Breaking Down the Lockdown:

The Causal Effect of Stay-At-Home Mandates on Uncertainty and Sentiments During the COVID-19 Pandemic

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Motivation

Non-pharmaceutical stay-at-home interventions (or **lockdowns**):

- **Effective** against the spread of contagious diseases like COVID-19
  - (Alfano and Ercolano 2020; Sen, Karaca-Mandic, and Georgiou 2020; Cauchemez et al. 2020)
- Rising **uncertainty** and **negative emotions**, resulting in economic and social costs.
  - (Caggiano, Castelnuovo, and Kima 2020; S. Baker et al. 2020; Abosedra, Laopodis, and Fakih 2021; Çevik et al. 2022; Ferrante et al. 2022; T. T. Nguyen et al. 2020)

Understanding the **causal impact** of **stay-at-home mandates** is crucial for policy makers to assess the **benefits** and **costs**.

Ongoing debate on effects of lockdowns

- Potential ***trade-offs*** of lockdown measures
  - Higher inequality (Palomino, Rodriguez, and Sebastian 2020)
  - Worse mental health conditions (Banks and Xu 2020; Elmer, Mepham, and Stadtfeld 2020; Anand et al. 2022)
  - Attitudes towards incumbent politicians (Bol et al. 2020; Devine et al. 2020; Hegewald and Schraff 2022)
- **Uncertainty** and **Sentiments**
  - Economic uncertainty and sentiment (S. R. Baker, Davis, and Levy 2022; van der Wielen and Barrios 2021; J. Yang and C. Yang 2021)
  - Health-related emotions (Lwin et al. 2020)
  - Political polarization (Jiang et al. 2020; Jungkunz 2021)

No evidence on the **causal impact** of **micro-targeted restriction measures** on **uncertainty** and **sentiments**.

- Problems of **endogeneity**

Research Proposal

Do lockdowns fuel or mitigate uncertainty and negative sentiment?

Our aim is to identify the **causal effect** of **lockdown policies** on

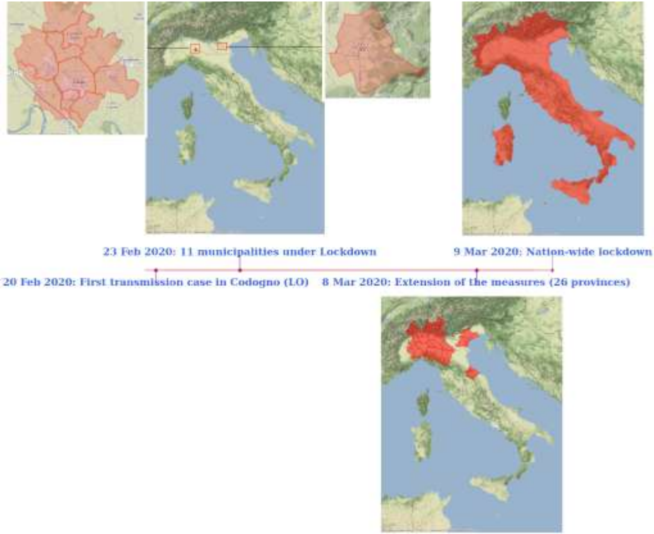
- **Uncertainty**
- **Negative sentiments**

across different **dimensions of the public's debate**.

*How can we **isolate** the effect of **lockdowns** from **confounding factors**?*

- **First Western COVID-19 lockdown** of February 2020 in Northern Italy.
- **Random** allocation of lockdown between two areas with homogeneous exposure to COVID-19 and balanced soci-economic, demographic characteristics:
  1. **Area under lockdown** (**Red zone**)
  2. **Neighboring** cities
- **Exogenous allocation** of cities to lockdown enables us to study the **causal effect** of lockdown policies on uncertainty and sentiments.
- **Text analysis** on **Twitter messages** from *inside* and *outside* of area under lockdown, *before* and *after* the introduction of the policy.
- **Diff-in-Diff**

Background: The Italian COVID-19 lockdowns



First Lockdown in Lombardia

- ***Red zone***: strict quarantine zone for 10 municipalities in **Lombardia** (DL n. 6, Feb 23, 2020).

  - Residents were permitted to leave their homes just for supplies such as food and medicine.
  - Attending school, going to workplaces and public gatherings was prohibited.
  - Train services bypassed the region.
- **Orange zone**: larger area around the red zone (Lombardia, Emilia-Romagna) subjected to **milder limitations** (DPCM Mar 03, 2020)
  - Closures of schools and gyms, limitations to bars, restaurants and public gatherings, suspension of sports competitions.

Random Selection of the Lockdown Areas

- The discovery of the **first case** in Codogno was **random**
- **Homogeneous transmission potential** of the virus across provinces of Lombardy around the time of the discovery of the virus in Codogno (Cereda et al. 2021).
- The incidence of the disease was **balanced** between the **red zone** and the **orange zone** cities neighboring with the quarantine area.

Identification Strategy:

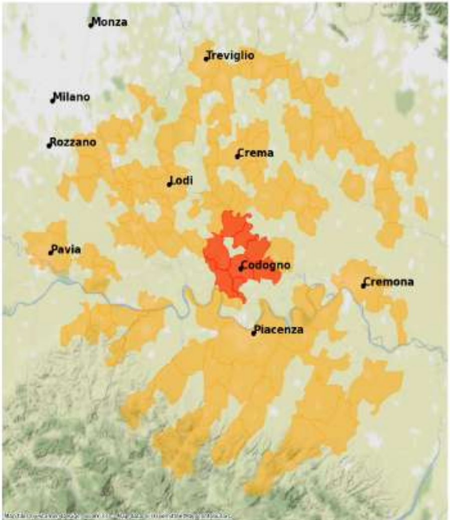
- **Exogenous shock** of **unanticipated lockdown** of Feb. 23, 2020
- Neighboring **Orange zone** cities are a suitable *control group* for outcomes in the **red zone** (*treatment group*).
  - Equally exposed to risk of contagion (Cereda et al. 2021)
  - Balanced pre-lockdown **socio-economic, demographic characteristics**.

Data

We collect Twitter data using the official **Twitter Stream API**

- selecting **"Italian language"**
- **"geographical filtering"**; center coordinates on Codogno and elect a radius of 42km
- No topic-based filter

- **User-defined location** to **identify the municipality of origin**:
  - 8 *red zone* cities (1 604 tweets, 61 accounts)
  - 111 *orange zone* cities (26 766 tweets, 1 022 accounts)
- **January 1st, 2020 - March 22, 2020**



Topics Classifier

- ***Dictionary-based classifiers*** by defining topic-specific lists of commonly used words:
  - **Economics**: economi*, investiment*, banc*, spes*, mercat*, turist*, lavor* ...
  - **Health**: contag*, covid, ospedal*, malat*, sanità, medic*, infermier* ...
  - **Politics**: politic*, govern*, salvini, conte, meloni, presidente, decreto, legge ...
  - **Policy**: chius*, sospes*, cancellat*, limitazion*, sospension*, isolat*,restrizion* ...
- We create **Economics, Health, Politics and Policy identifiers**:
  - 1 if the tweet contains at least one term from the topic-related dictionary, 0 otherwise

Economics

Health

Politics

Policy

Uncertainty and Negative Sentiments Classifier

- Measure **uncertainty** and **sentiments** using **AlBERTo** (Polignano et al. 2019)
  - **BERT** (Devlin et al. 2018), **state-of-the-art** in the analysis of public opinions and sentiments expressed via Twitter (Blanco and Lourenço 2022; Min et al. 2021; Chintalapudi, Battineni, and Amenta 2021)
  - $\sim$ 20% of the tweets (6 318) **manually** assigned to classes indicating ***uncertainty*** and ***negative sentiment***
  - Adapt model on binary classification tasks and predict the labels of tweets without manual annotations
- ***Uncertainty*** and ***Negative Sentiment*** binary variables:
  - 1 if tweet is labelled as uncertain, 0 otherwise (neutral, certainty).
  - 1 if tweet expresses negative sentiment, 0 otherwise (neutral, positive).

Diff-in-Diff Model

Difference-in-Difference (DiD) on repeated cross-sections of tweets:

$$Y_{ij,t} = \alpha + \beta_j + \sum_{t \in \{1,2\}} \lambda_t [post_{ij} = t] + \sum_{t \in \{1,2\}} \delta_t ([post_{ij} = t] \times redzone_{ij}) + \epsilon_{ij,t}$$

- $Y_{ij,t}$ is binary outcome variable of tweet i from user j observed in period t
- $post_{ij} = t$ for $t \in \{0, 1, 2\}$ indicates the **pre-post-post lockdown periods** (before and after Feb. 23rd, and after Mar. 9th - i.e. nation-wide lockdown)
- β_j, user-level fixed effect
- λ_t, time trend common to control and treatment groups
- $redzone_{ij}$ is the *treatment status indicator*
- δ_1 identifies the *average treatment effect on the treated (ATT) at period 1* (**redzone=1** $\times$ **post=1**)

Results

Table 1: DiD Regression table for *Uncertainty* and *Negative Sentiment*, aggregated and grouped by topics with user fixed effects (omitted).

	Uncertainty					Negative Sentiment				
	(1) **Aggregate**	(2) Economics	(3) **Health**	(4) **Politics**	(5) **Policy**	(6) Aggregate	(7) Economics	(8) **Health**	(9) **Politics**	(10) **Policy**
post=1	0.0378**	0.00819*	0.0592***	-0.00679	0.0198***	-0.0337	-0.000346	0.0365***	-0.0108	0.00736***
	(2.94)	(2.52)	(4.94)	(-1.81)	(5.79)	(-1.76)	(-0.07)	(4.58)	(-1.79)	(3.99)
post=2	0.0500**	0.0169***	0.0673***	-0.00253	0.0191***	-0.0405*	0.00614	0.0401***	-0.0159*	0.00783***
	(2.96)	(3.47)	(6.04)	(-0.62)	(3.55)	(-2.12)	(1.12)	(5.20)	(-2.51)	(4.02)
$\hat{\delta}_1$ (red zone=1 $\times$ post=1)	0.145*	0.00222	0.0606***	0.0158***	0.0281**	-0.0168	-0.0176	0.0614***	0.0281***	0.0389*
	(2.37)	(0.34)	(4.48)	(3.40)	(3.01)	(-0.48)	(-1.49)	(3.46)	(3.66)	(2.49)
red zone=1 $\times$ post=2	0.0475	-0.00495	0.00294	-0.00647	-0.000174	-0.0224	-0.0115	0.0419	0.0358***	0.0233
	(0.69)	(-0.54)	(0.15)	(-1.07)	(-0.01)	(-0.53)	(-1.39)	(1.85)	(3.57)	(1.70)
Constant	0.902***	-0.0119	-0.0702***	0.00900*	-0.0189	0.0629	0.00535	-0.0819***	-0.0199*	-0.0311*
	(13.45)	(-1.54)	(-4.56)	(2.02)	(-1.57)	(1.65)	(0.87)	(-3.84)	(-2.57)	(-2.29)
Observations	28370	28370	28370	28370	28370	28370	28370	28370	28370	28370
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robustness Checks

- **Benjamini-Hochberg** adjusted p-values for multiple Hps testing
  - Significance of all p-values of (**redzone=1** $\times$ **post = 1**) unaltered.
- **Placebo Test**: Can we retrieve the lockdown effect when quarantine measures are **not unexpected**?
  - Italian tweets from the **North of Italy**: ***Placebo*** treated (control) city if excess of mortality of January and February 2020 wrt to same months in 2015-2019 is *closest to* (*most far from*) the **red zone**.
  - Diff-in-Diff on **placebo sample** with **national lockdown** as treatment. **No significant effect**.
- **Test for pre-existing trends** (Pischke 2005):
  - DID model on m leads and q lags of the treatment variable over multiple periods (baseline: February 1 - February 19, 2020)

> - **Violation** of the parallel trends condition for **aggregate uncertainty** and **negative sentiment about health**

Conclusions

	Uncertainty					Negative Sentiment				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Aggregate	Economics	**Health**	**Politics**	**Policy**	Aggregate	Economics	Health	**Politics**	**Policy**
$\hat{\delta}_1$ **(red zone=1 $\times$ post=1)**	0.145*	0.00222	0.0606***	0.0158***	0.0281**	-0.0168	-0.0176	0.0614***	0.0281***	0.0389*
	(2.37)	(0.34)	(4.48)	(3.40)	(3.01)	(-0.48)	(-1.49)	(3.46)	(3.66)	(2.49)

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Policymakers failed to increase public support:

- Lockdown increases uncertainty around health conditions.
- Political costs could inhibit timely implementations of stay-at-home mandates.
- Behavioral guidelines not effectively communicated.
- Policy does not come at the cost of worsened economic sentiments.

Thank you for your attention!

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Appendix

Uncertainty and Sentiment Classification Model

- We classify tweets with **AlBERTo** (Polignano et al. 2019), a BERT model (Devlin et al. 2018) pre-trained the TWITA dataset (huge corpus of Italian tweets from 2012-2015 - 200 mln).
  - *Preprocessing* phase of *normalization* with Ekphrasis and *tokenization* with SentencePiece.
  - Pre-train (*masked learning*).
  - Fine-tune to perform specific classification task.
- *Manual classification*: we manually classified $\sim 20\%$ of the tweets (6318) split into train-validation-test sub-samples, with 50-30-20 proportions.
- The *Uncertainty* and *Sentiment* consist of three **highly unbalanced classes**: medium, high and low.
- **Two-step procedure**:
  - *Step 1* classifies tweets as medium Uncertainty (medium Sentiment) (1) vs rest (0).
  - *Step 2* classifies non-medium tweets as Uncertainty (Negative Sentiment) (0) vs Certainty (Positive Sentiment) (1)
- Fine-tune on each binary classification task (hyperparameters selected via *GridSearch*) sizes of 512.
- Predict the labels of the remaining tweets without manual annotations.

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Model's Performance

Table 2: ROC AUC, Average Precision Score and Balanced Accuracy Score with fine-tuning of pre-trained Alberto on Uncertainty and Negative Sentiment classification tasks (step 1 and step 2).

	Classification Step	Accuracy	PR-AUC	ROC-AUC
Uncertainty	Step 1	0.738924	0.659693	0.734781
	Step 2	0.713869	0.661466	0.713731
Negative Sentiment	Step 1	0.735759	0.75535	0.731836
	Step 2	0.841683	0.671	0.809594

Topic Dictionaries

- **Economics**: economia, economic*, soldi, investiment*, banc*, finanz*, disoccupa*, bancarott*, imprenditor*, impres*, lavoro, bonus, commerci*, gestione, piano, sostegno, crisi, iva, dipendent*, fiscal*, coldiretti, agevolazioni, contribut*, reddito, salari*, confedilizia, confindustria, cgil, professionist*, negoz*, euro, mutuo, mutui, tasse, tassa, tassazione, tassat*, evasione, fisco, sindacat*, inps, credit*, prestit*, stipendio, deficit, lavorator*, produzion*, produttiv*, aziend*, client*, soci, salone, ristorant*, smart-working, smart working, commercial*, supermercat*, spes*, mercat*, turist*, turismo, licenzia* fiera, fiere, cassa integrazione, lavorare, lavorare a casa.
- **Health**: coronavirus, virus, contag*, covid, tampon*, mascher*, casi, quaranten*, mort*, ospedal*, malat*, malatti*, sanità, sanitari*, medic*, medicina, infermier*, positiv*, farmaci*, kn95, terapi*, terapia intensiva, terapie intensive, sars, sars-cov-2, paziente zero, pazient*, infett*, salute,decess*, influenza, peste, sanita, guarit*, guarigion*, ammarlarsi, ammalarci, ammalat*, ammalare, covid19, croce rossa, epidemiolog*, oms, febbre, asintomatic*, rianimazione, epidemia, respiratori, ricoverat*, portatore sano.
- **Politics**: politic*, govern*, italiaviva, salvini, renzi, conte, meloni, presidente, lega, ministro, sindaco, decreto, legge, movimento5stelle, mattarella, segretari*, legislativo, parlament*, giunta, assessor*, ue, politic*, profughi, pd, ong, sinistra, migranti, democrazia, democratic*, partito, partiti, sardine, dimettiti, dimission*, fascismo, fascist*, 5s, protesta, contedimettiti, nazismo, nazist*, destra, casta, m5s.
- **Lockdown Policy**: chius*, sospes*, cancellat*, limitazion*, annullat*, chiud*, sospension*, isolat*, isolamento, rinviat*, scorte, viveri necessari, zona rossa, zona arancione, luoghi di aggregazione, distanza, restrizion*, controlli, posto di blocco, posti di blocco, spostamenti, autocertificazione.

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WordClouds of first 100 most common terms

Uncertainty

Negative Sentiment

Examples of Tweets

- ***Uncertainty***:
  - ***Health***: "più che altro non so che pensare molti dicono che è una banale influenza ma i protoc..." , "quanti posti letto ci sono negli ospedali italiani di ..."
  - ***Economics***: "il problema e andare a fare la spesa domaniii riempite gli scaffali", "l economia ne uscirà a pezzi da questa storia stiamo accettando di dover avere un lascia..."
  - ***Politics***: "in difficoltà tante aziende piacentine tarasconi il governo intervenga con urgenza", "hai voglia a dì non generiamo inutile allarmismo poi vedi il presidente della lombardia con mascherina e altri ti..."
  - **Lockdown Policy**: "dovrebbero trovare un altra soluzione per rifornire la popolazione dei viveri necessari altrimenti se li m...", "cosa dice il decreto quali negozi sono chiusi e quali no"
- ***Negative Sentiment***:
  - ***Economics***: "stai rubando il lavoro a che immigrato che sei tornatene a casa tu", "scuole e asili chiusi per una settimana bene ma se non ho nessuno che mi tiene mia figlia io a lavorare ci devo andare lo stesso"
  - ***Health***: "hai scritto di essere d accordo con un branco di imbecilli che hanno devastato un ospedale e ti lam...", "collegate il cervello pensate veramente che chi è infetto stando in casa guarisca ma fatevi curare"
  - ***Politics***: "pensavo dopo napolitano avessimo toccato il fondo ma mattarella non ha perso occasione per fare peggio", "ancora una volta bla bla bla corona vairus bla bla bla moriremmo tutti bla bla bla conte è il max"
  - **Lockdown Policy**: "come se cambiasse qualcosa chiudere i locali dalle 18 il coronavirus alle 18 va a letto", "6 giorno di isolamento a codogno svegliarsi e sentirsi come i carcerati ingiustamente incolpati di un reato non..."

Shannon Entropy Scores

Examples of tweets that presented the highest Shannon entropy scores for each emotion-topic pair.

- Economics Uncertainty
  - It seems so. We await technical details on closing all commercial activities except for public utilities [**.99**]
  - It will be the beginning of our financial monetary crisis that we will not be able to sustain which will force us to leave the URL [**.97**]
  - #fightcoronavirus hashtag #cremona don't come to the bank better do everything online - appeal of the bank unions URL [**.93**]
- Economics Negative Sentiments
  - I live in #Casalpusterlengo #Iamblocked without being able to go to work. Wake up! [**.79**]
  - The lightness of #italianpolitics in facing #covid is provoking incalculable economic damage [**.64**]
  - Meanwhile those who are part of the productive sector must not stay at home but go and get infected for the good of the capital [**.62**]
- Health Uncertainty
  - I think that in November in the red zone there will be a demographic explosion of positive covid obviously [**.99**]
  - Coronavirus Amendola [Minister of European Affairs]: it is possible that the EU [European Union] will give us more budget flexibility [**.99**]
  - For the first time since the beginning of the emergency I have news of a person in intensive care and another who died [**.98**]

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Shannon Entropy Scores

- Health Negative Sentiments
  - #Conte [Italy's prime minister] #wakeup the #coronavirus advances and reached Lodi [one of the main cities in the red zone] big congratulations to you, perfect checks [**.93**]
  - My mom is in the hospital and they don't have face masks #coronavirus #covid #italy and they made everyone swab [**.90**]
  - more than a month to declare we are ready everything is under control and then the infection comes [**.76**]
- Politics Uncertainty
  - Where is Mattarella [President of the Republic] in all this? [Meaning: what is Mattarella doing to deal with the current situation?] [**.99**]
  - By now we know who Salvini [leader of the right-wing political party] is. The problem is how much is true about this virus [**.98**]
  - If we all closed the borders we would all be [considered] fascists [**.95**]
- Politics Negative Sentiments
  - #Conte [Italy's prime minister] #wakeup the #coronavirus advances and reached Lodi [one of the main cities in the red zone] big congratulations to you, perfect checks [**.93**]
  - #Conte shifts the blame of #covid contagions to the hospital of Codogno where they have worked hard and they keep working hard with their shifts [**.51**]
  - #coronavirus taught us that the #nationalhealthservice must be refounded and that the #TAV [high speed train project that has been subject to heated politically debates] is useless and #Conte is useless [**.36**]

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Shannon Entropy Scores

- Lockdown Policy Uncertainty
  - I am biased but yes we are apparently closed but all of a sudden you will find yourself at the [same] table with us [i.e., in the same situation] [**.99**]
  - If they extend the red zone to Lombardy, Italy risks sinking more than it is [already] doing [**.95**]
  - It's absurd that the TV information we have in the red zone is the same as the rest of Italy [**.85**]
- Lockdown Policy Negative Sentiments
  - I work in psychiatry I can tell you that in the red zone there is madness as they say [**.97**]
  - it is yet to be clarified if the match will be played behind closed doors [**.87**]
  - but I ask how can you really close everything [?] what a desolation all places ['locali', meaning bars, restaurants...] closed #coronavirus #italy #cremona [**.60**]

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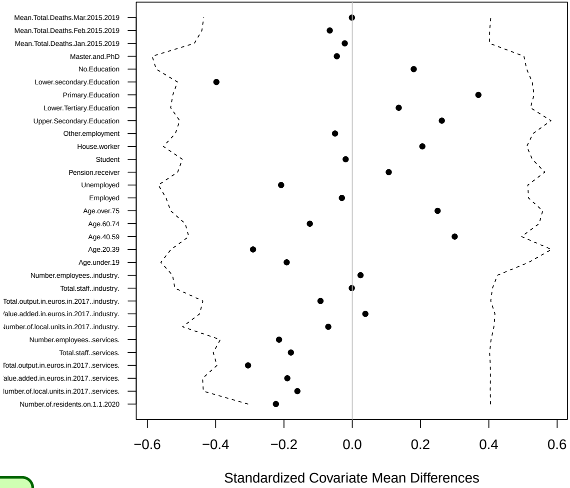
Covariate Balance

- Standardized Mean Difference $:= (\bar{x_1} - \bar{x_2})/\sqrt{(S_1^2 + S_2^2/2)}$ with 7.5 and 92.5 *complete randomization quantiles* (2000 permutations of treatment status)
- Balanced pre-lockdown **socio-economic, demographic characteristics** (ISTAT).



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Regression Model without DiD

Table 3: Regression model $y_{ij,t} = \alpha + \gamma_j + \lambda_t + \epsilon_{ij,t}$ for *Uncertainty* and *Negative Sentiment* with clustered standard errors - aggregated and grouped by topic. Used fixed effects are omitted.

	Uncertainty					Negative Sentiment				
	(1) All	(2) Economics	(3) Health	(4) Politics	(5) Lockdown pol	(6) All	(7) Economics	(8) Health	(9) Politics	(10) Lockdown pol
post=1	0.0447**	0.00825**	0.0619***	-0.00612	0.0211***	-0.0347	-0.00122	0.0396***	-0.00926	0.00928***
	(3.35)	(2.68)	(5.40)	(-1.77)	(6.32)	(-1.89)	(-0.25)	(5.02)	(-1.67)	(4.14)
post=2	0.0532**	0.0167***	0.0679***	-0.00271	0.0193***	-0.0417*	0.00548	0.0425***	-0.0141*	0.00919***
	(3.22)	(3.61)	(6.42)	(-0.68)	(3.75)	(-2.28)	(1.07)	(5.69)	(-2.40)	(4.38)
Constant	0.947***	-0.0167***	-0.0679***	0.00271	-0.0193***	0.0417*	-0.00548	-0.0425***	0.0141*	-0.00919***
	(57.29)	(-3.61)	(-6.42)	(0.68)	(-3.75)	(2.28)	(-1.07)	(-5.69)	(2.40)	(-4.38)
Observations	28370	28370	28370	28370	28370	28370	28370	28370	28370	28370

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Model Estimates with White Standard Errors

Table 4: DiD Regression table for *Uncertainty* and *Negative Sentiment*, aggregated and grouped by topics with user fixed effects (omitted) with White Standard Errors.

	Uncertainty					Negative Sentiment				
	(1) Aggregate	(2) Economics	(3) Health	(4) Politics	(5) Policy	(6) Aggregate	(7) Economics	(8) Health	(9) Politics	(10) Policy
post=1	0.0378***	0.00819**	0.0592***	-0.00679*	0.0198***	-0.0337***	-0.000346	0.0365***	-0.0108**	0.00736***
	(4.64)	(3.00)	(16.59)	(-2.50)	(9.40)	(-3.94)	(-0.12)	(11.74)	(-2.78)	(4.34)
post=2	0.0500***	0.0169***	0.0673***	-0.00253	0.0191***	-0.0405***	0.00614	0.0401***	-0.0159***	0.00783***
	(5.69)	(5.43)	(16.21)	(-0.87)	(8.25)	(-4.45)	(1.92)	(11.09)	(-3.97)	(4.50)
red zone=1 × post=1	0.145***	0.00222	0.0606**	0.0158	0.0281*	-0.0168	-0.0176	0.0614**	0.0281**	0.0389**
	(3.65)	(0.16)	(3.09)	(1.86)	(2.12)	(-0.40)	(-1.04)	(3.12)	(2.82)	(2.91)
red zone=1 × post=2	0.0475	-0.00495	0.00294	-0.00647	-0.000174	-0.0224	-0.0115	0.0419*	0.0358***	0.0233*
	(1.11)	(-0.28)	(0.15)	(-0.81)	(-0.02)	(-0.49)	(-0.59)	(2.13)	(3.54)	(2.00)
Constant	0.902***	-0.0119	-0.0702***	0.00900	-0.0189	0.0629	0.00535	-0.0819***	-0.0199*	-0.0311**
	(21.47)	(-0.69)	(-3.59)	(1.21)	(-1.67)	(1.42)	(0.28)	(-4.23)	(-2.14)	(-2.70)
Observations	28370	28370	28370	28370	28370	28370	28370	28370	28370	28370

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Adjusted P-values for Multiple Hypothesis Testing

P-values are jointly tested for correlations among:

- Aggregated uncertainty (neg. sentiment) with **medium** and **low** uncertainty (**medium** and **positive** sentiment)
- Topic-related uncertainty (neg. sentiment)

Table 5: Benjamini Hochberg (1995) adjusted p-values for DID models (original p-values in parenthesis)

	Uncertainty					Negative Sentiment				
	Aggregate	Economics	Health	Politics	Policy	Aggregate	Economics	Health	Politics	Policy
post = 1	0.01	0.02	0.00	0.11	0.00	0.10	0.95	0.00	0.11	0.00
	(0.00)	(0.01)	(0.00)	(0.07)	(0.00)	(0.08)	(0.95)	(0.00)	(0.07)	(0.01)
post = 2	0.01	0.00	0.00	0.72	0.00	0.00	0.28	0.00	0.02	0.00
	(0.00)	(0.00)	(0.00)	(0.54)	(0.00)	(0.03)	(0.26)	(0.00)	(0.01)	(0.00)
red zone = 1 x post = 1	0.03	0.84	0.00	0.00	0.01	0.63	0.17	0.00	0.00	0.02
	(0.02)	(0.78)	(0.00)	(0.00)	(0.00)	(0.63)	(0.14)	(0.00)	(0.00)	(0.01)
red zone = 1 x post = 2	0.57	0.72	0.94	0.41	0.99	0.63	0.19	0.10	0.00	0.12
	(0.49)	(0.59)	(0.88)	(0.10)	(0.29)	(0.99)	(0.16)	(0.07)	(0.00)	(0.09)

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Placebo Test

- After the national lockdown, **there should not be any significant difference** in the reaction between cities with **perceived risk** of the danger ***similar*** to the red zone and cities with ***dissimilar*** perceived risk.
- We proxy **perceived risk** with **2020 monthly excess mortality** at city level
  - If J = tot deaths of January 2020 and M = 2015-2019 average January tot deaths, then $excmort = \frac{J-M}{M}$
- For each city, we compute the **percentage increase** of deaths of **January and February 2020**
  - $x = (ExcMort_{Jan}, ExcMort_{Feb})$
- **Euclidean distance** between each city's 3-months excess mortalities and the **monthly averages** of the **red zone**.
- The binary variable ***sim*** equals one if a city falls within the 10th percentile of the distribution of distance values, 0 if the distance is equal or above the 90th percentile.

Map of cities featured in Placebo Test

- We collect Italian tweets from the **North of Italy**, and drop the orange zone municipalities featured in the analysis.
- We identify 231 ***placebo treated* cities** with **high similarity** (6 967 obs) and 295 with **low similarity** (7 082 obs).

Placebo Test Results

Table 6: Placebo Test regression table for *Uncertainty* and *Negative Sentiment*, aggregated and grouped by topics, with user level fixed effects (omitted).

	Uncertainty					Negative Sentiment				
	(1) Aggregate	(2) Economics	(3) Health	(4) Politics	(5) Policy	(6) Aggregate	(7) Economics	(8) Health	(9) Politics	(10) Policy
post=1	-0.0960***	-0.00796	-0.0771***	-0.0134*	-0.0248**	-0.0434**	-0.00159	-0.0397**	-0.0127	0.00225
	(-6.73)	(-1.12)	(-5.38)	(-2.15)	(-3.20)	(-2.89)	(-0.29)	(-3.20)	(-1.70)	(0.49)
sim=1 × post=2	0.0475	0.0105	0.0476	0.00491	0.0122	-0.0322	-0.0102	-0.0145	-0.00556	-0.000633
	(1.76)	(0.93)	(1.89)	(0.53)	(1.17)	(-1.61)	(-1.24)	(-0.77)	(-0.62)	(-0.10)
Constant	0.564***	0.00530	0.385***	0.00894*	0.0166**	0.862***	0.00106	0.360***	0.00850	-0.00150
	(59.25)	(1.12)	(40.32)	(2.15)	(3.20)	(86.05)	(0.29)	(43.54)	(1.70)	(-0.49)
Observations	14049	14049	14049	14049	14049	14049	14049	14049	14049	14049
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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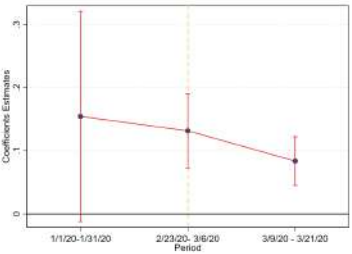
Parallel trends

- We test whether the assumption holds by regressing the DID model on m lags and q leads of the treatment variable over multiple periods (Pischke 2005):

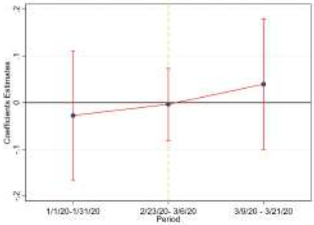
$$Y_{ij,t} = \alpha + \gamma_j + \sum_{l=-m}^{q} \lambda_l [T_{ij} = l] + \sum_{l=-m}^{q} \delta_l ([T_{ij} = l] \times D_{ij}) + \epsilon_{ij,t} \quad (1)$$

- δ_l coefficient should be small in magnitude and non-significant for $l < 0$, that is, for the lth period occurring before the lockdown.
- We take as baseline the period between February 1, and February 19, 2020.
- δ_{-1} is defined as the coefficient on the interaction of the treatment indicator with the January dummy, δ_0 with the post-treatment period dummy, and δ_1 with the post-post-treatment dummy.

Parallel trends



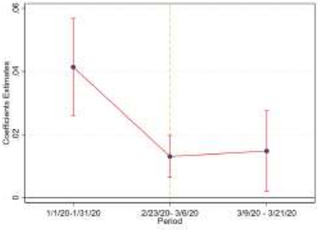
(a) Uncertainty



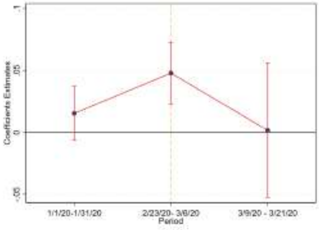
(b) Negative Sentiment

Figure 4: Coefficient Estimates and Confidence Intervals (% 95) of interaction between the treatment variable and time dummies. The dependent variable is Share of *Uncertainty* and *Negative sentiment* tweets. Baseline period is given by February 1, 2020 - February 19, 2020.

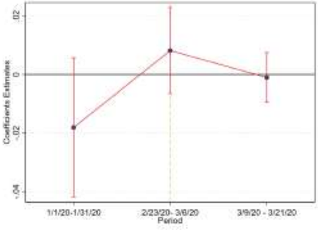
Parallel Trends



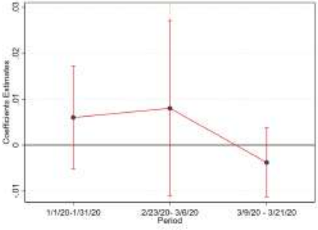
(a) Uncertainty-Economics



(b) Uncertainty-Health

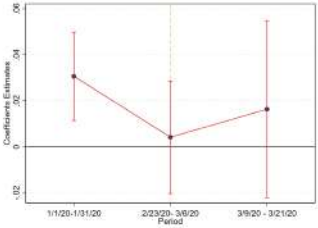


(c) Uncertainty-Politics

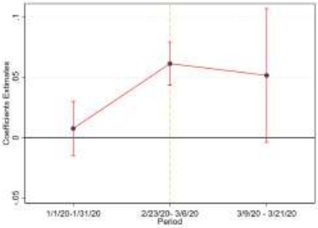


(d) Uncertainty-Lockdown Policy

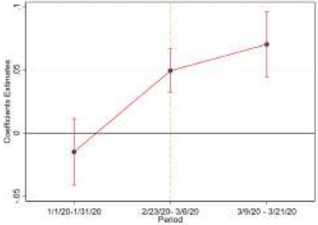
Parallel Trends



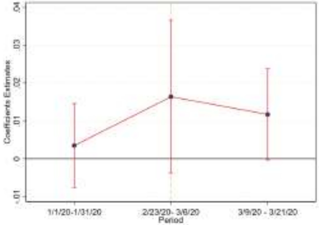
(a) Negative Sentiment-Economics



(b) Negative Sentiment-Health



(c) Negative Sentiment-Politics



(d) Negative Sentiment-Lockdown Policy

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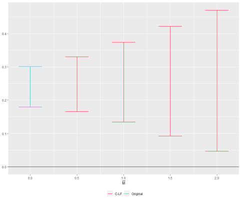
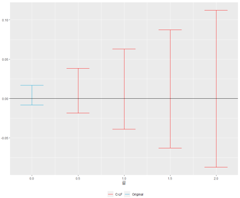
Sensitivity analysis with bounds on pre-trends

- Test robustness of the estimates of δ_0 in equation 1 -allowing for some violation of the parallel trends conditions Rambachan and Roth (2023).
- Size of post-treatment violation of parallel trends cannot be larger than $\bar{M}$ times the largest pre-treatment violation (Roth et al. 2023).
- We drop all observations from after the extension of the measure at the national level to avoid dealing within a staggered setting
- Sensitivity analysis with **HonestDiD**: we allow for different values of $\bar{M}$ and report the *robust* confidence intervals of δ_0 for changing the value of $\bar{M}$.

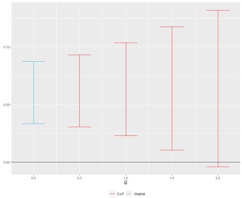
Sensitivity analysis with bounds on pre-trends



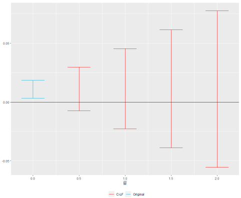
(a) Uncertainty



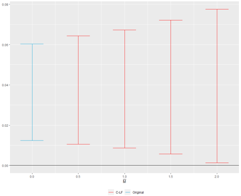
(b) Uncertainty-Economics



(c) Uncertainty-Health

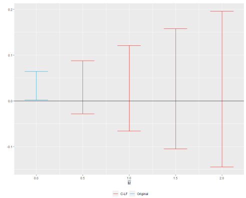


(d) Uncertainty-Politics

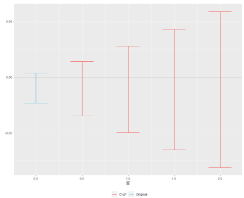


(e) Uncertainty-Policy

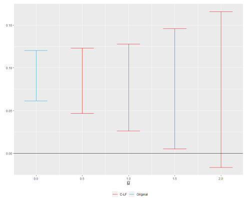
Sensitivity analysis with bounds on pre-trends



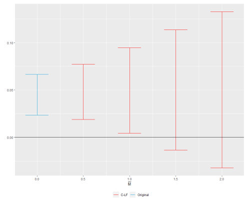
(a) Negative Sentiment



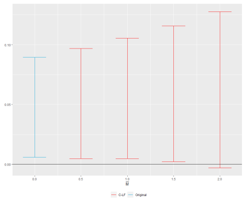
(b) Negative Sentiment-Economics



(c) Negative Sentiment-Health



(d) Negative Sentiment-Politics



(e) Negative Sentiment-Policy

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