

When War Crowds Out the Pandemic: The Health and Political Effects of Media Attention Shift

Gianluigi Conzo*

Pierluigi Conzo[†]
(Speaker)

[†]University of Turin (ESt Cognetti de Martiis) & Collegio Carlo Alberto

*Tor Vergata University of Rome & University of Turin (ESOMAS)

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Motivation

- ▶ 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)

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 - ↪ Prompting citizens to reassess their priorities and perceptions of political issues (Casero-Ripollés, 2020)

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- ▶ What are the effects of such a rapid change in media attention?
- ▶ This paper provides causal evidence on how media-driven shift in public attention can shape citizens' health and political behavior
- ▶ Research questions:
 - ↔ Health behaviors:
 - ▶ Does the decreased salience of COVID-19 lead to a rise in contagion?
 - ↔ Political outcomes:
 - ▶ Do politicians use different political messaging at the onset of the war?
 - ▶ Does this turn into differential electoral benefits in later *unexpected* political elections?

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- ▶ **Setting:** Italy 5 weeks before/after the start of the Russian-Ukrainian war & Italian national elections (September)
- ▶ **Data:** Covid-19 cases at municipal level (ISS); Spatial data on Google Maps; Twitter data; Electoral data
- ▶ **Approach:** Identify as a shock of salience the proximity to US military bases
 - ▶ DID comparing municipalities closer and far from US bases before and after the start of the war
 - ▶ why US bases?
 1. NATO intervention frequently discussed in public debates
 2. NATO bases in Italy mostly framed as American in media outlets
 - ▶ closer to US bases → ↑ higher war salience / proximity to war
 - ▶ OLS analyzing the impact of politicians' messages at the onset of the war on later electoral outcomes

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Preview of results

► Health Impact

- ↔ Differential increase in COVID-19 cases in municipalities closer to U.S. military bases after the media shift
 - Effects more pronounced among young and young adult citizens
 - ...and driven by municipalities with better access to broadband services
- ↔ Increased Google searches for "bunker" and larger mobility ⇒ fear of a new international conflict reduced attention to COVID-19

► Political Impact

- ↔ Differential political messaging between right- and left-wing parties at the onset of the war
- ↔ Political messaging is orthogonal to the location of US bases (no strategic political campaign)
 - Right-wing parties gained electoral advantages in war-affected areas by relying on emotional messaging (war)
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Outline of Talk

1. Contribution to the Literature
2. Descriptive change in salience
3. Data Construction
Distance to US bases
4. Empirical Strategy and Results
Media framing of NATO-related bases in Italy
Effect on Health Behaviors (contagion)
5. Heterogeneity and Mechanisms
6. Electoral consequences of shifting media attention
Salience and Emotional Tone in Politicians' Tweets 
7. Conclusion

Contribution to the Literature

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► Political Consequences:

- ↪ Builds on studies of media shifts and voter behavior during campaigns and media changes (Strömberg, 2004; Gentzkow, 2006; Snyder Jr and Strömberg, 2010; Drago et al., 2014; George and Waldfogel, 2008; Campante et al., 2018; Gavazza et al., 2019; Caprini, 2023; Durante et al., 2019; Djourelova and Durante, 2022)
- ↪ Focuses on a **single, unexpected event**, providing novel evidence on how a sudden media shift can reshape broader political preferences in an unanticipated context

► Public Health Behaviors:

- ↪ Provides causal evidence on how a **limited but critical shift in media attention** affects **public health behaviors**, particularly adherence to health-protective measures (Wakefield et al., 2010)

► Emotional Content and Fear:


- ↪ Highlights the role of **fear-based messaging**, distinct from volume of coverage (Gentzkow and Shapiro, 2010; Larcinese et al., 2011; Sobbrío, 2014)
- ↪ Shows how **emotional narratives** on social media amplify effects on political and health behaviors (Bakshy et al., 2015; Flaxman et al., 2016; Enikolopov et al., 2020; Allcott et al., 2020)

Descriptive change in salience

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Salience of pandemic vs. salience of war


Social Media

- ▶ We collected Italian Twitter data, using the Twitter  API for Academic Research
- ▶ 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 [▶ Query List](#)
- ▶ Each tweet includes text, ID, timestamp, and engagement metrics (likes, retweets, replies, hashtags)

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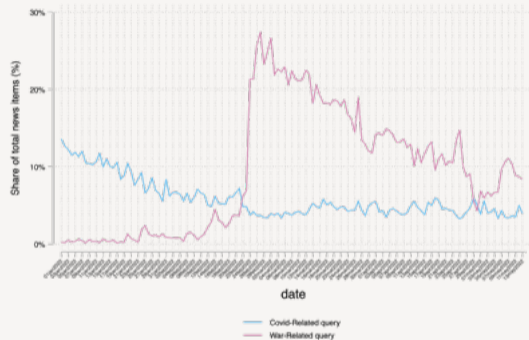
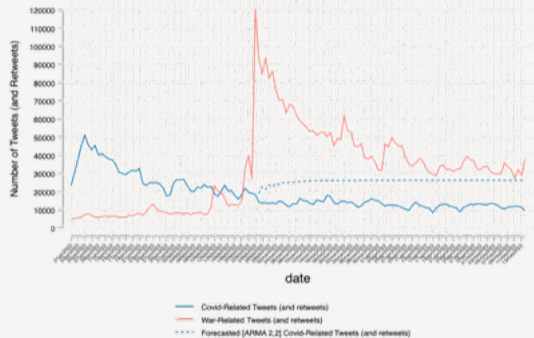
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Traditional media (online newspapers)

- ▶ Used Media Cloud (national local outlets) to track coverage
- ▶ Built daily counts of articles with any COVID-19 vs. any Russia–Ukraine war query [▶ Query List](#)
- ▶ Divided by total articles per day to get comparable salience shares

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Data Construction

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2. To examine the impact of proximity to military bases, we used data from Google Maps to pinpoint exact locations and calculated the distance to each municipality using Q-Gis

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 - ↪ We then scrape through Google Maps in order to extract the exact locations of these bases and calculated the distance between each municipality and the nearest US base

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Distance to US bases



Figure: US bases in Italy

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- We excluded Radar stations and depot bases and focused on the distance to all other bases

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 - ↪ Radars are often represented by antennas
 - ↪ Depot bases are typically underground

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Figure: US bases for the analysis

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Figure: US bases for the analysis

- For each municipality we extract the exact centroid

Data Construction

Distance to US bases



Figure: US bases - Italian Centroids

Data Construction

Distance to US bases



Figure: US bases - Italian Centroids

- We computed the shortest distance between Italian municipalities (centroids) and the nearest US base

Data Construction

Distance to US bases

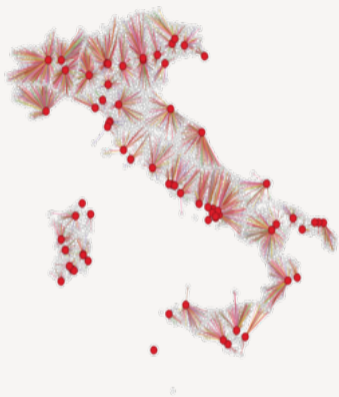


Figure: Minimum Distance

Data Construction

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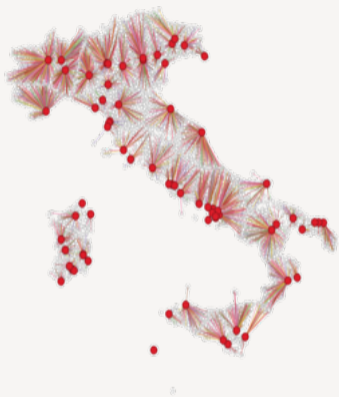


Figure: Minimum Distance

- We obtain an index of proximity to US bases that we split into 4 quartiles

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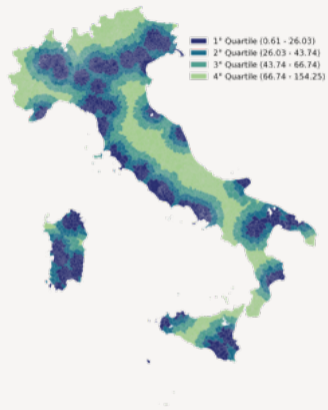
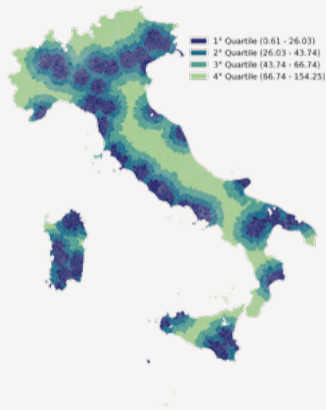


Figure: Index of proximity to US bases

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Distance to US bases



- Finally we construct our treatment as a dummy variable

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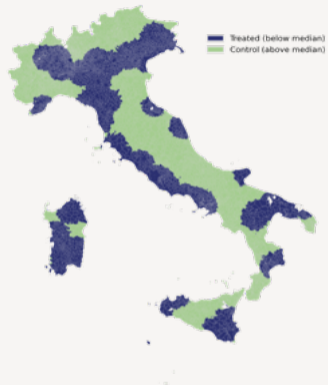
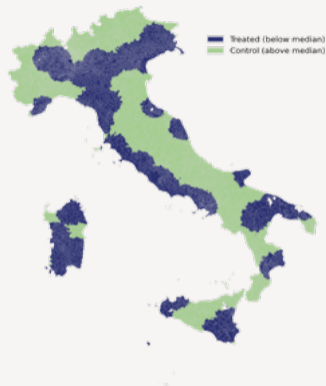


Figure: Treatment (Above/Below Median)

Data Construction

Distance to US bases



- ▶ We consider a municipality:
 - ↪ Treated if the municipality is close to the US base (below median)
 - ↪ Control if the municipality is far from the born base (above median)

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Empirical Strategy and Results

Media framing of NATO-related bases in Italy

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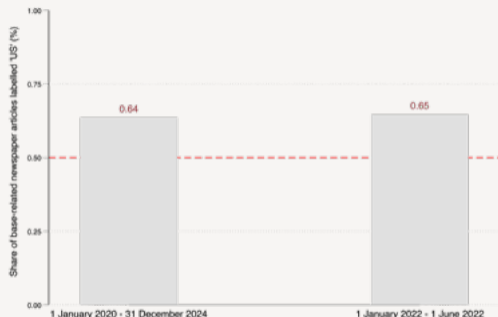
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Empirical Strategy

Effect on Health Behaviors (contagion)

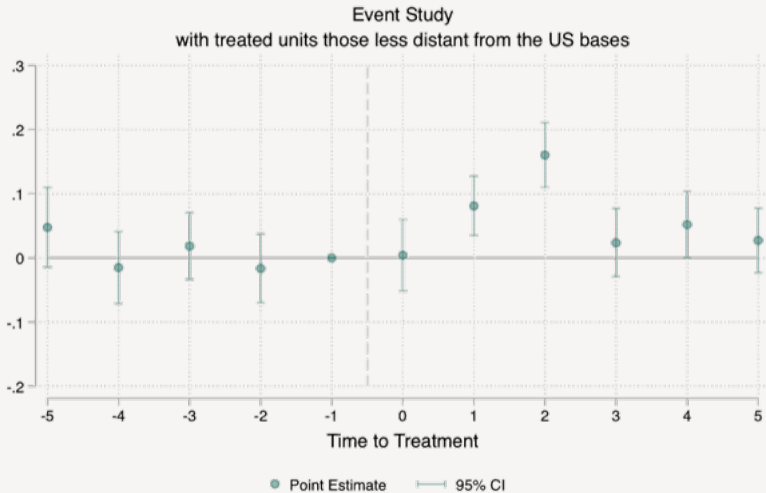
To estimate the impact of the reduced salience of COVID-19 caused by the Ukraine-Russia conflict on the number of COVID-19 cases, we rely on a dynamic DiD framework:

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

- ▶ y : New Covid Cases (IHS)
- ▶ **Treat**: Municipalities less distant from US bases (below median)
- ▶ X' : A battery of baseline controls at municipal level interacted with dummy Post (Baker et al., 2025)
- ▶ $\theta_m, \gamma_w, \phi_{r,w}$ are respectively municipality, week and region by week fixed effects
- ▶ Error clustered at Municipal level

Results

Effect on Health Behaviors (contagion)



Some Robustness

Effect on Health Behaviors (contagion)

- ▶ **Treatment refinement:** Compare treated units, those hosting a US base, with a subset of control units composed by municipalities bordering those hosting a US base [▶ Results](#) [▶ Spatial Distribution](#)
- ▶ **Continuous treatment**
- ▶ **Falsification test:**
 1. Distance from TripAdvisor 🏖️ “Top Rated Beaches” [▶ Results](#) [▶ Spatial Distribution](#)
 2. Distance from Italian Military Bases (Reggimenti) [▶ Results](#) [▶ Spatial Distribution](#)
 3. In-time placebo - using Fake treatment time 2021 [▶ Results](#)
- ▶ Excluding from the sample of cities that host a US base [▶ Results](#)
- ▶ COVID-19 cases marked as “< 4” by ISS: as 3 [▶ Results](#) - as 1 [▶ Results](#) [▶ Dataset ISS](#)
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Heterogeneity and Mechanisms

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Heterogeneity ▶ Results

▶ Age groups:

- ↪ Younger people tend to rely more on **social media**, which may amplify the shift in media attention
- ↪ Older individuals depend more on traditional media, resulting in a smaller effect

▶ Broadband Access:

- ↪ Stronger effects in areas with better internet connectivity
- ↪ Suggests that access to online platforms amplifies the media shift's impact

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Mechanism ▶ Construction ▶ Results

▶ Mobility Patterns:

- ↪ Google Mobility data
 - ▶ Decline in perceived threat [⇒ Risk-salience attenuation]
 - ▶ Expecting catastrophic event of a world war [⇒ Consumption anticipation]

▶ Fear

- ↪ Google Trends data
 - ▶ Fear-related searches (e.g., "bunker") after the invasion for municipalities closer to US military base

Electoral consequences of shifting media attention

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Context

- ▶ Unexpected national elections on September 25, 2022 (after Draghi government crisis)



Electoral Consequences of Shifting Media Attention

Context

- ▶ **Unexpected national elections** on September 25, 2022 (after Draghi government crisis)
- ▶ Right-wing coalition led by Giorgia Meloni won with 44% of the vote
- ▶ The war significantly shaped the political campaign, particularly on Italy's role in supporting Ukraine



Electoral consequences of shifting media attention

- ▶ We analyze how **votes in the national elections**—held **seven months after Russia's invasion of Ukraine**—were influenced by the **volume and tone** of candidates' social-media messaging at the onset of the war
- ▶ We test whether this emphasis and sentiment gave an **electoral advantage** in districts where perceived threats were higher during the first weeks, namely those **closest to U.S. military bases**
- ▶ *Exogeneity check: Pre-candidacy messaging is orthogonal to distance (districts assigned later by the party) ⇒ no location-targeted campaigning*
 - ↔ Politicians' messaging on war, in areas where they are later nominated as candidates, does not vary with proximity to U.S. military bases
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- ▶ *Exogeneity check*: **Pre-candidacy** messaging is orthogonal to distance (*districts assigned later by the party*) ⇒ no location-targeted campaigning
 - ↪ Politicians' messaging on war, in areas where they are later nominated as candidates, does not vary with proximity to U.S. military bases
- ▶ Which messaging? We focus on **Salience** (share of *war* vs. *COVID-19* tweets) and **Emotional tone** (fear, anger, joy, sadness) in the **first three weeks** after the invasion

Salience and Emotional Tone in Politicians' Tweets

- ▶ We restrict our analysis to tweets from politicians who later became candidates in the September 2022 national election
- ▶ “FEEL-IT: Emotion and Sentiment Classification for the Italian Language” (Blanchi et al., 2021) to assess the sentiment of each tweet

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

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Electoral consequences of shifting media attention

► Dynamics of Salience and Fear:

- ↪ **Salience:** All political groups increased focus on war-related topics, but **right-wing parties** showed the largest increase in war-related tweets, reducing attention on COVID-19 [► Results](#)
- ↪ **Fear:** Right-wing parties uniquely adopted fear-based messaging, with a spike in fear-related tweets immediately after the war outbreak [► Results](#)
- ↪ **Left-wing and other parties:** More stable communication pattern, focusing on the war but without the emphasis on fear. More neutral messages in tone compared to right-wing parties

► Exogeneity Check:

- ↪ Proximity to U.S. military bases did not systematically influence the volume or emotional tone of politicians' tweets, supporting the exogeneity of our treatment [► Results \(Salience\)](#) [► Results \(Fear\)](#)

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Empirical Strategy

Effect on Voting Outcomes

To estimate the effect of war salience and emotional tone on voting outcomes, we rely on a fixed-effects regression model:

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

- ▶ y : Number of votes received by candidate i in electoral district c (IHS transformed)
- ▶ \mathbf{Treat}_c : Districts closer to U.S. military bases (below median distance)
- ▶ Salience: Proportion of war-related tweets compared to COVID-19
- ▶ Emotion: Emotional tone of tweets (e.g., fear, anxiety, joy, anger)
- ▶ δ_r : District fixed effects
- ▶ θ_i : Candidate-specific controls (age, gender)
- ▶ ζ_c : Controls for electoral characteristics (e.g., major party affiliation)
- ▶ Error double at the electoral district and municipality levels

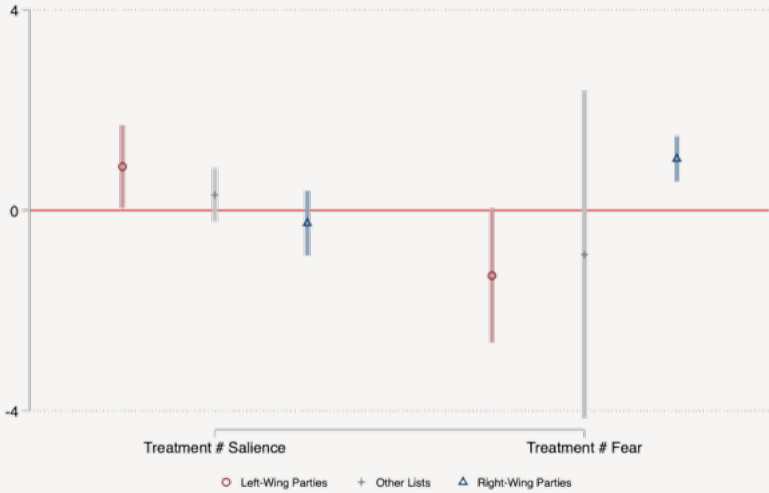
Results

Effect on Voting Outcomes

	(1)	(2)	(3)	(4)
	Votes (IHS)	Votes (IHS)	Votes (IHS)	Votes (IHS)
Treatment	0.221 (0.277)	0.257** (0.128)	-0.167 (0.228)	0.230 (0.284)
Salience	0.151 (0.269)			0.195 (0.265)
Treatment#Salience	0.141 (0.315)			0.0387 (0.319)
Fear		-1.340 (0.931)	-1.487* (0.870)	-1.383 (0.941)
Treatment#Fear		2.025** (0.801)	2.307*** (0.758)	2.009** (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*** (0.518)	4.875*** (0.504)	4.833*** (0.516)	4.756*** (0.523)
District FE	✓	✓	✓	✓
Election Controls	✓	✓	✓	✓
Candidate controls	✓	✓	✓	✓
Observations	77,757	77,757	77,757	77,757
R-squared	0.210	0.212	0.224	0.213

Heterogeneity by political parties

Effect on Voting Outcomes



Conclusion

Conclusion

- ▶ The outbreak of the Russia–Ukraine war caused a drop in pandemic coverage, crowding out the pandemic from public attention
- ▶ **Health Impact:** Municipalities closer to U.S. bases saw a significant post-war increase in COVID-19 cases, driven by reduced risk salience, higher mobility (fear-induced stockpiling) and fear of a new world war
- ▶ **Political Impact:** In war-salient areas, fear-based messaging amplified right-wing electoral gains, while overall war salience benefited left-wing parties irrespective of emotional tone
- ▶ **Contributions:**
 - ↪ Causal evidence on how sudden media shifts affect **public health behaviours** and **long-term political preferences**
 - ↪ Highlights the power of **emotional framing**, beyond mere volume of coverage
- ▶ Our findings highlight the pivotal role of issue salience in shaping both health behaviors and political preferences during times of overlapping crises

Thank you!



My website :)

Chapter I

Appendix

Data Construction

ISS dataset on Covid-19 Cases

- ▶ The records span from February 2020 to May 2022 and include daily counts of confirmed COVID-19 cases at the municipality level in Italy

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Data Construction

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- ▶ This dataset is a valuable source of information on the number of cases in each municipality. However, the institute labels the number of less than 4 but greater than 0 as “< 4” without specifying the exact number of cases

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 1. with “< 4” as 1
 2. with “< 4” as 3

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 1. with “< 4” as 1
 2. with “< 4” as 3
 3. with “< 4” as randomly drawn value from a uniform distribution between 1 and 3

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'

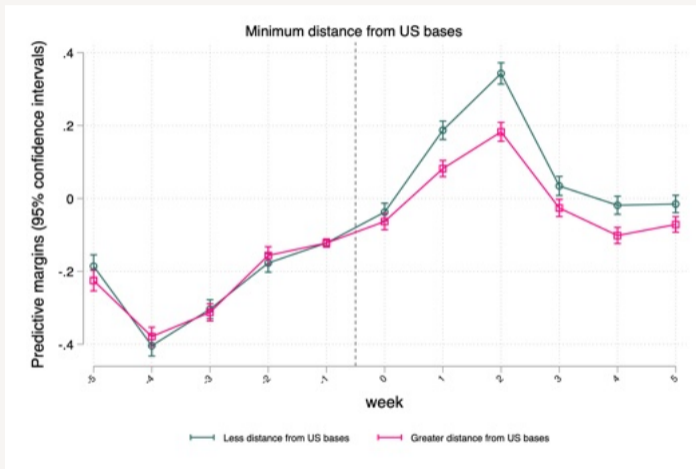
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Query List for Traditional media (online newspapers)

- ▶ 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
- ▶ 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").

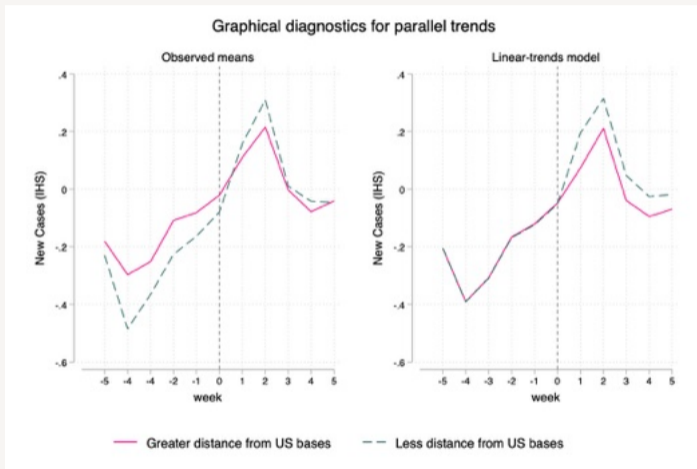
Results

Effect on Health Behaviors (contagion) - Parallel Trend



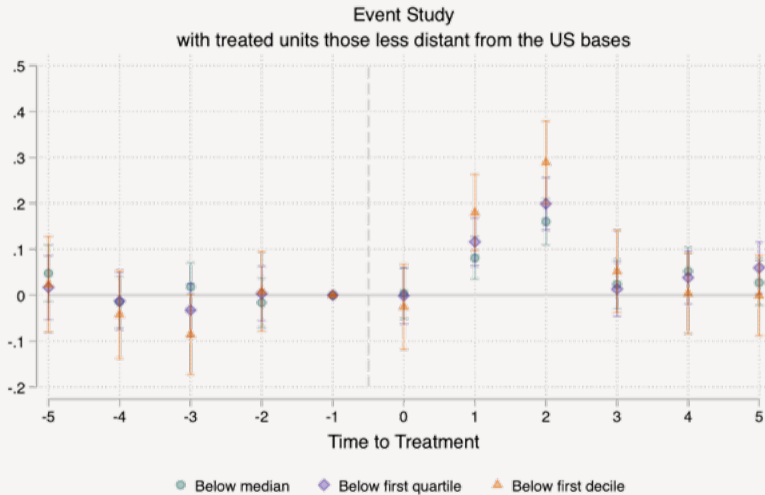
Results

Effect on Health Behaviors (contagion) - Parallel Trend



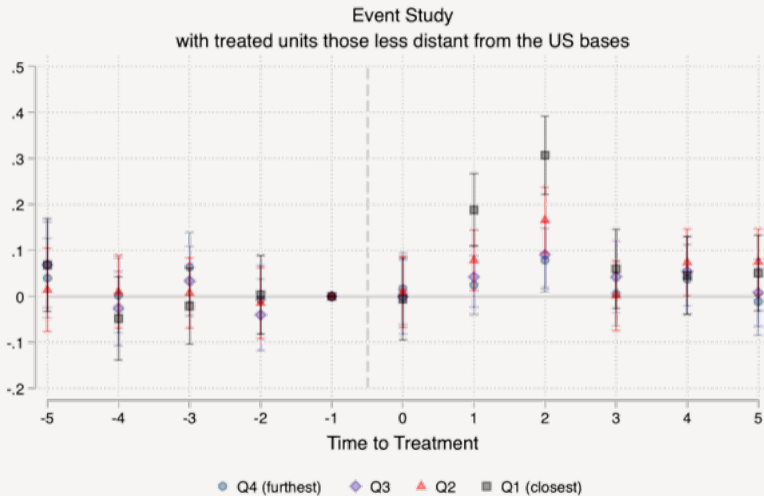
Results

Effect on Health Behaviors (contagion)



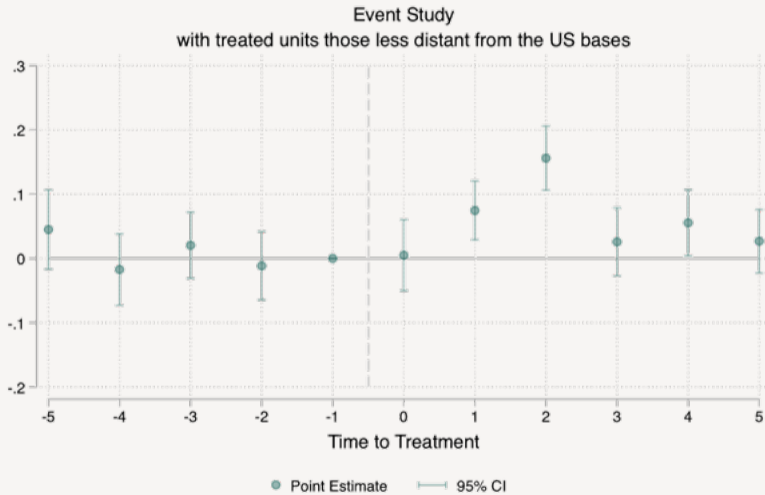
Results

Effect on Health Behaviors (contagion)



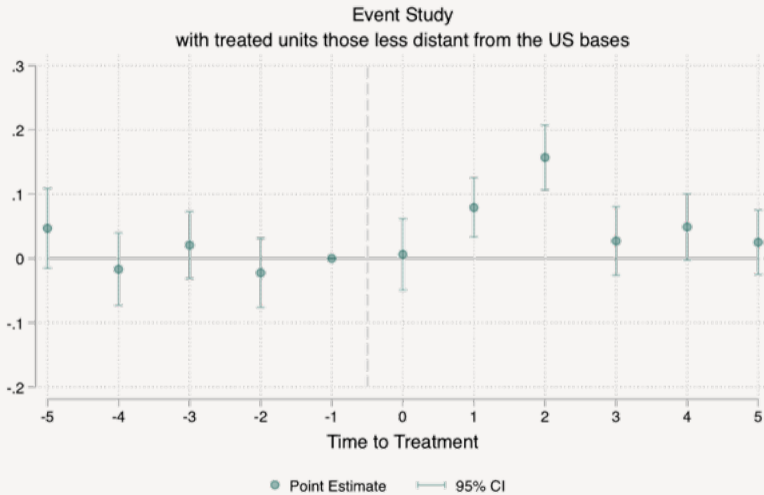
Results

Effect on Health Behaviors (contagion) - COVID-19 cases marked as " < 4 " as 3



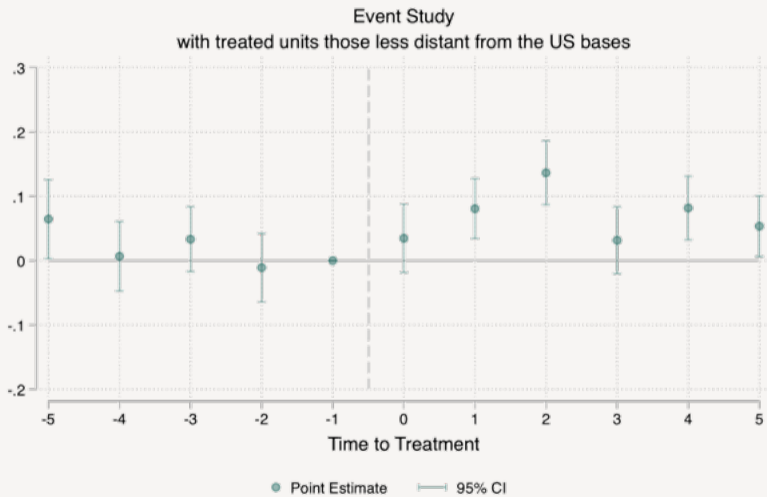
Results

Effect on Health Behaviors (contagion) - COVID-19 cases marked as " < 4 " as 1



Results

Effect on Health Behaviors (contagion) - COVID-19 cases marked as " < 4 " as 1



Results

Effect on Health Behaviors (contagion) - Cluster the standard errors without using Wild Bootstrapping

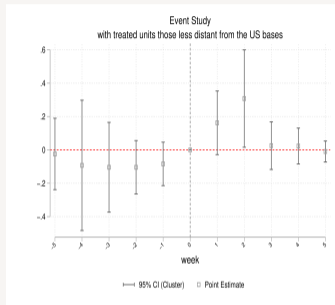


Figure: “< 4” as uniform

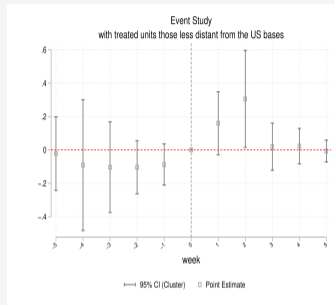


Figure: “< 4” as 3

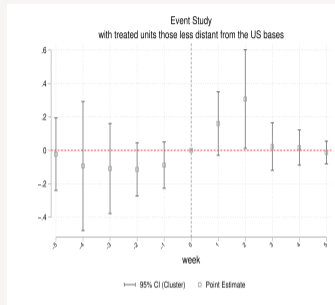
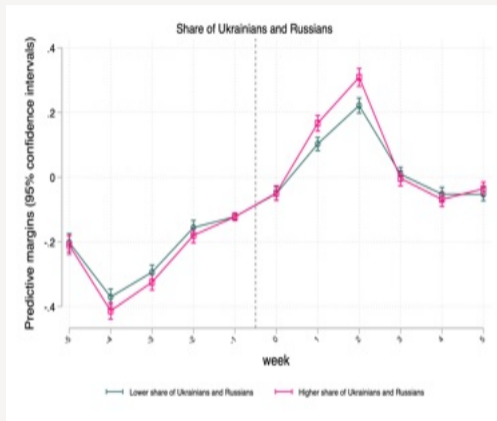
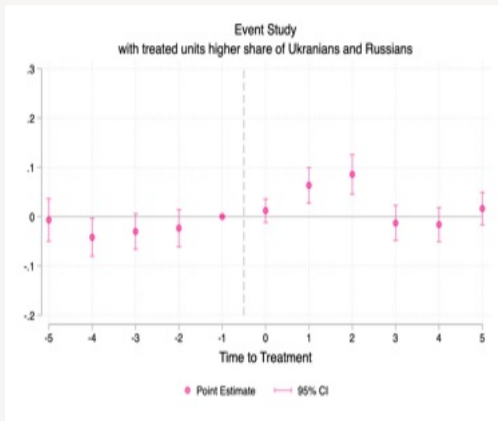


Figure: “< 4” as 1

Results

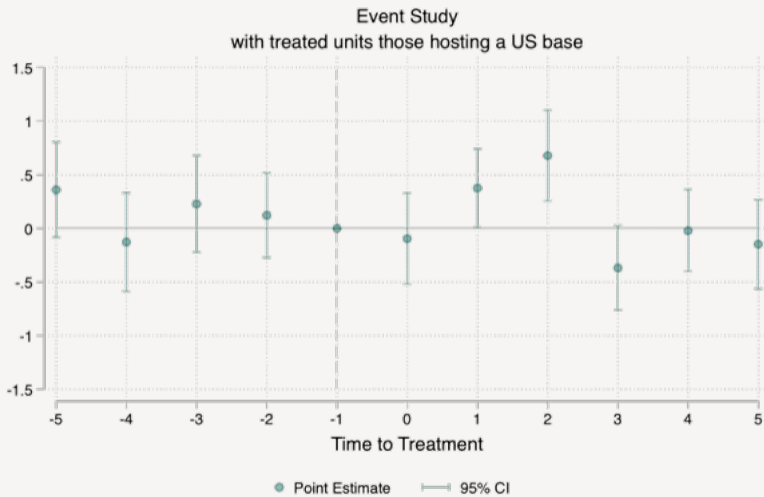
Effect on Health Behaviors (contagion) - Alternative Treatment variable



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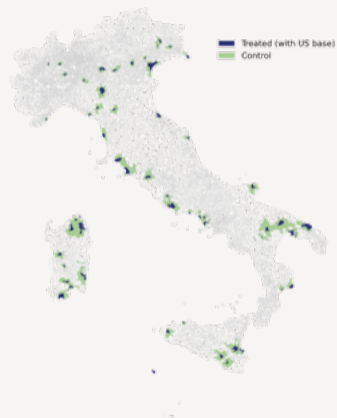
Results

Effect on Health Behaviors (contagion) - Treatment Refinement



Results

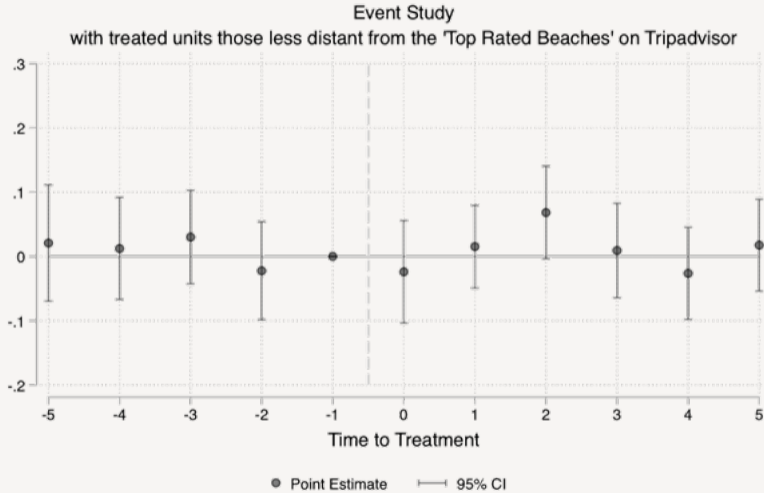
Spatial Distribution - Treatment Refinement



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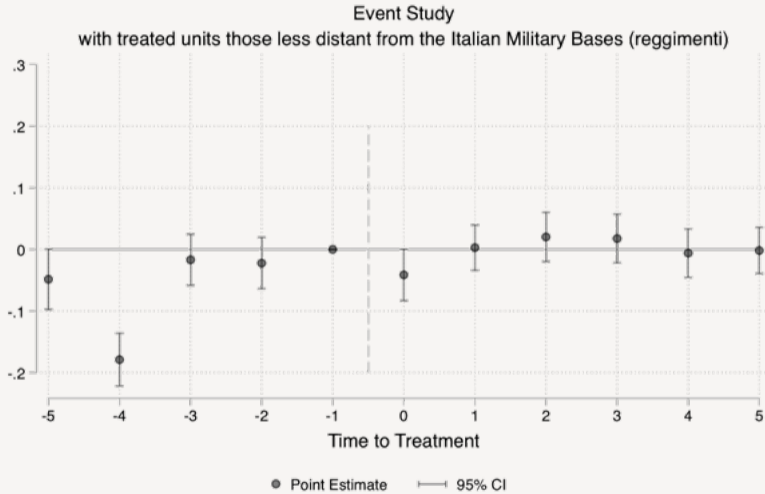
Results

Falsification using distance from 'Top Rated Beaches' on TripAdvisor 



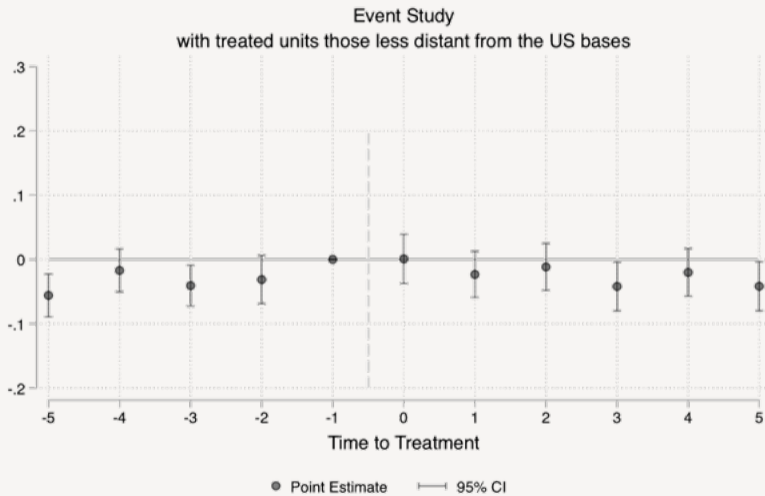
Results

Falsification using distance from Italian Military Bases (Reggimenti)



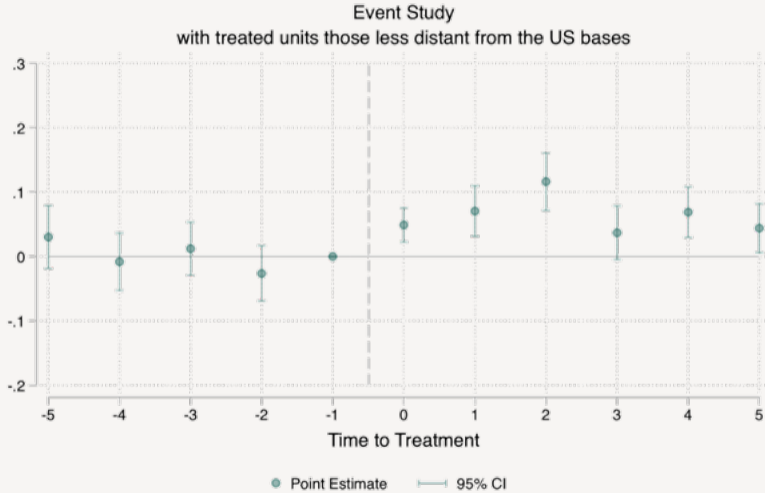
Results

Falsification in-time placebo (using Fake treatment time 2021)



Results

Excluding from the sample of cities that host a US base



Results

Spatial Distribution of Italian Military Bases (Reggimenti)



Some Heterogeneous Effects

Age group

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

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Time Fixed Effects	✓	✓	✓	✓	✓
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Observations	63316	63382	63668	63107	60962

Some Heterogeneous Effects

Broadband Connection

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

Some Heterogeneous Effects

Broadband Connection

		<i>Broadband</i>	
		<i>Slower Broadband</i>	<i>Faster Broadband</i>
Week			
	Lag -5	-0.000502 (0.0310)	0.0993* (0.0513)
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	Lead +1	-0.0234 (0.0208)	0.122*** (0.0378)
	Lead +2	0.0223 (0.0221)	0.185*** (0.0408)
	Lead +3	0.00975 (0.0222)	0.0329 (0.0440)
	Lead +4	0.0182 (0.0220)	0.100** (0.0428)
	Lead +5	-0.0262 (0.0211)	0.107*** (0.0412)
	Municipality Fixed Effects	✓	✓
	Time Fixed Effects	✓	✓
	Region X Time Fixed Effects	✓	✓
	Observations	28303	34166

Mechanisms

We posit that the crucial mechanisms by which shifts in media coverage translate into changes in real health-related behaviors is through:

- ▶ Their influence on **people's mobility** ⇒ Mechanism I
- ▶ their increased **fear of the war** ⇒ Mechanism II

Mechanisms

Mechanism I: Mobility patterns

1. Decline in perceived threat [⇒ Risk-salience attenuation]
 - ↪ The sudden media shift from COVID-19 to Russia-Ukraine lowers perceived pandemic risk, easing citizens' adoption of stringent health-related behaviors
 2. Expecting catastrophic event of a sudden world war [⇒ Consumption anticipation]
 - ↪ Fear of global conflict may drive individuals to stockpile essentials (long-term food, medication, fuel), resulting in increased mobility
- ▶ To obtain a measure of mobility, we use Google mobility data as a proxy at provincial level
1. Risk-salience attenuation ⇒ Composite mobility index
 - ▶ Persistent effect (DellaVigna and Kaplan, 2007): increased mobility may reflect a lasting behavioral shift, as individuals no longer perceive Covid-19 as a present or future threat.
 2. Consumption anticipation ⇒ Grocery and Pharmacy mobility
 - ▶ Short-term effect (Birkhøj et al., 1992): mobility driven by anticipated consumption tends to decrease over time, particularly as the perceived risk of war and the potential involvement of NATO begin to fade.

Mechanisms

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Mechanisms

Mechanism II: Fear of the war

- ▶ A key mechanism by which shifts in media coverage translate into changes in real health-related behaviors is through their increased **fear of the war**
- ▶ How to proxy fear at the municipal level?
- ▶ We downloaded Google searches, available from the Google Trends website (Brodeur et al., 2021; Campante et al., 2024)
 - ↔ It supplies an index for search intensity by topic over the time period requested in a geographical area
 - ↔ The number of daily searches for the specified topic divided by the maximum number of daily searches for this topic over the time period in question in that geographical area

Mechanisms

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Mechanisms

Mechanism II: Fear of the war

- ▶ A search-term query on Google Trends returns searches for an exact search-term, while a topic query includes related search-terms (in any language)
- ▶ As a query, we used the word "bunker" which denotes a sense of *fear* and *instability* at the start of the war

Mechanisms

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The screenshot shows the Huffpost website interface. At the top, there is a navigation bar with 'SEZIONI', 'CERCA', the 'HUFFPOST' logo, 'ABBONATI', and 'ACCEDI'. Below this is a 'Cronaca' section header. The main article title is in large, bold black text: "Per la prima volta in Italia c'è la corsa ai bunker. Ne abbiamo già venduti tre. Li cercano soprattutto gli avvocati". Below the title is the author's name, 'di Nadia Boffa', and a small teal icon. A sub-headline in smaller text reads: "Parla ad Huffpost Giulio Cavicchioni, titolare di 'Minus Energie': 'Negli ultimi giorni boom di richieste, soprattutto nel nord. E la situazione potrebbe peggiorare'". Below the sub-headline is the date and time: "03 Marzo 2022 alle 10:52". To the right of the text is a photograph of a concrete bunker interior with blue metal shelving units. Below the photo is a 'Segui i temi' section with two buttons: 'guerra ucraina' and 'vladimir putin', each with a teal plus icon.

Mechanisms

Results

	Grocery and Pharmacy Mobility	Composite Mobility Index	Google Searches
Week			
Lag -5			
Lag -4			
Lag -3			
Lag -2			
Lead 0			
Lead +1			
Lead +2			
Lead +3			
Lead +4			
Lead +5			
Province Fixed Effects	✓	✓	✗
Municipality Fixed Effects	✗	✗	✓
Time Fixed Effects	✓	✓	✓
Region X Time Fixed Effects	✗	✗	✓
Observations	1166	1166	63954

Mechanisms

Results

	Grocery and Pharmacy Mobility	Composite Mobility Index	Google Searches
Week			
Lag -5	0.566 (0.515)	0.140 (0.648)	0.000312 (0.00129)
Lag -4	0.410 (0.394)	0.554 (0.466)	-0.00211 (0.00134)
Lag -3	0.0929 (0.310)	0.189 (0.415)	0.000241 (0.00152)
Lag -2	0.181 (0.291)	0.122 (0.462)	0.000806 (0.00149)
Lead 0			
Lead +1			
Lead +2			
Lead +3			
Lead +4			
Lead +5			
Province Fixed Effects	✓	✓	✗
Municipality Fixed Effects	✗	✗	✓
Time Fixed Effects	✓	✓	✓
Region X Time Fixed Effects	✗	✗	✓
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Lead 0	0.759** (0.379)		
Lead +1	0.997** (0.412)		
Lead +2	0.311 (0.548)		
Lead +3	0.384 (0.501)		
Lead +4	0.338 (0.561)		
Lead +5	0.693 (0.709)		
Province Fixed Effects	✓	✓	✗
Municipality Fixed Effects	✗	✗	✓
Time Fixed Effects	✓	✓	✓
Region X Time Fixed Effects	✗	✗	✓
Observations	1166	1166	63954

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Lag -2	0.181 (0.291)	0.122 (0.462)	0.000806 (0.00149)
Lead 0	0.759** (0.379)	3.975*** (0.905)	
Lead +1	0.997** (0.412)	2.921*** (0.836)	
Lead +2	0.311 (0.548)	0.325 (0.879)	
Lead +3	0.384 (0.501)	1.885** (0.863)	
Lead +4	0.338 (0.561)	2.201** (0.877)	
Lead +5	0.693 (0.709)	2.691** (1.043)	
Province Fixed Effects	✓	✓	✗
Municipality Fixed Effects	✗	✗	✓
Time Fixed Effects	✓	✓	✓
Region X Time Fixed Effects	✗	✗	✓
Observations	1166	1166	63954

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Lag -2	0.181 (0.291)	0.122 (0.462)	0.000806 (0.00149)
Lead 0	0.759** (0.379)	3.975*** (0.905)	0.00259 (0.00193)
Lead +1	0.997** (0.412)	2.921*** (0.836)	0.00349** (0.00162)
Lead +2	0.311 (0.548)	0.325 (0.879)	0.00104 (0.00178)
Lead +3	0.384 (0.501)	1.885** (0.863)	0.000856 (0.00165)
Lead +4	0.338 (0.561)	2.201** (0.877)	-0.00110 (0.00159)
Lead +5	0.693 (0.709)	2.691** (1.043)	0.00104 (0.00149)
Province Fixed Effects	✓	✓	✗
Municipality Fixed Effects	✗	✗	✓
Time Fixed Effects	✓	✓	✓
Region X Time Fixed Effects	✗	✗	✓
Observations	1166	1166	63954

Results

Dynamics of Fear

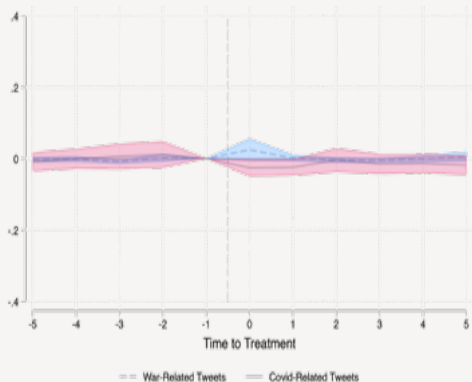


Figure: All parties

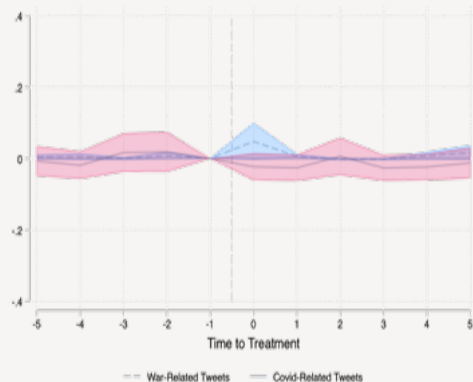


Figure: Right-wing parties

Results

Dynamics of Fear

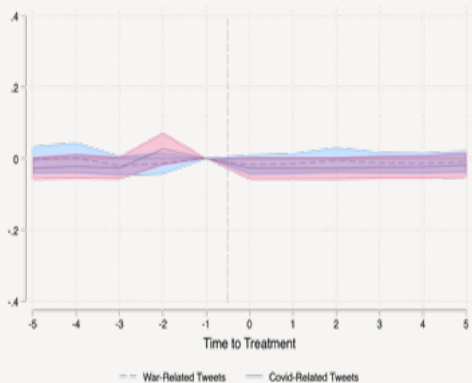


Figure: Left-wing parties

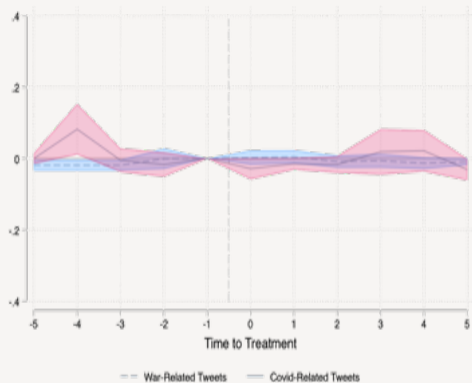


Figure: Other parties

Results

Dynamics of Salience

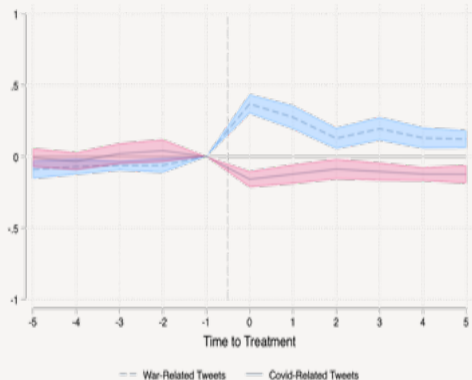


Figure: All parties

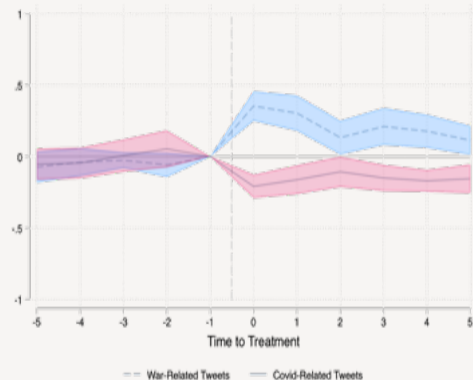


Figure: Right-wing parties

Results

Dynamics of Salience

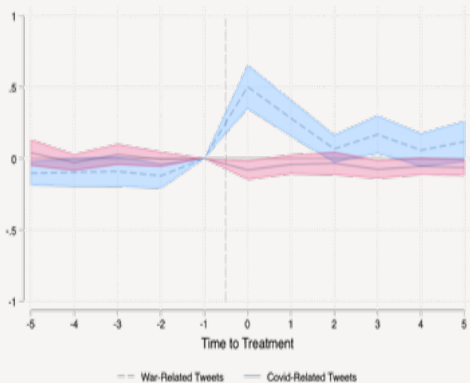


Figure: Left-wing parties

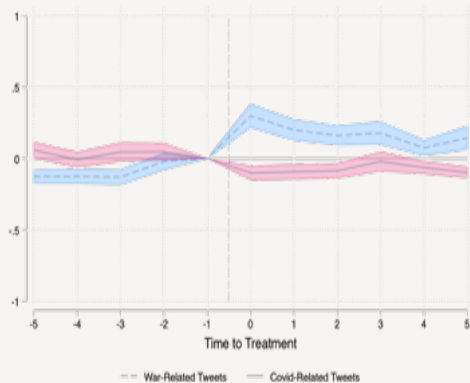


Figure: Other parties

Results

Exogeneity check (Fear)

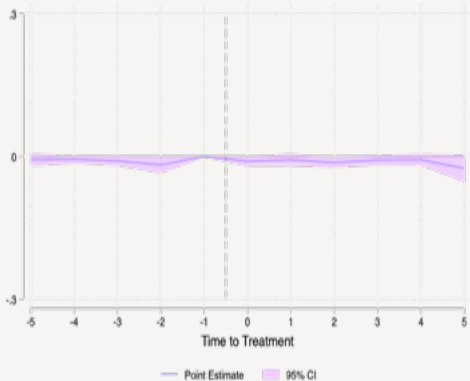


Figure: All parties

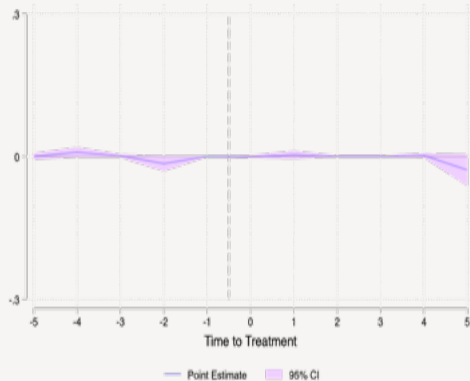


Figure: Right-wing parties

Results

Exogeneity check (Fear)

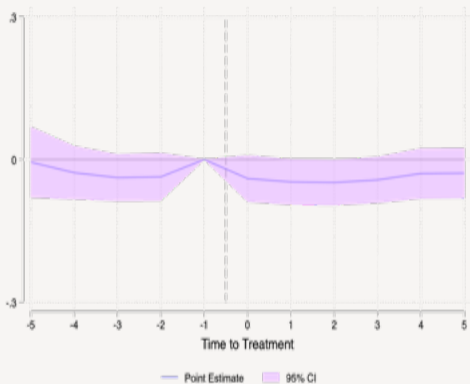


Figure: Left-wing parties

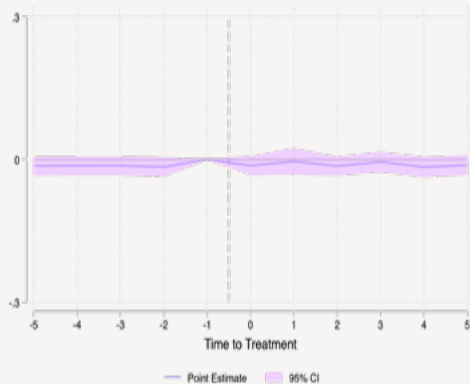


Figure: Other parties

Results

Exogeneity check (Salience)

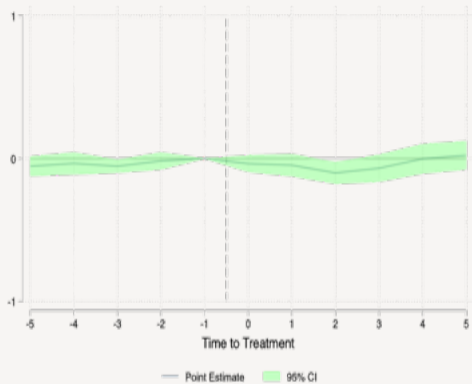


Figure: All parties

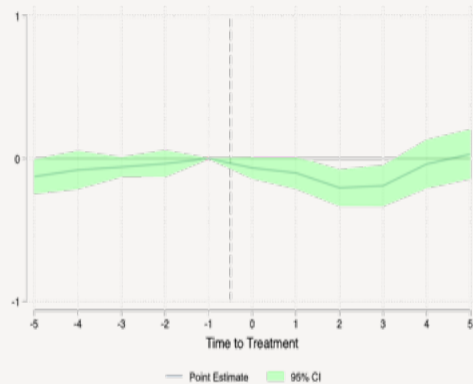


Figure: Right-wing parties

Results

Exogeneity check (Salience)

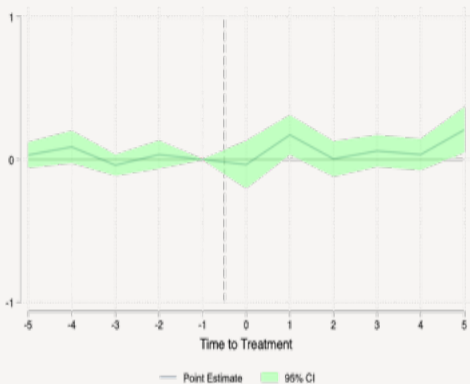


Figure: Left-wing parties

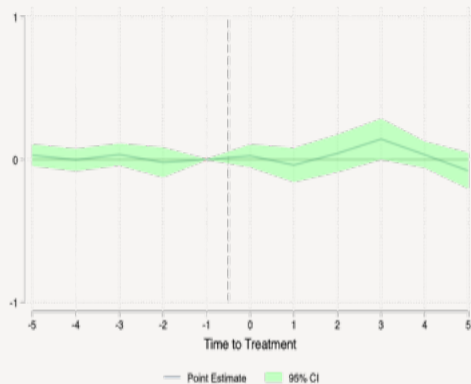


Figure: Other parties

Results

Treatment refinement

	(1)	(2)	(3)	(4)
	Votes (IHS)	Votes (IHS)	Votes (IHS)	Votes (IHS)
Municipalities with US base	0.722* (0.387)	0.896*** (0.151)	0.870** (0.333)	0.736* (0.381)
Salience	-1.297*** (0.433)			-1.379*** (0.428)
Municipalities with US base#Salience	0.321 (0.485)			0.247 (0.492)
Fear		2.147*** (0.312)	0.610 (0.952)	2.339*** (0.325)
Municipalities with US base#Fear		0.835 (0.770)	0.884 (0.942)	0.724 (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*** (1.756)	7.087*** (1.680)	6.868*** (1.478)	7.451*** (1.697)
Province FE	✓	✓	✓	✓
Election Controls	✓	✓	✓	✓
Candidate controls	✓	✓	✓	✓
Observations	839	839	839	839
R-squared	0.464	0.463	0.479	0.480

Results

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 (0.640)	0.177 (0.185)	0.307 (0.547)	-0.337 (0.648)
Sallience	0.143 (0.525)			0.0721 (0.535)
Distance from TripAdvisor#Sallience	0.511 (0.795)			0.631 (0.804)
Fear		1.217 (0.889)	1.518 (1.173)	1.202 (0.890)
Distance from TripAdvisor#Fear		-3.159* (1.889)	-2.804 (1.951)	-3.502* (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*** (1.381)	8.137*** (1.263)	7.596*** (1.404)	8.179*** (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

[← Back to Main](#)

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