with US base#Anger			-0.0104	
			(0.655)	
Constant	7.528***	7.087***	6.868***	7.451***
	(1.756)	(1.680)	(1.478)	(1.697)
Province FE	✓	✓	✓	✓
Election Controls	✓	✓	✓	✓
Candidate controls	✓	✓	✓	✓
Observations	839	839	839	839
R-squared	0.464	0.463	0.479	0.480

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at electoral district and municipal level in parentheses. The dependent variable in all columns is the number of votes received by each candidate, transformed using the inverse hyperbolic sine (IHS). "Municipalities with US base" refers to the treatment refinement shown in section 3.4. "Salience" captures the proportion of war-related tweets relative to other topics, and the emotional tone variables ("Fear," "Sadness," "Joy," and "Anger") refer to the emotional content of candidates' tweets. Interaction terms show how municipalities hosting a US base interacts with salience and emotional tone. All models include province fixed effects, election controls (e.g., type of election), and candidate controls (e.g., age, gender, party affiliation).

Figure A.3: Panel Event Study comparing below mean, first quartile and first decile

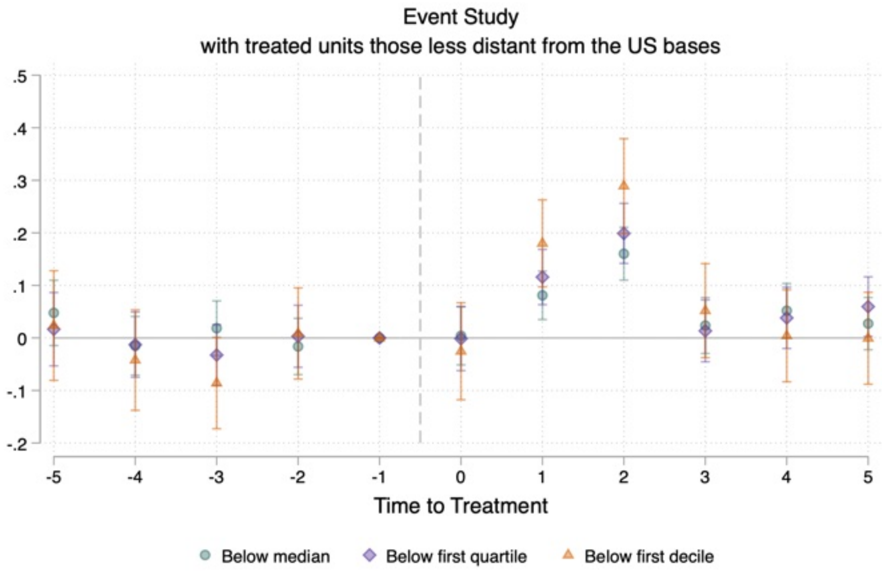


Figure A.4: Parallel trends

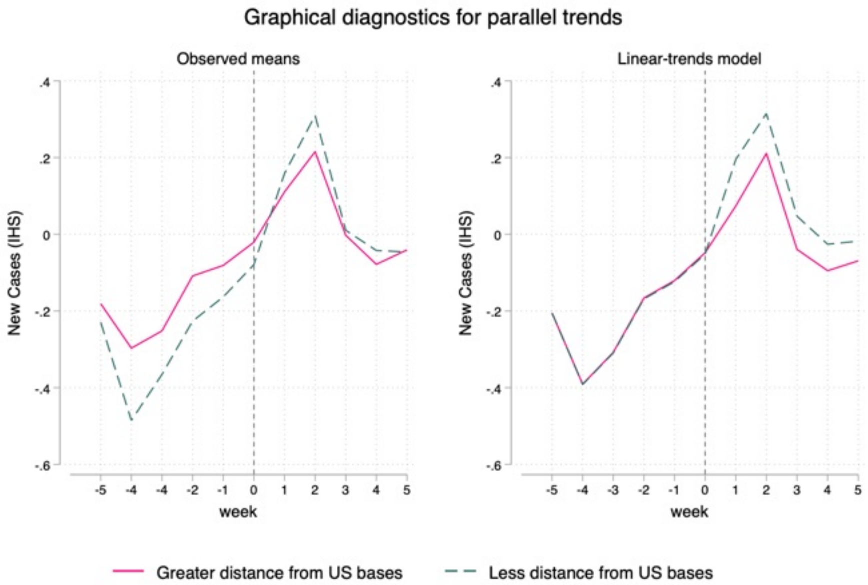


Figure A.5: Differences-in-Differences Event Study Estimates ("<4" as 3)

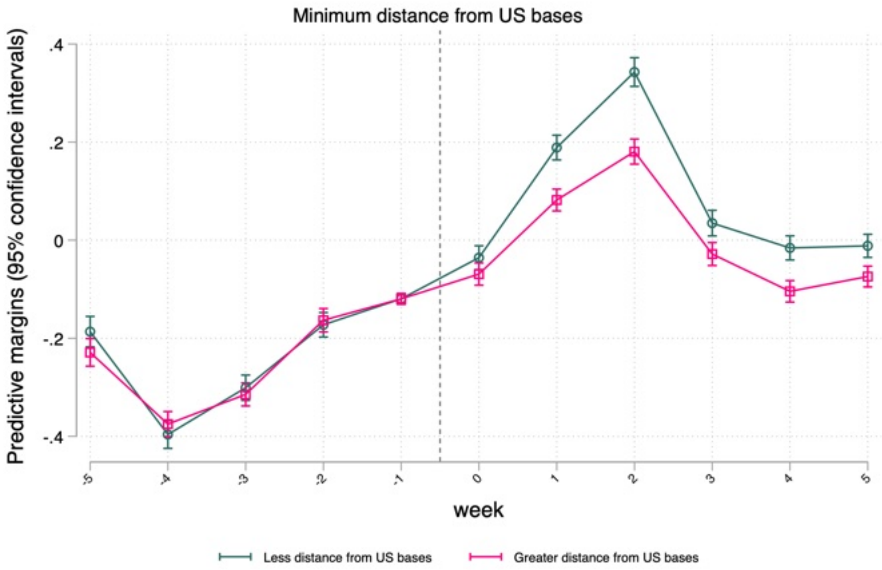


Figure A.6: Panel Event Study ("<4" as 3)

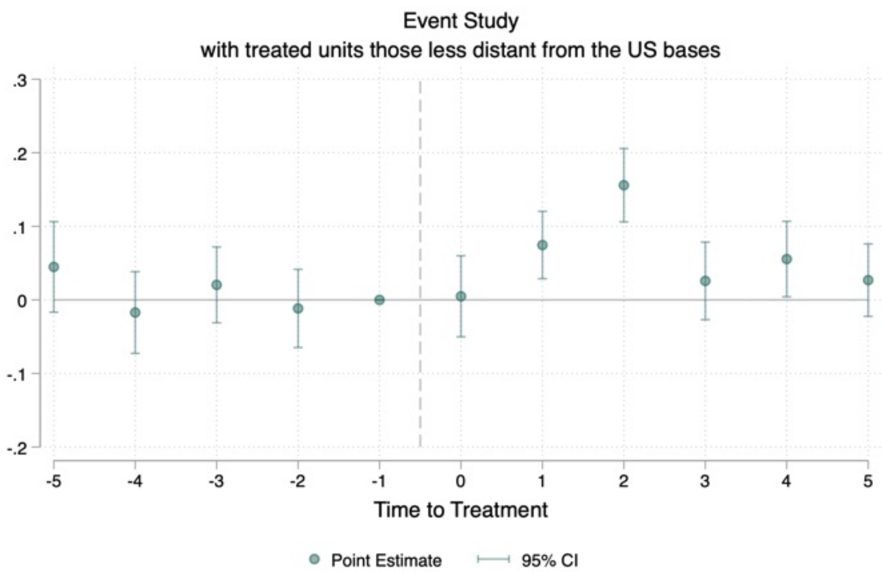


Figure A.7: Differences-in-Differences Event Study Estimates (“<4" as 1)

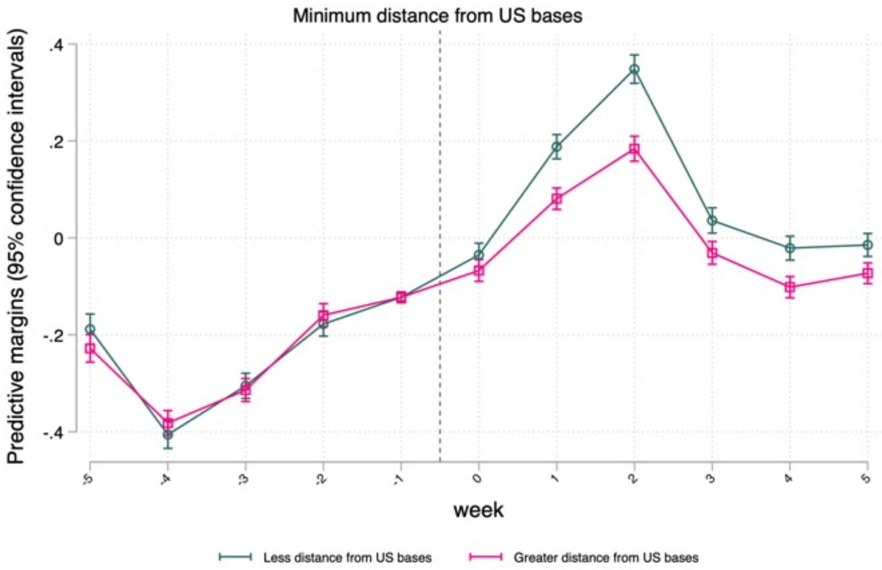


Figure A.8: Panel Event Study (“<4" as 1)

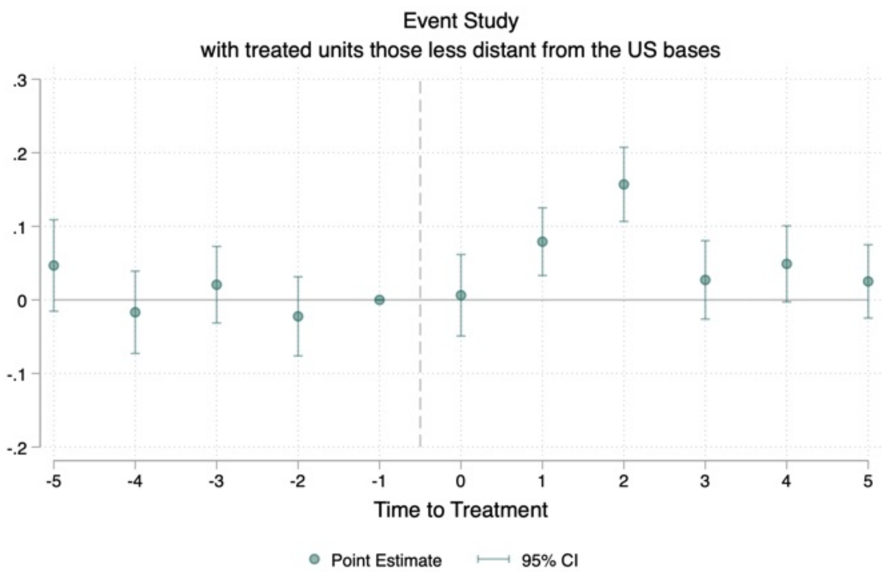


Figure A.9: Panel Event Study not considering city with an U.S. base (<10km)

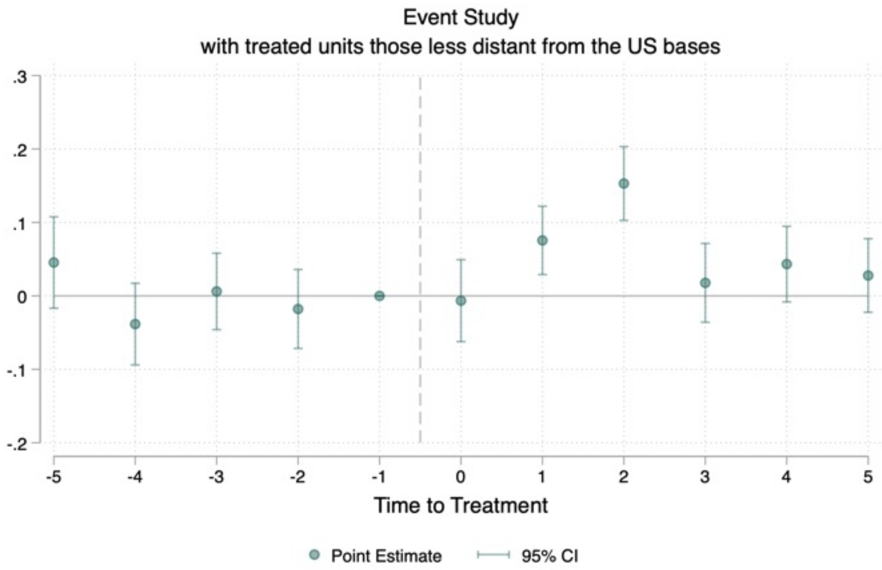


Figure A.10: Differences-in-Differences Event Study Estimates

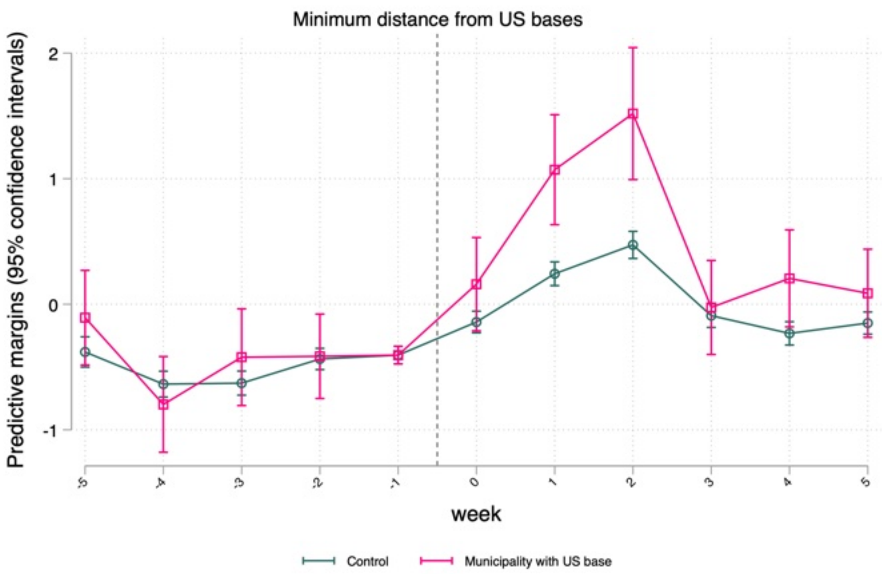


Figure A.11: Panel Event Study

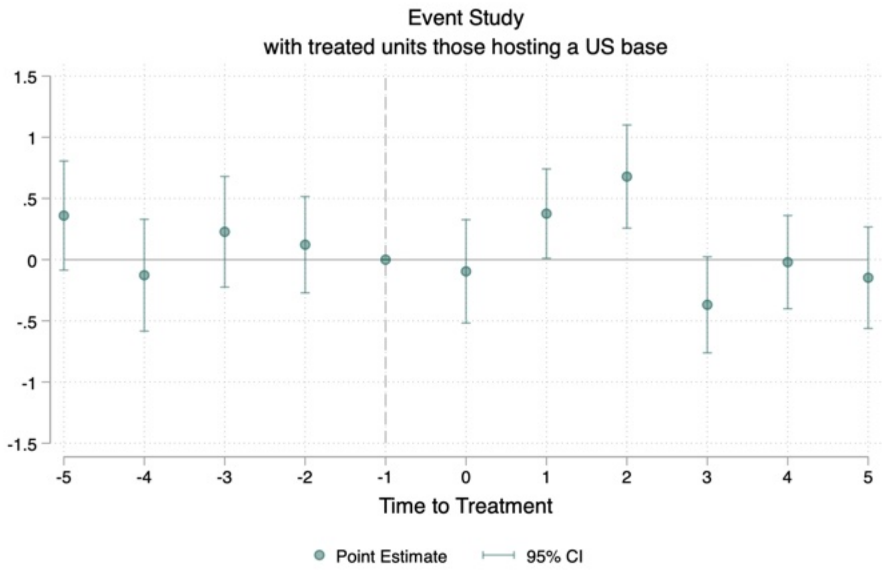


Figure A.12: Spatial Distribution of 'Top Rated Beaches' on TripAdvisor

Figure A.13: Panel Event Study - Placebo using distance from 'Top Rated Beaches' on TripAdvisor

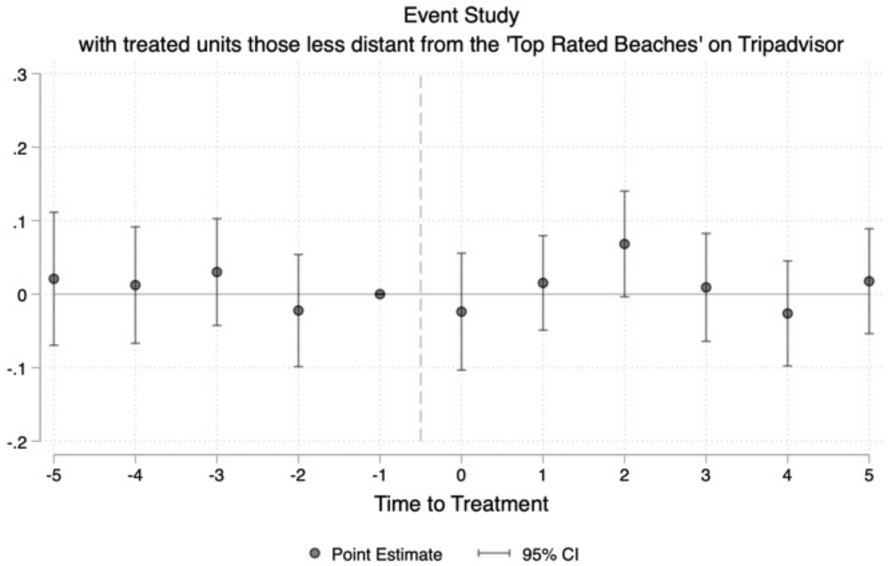


Figure A.14: Spatial Distribution of Italian Military Regiments

Figure A.15: Panel Event Study - Placebo using distance from Italian Military Regiments

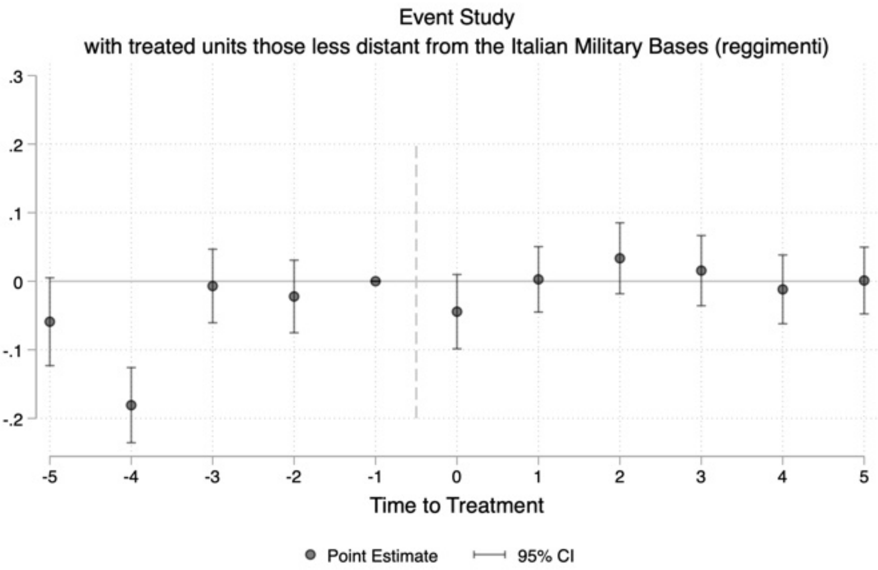


Figure A.16: Panel Event Study - Placebo using fake treatment year (2021)

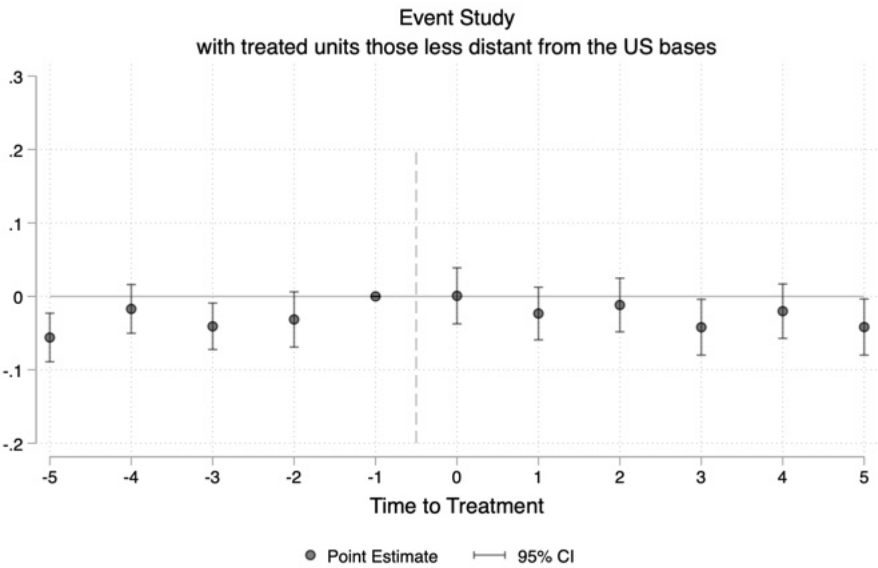
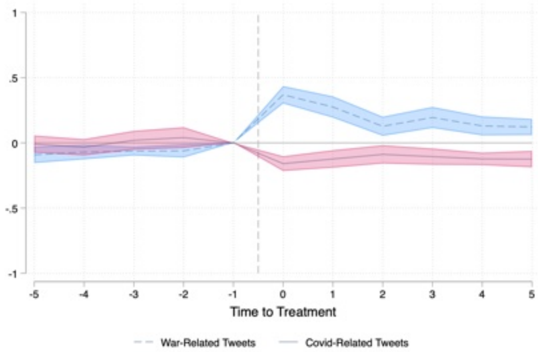
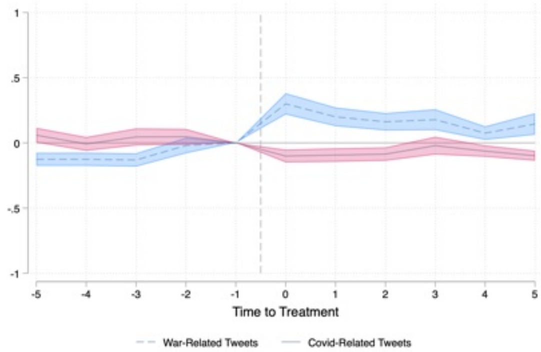


Figure A.17: Salience and Fear Event Study

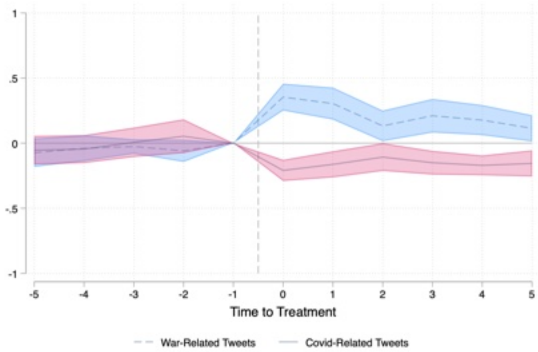
(a) Salience - All parties



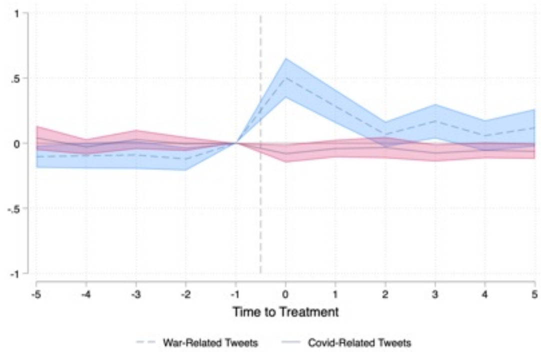
(b) Salience - Other Lists



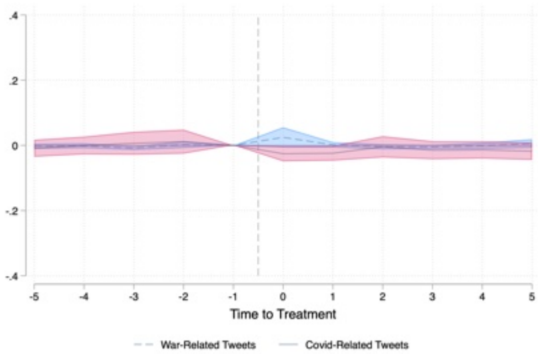
(c) Salience - right-wing parties



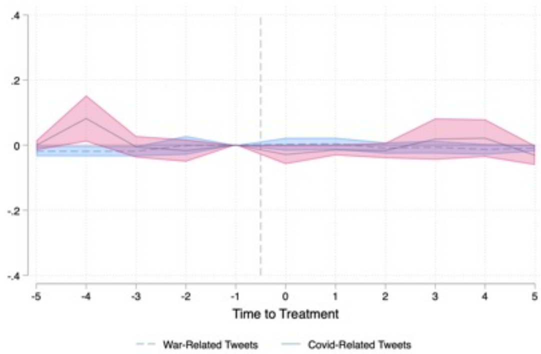
(d) Salience - left-wing parties



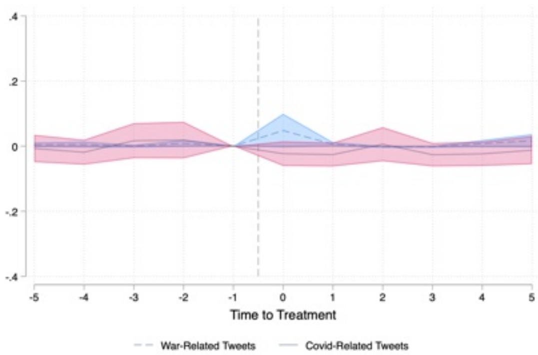
(e) Fear - All parties



(f) Fear - Other lists



(g) Fear - right-wing parties



(h) Fear - left-wing parties

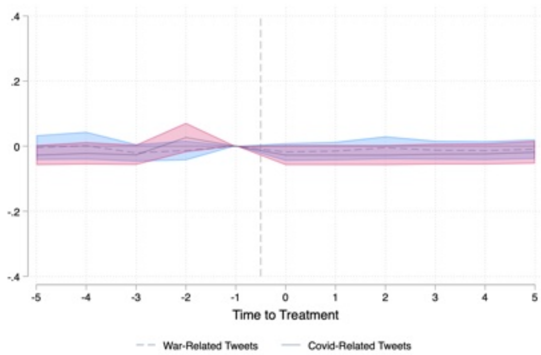
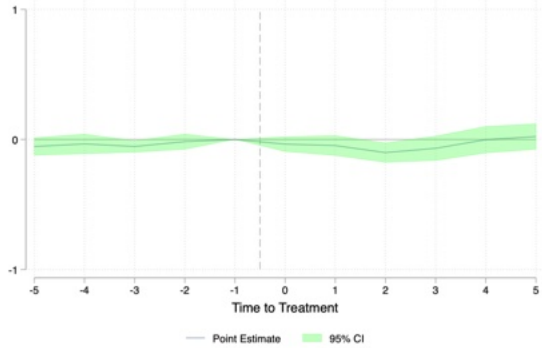
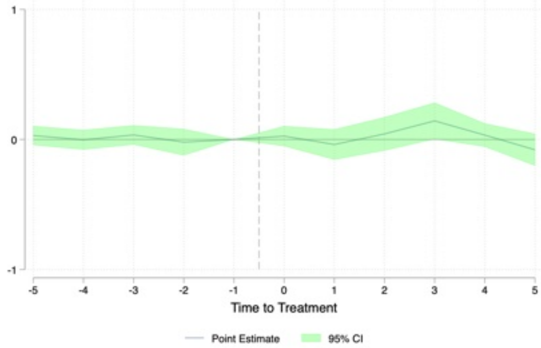


Figure A.18: Random test: Salience and Fear Event DID Study

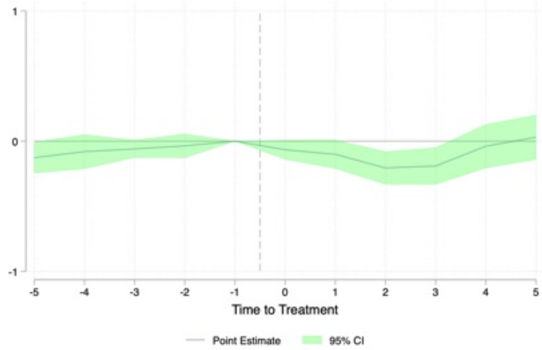
(a) Salience - All parties



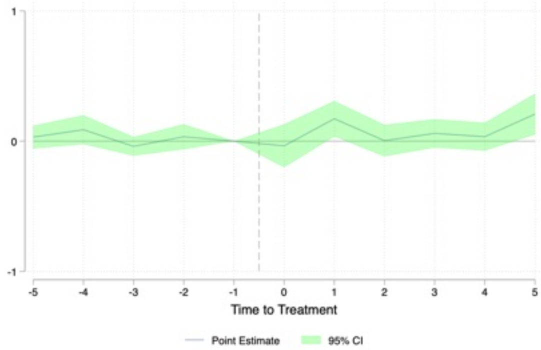
(b) Salience - Other lists



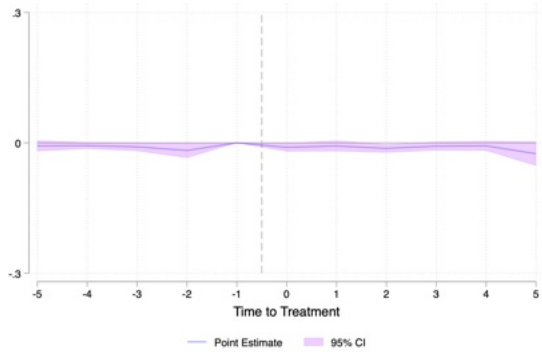
(c) Salience - right-wing parties



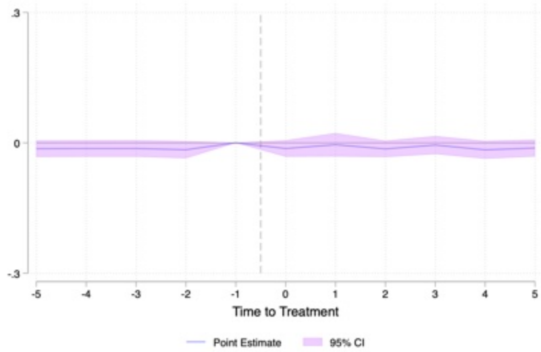
(d) Salience - left-wing parties



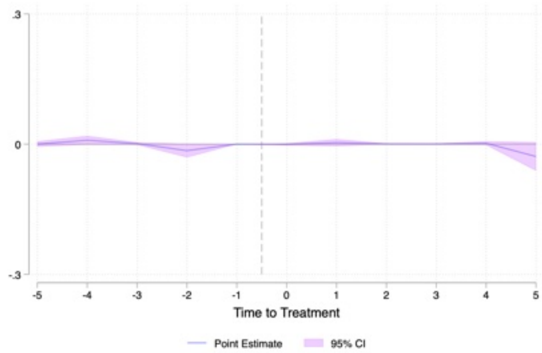
(e) Fear - All parties



(f) Fear - Other lists



(g) Fear - right-wing parties



(h) Fear - left-wing parties