Vax populi: the social costs of online vaccine skepticism

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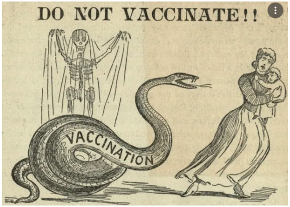
Fake news and social media

Nothing spreads faster than a newly discovered airborne disease that could potentially kill millions...except rumors on social media.

- New tech internet & social media $\rightarrow$ **free access to news at lower quality** (not subject to fact-checking/editorial judgement)

- Result: **lower ability of consumers to distinguish good from fake news** $\rightarrow$ also due to the ideological echo chambers (Cinelli et al., 2021), increasing polarization (Flaxman et al., 2016, Sunstein, 2001, 2017, 2018), ideological self-segregation (Berinsky, 2017, Gentzkow and Shapiro, 2011) and misinformation spread (Allcott and Gentzkow, 2017)

Fake news and pediatric vaccines



Recent leading fake news: 1998 Wakefield's study **published and retracted** in The Lancet on the link between measles, mumps and rubella **(MMR) vaccine and autism**.

Italian novax movement exploded in 2012: the Court of Rimini recognizes the causal link between the MMR and autism → decrease in child immunization rates (Carrieri et al., 2019).

LANGUAGE

novax = anti-vax
activism = activity, movement, propaganda
hesitancy = opting-out, avoidance, skipping shots

Pediatric vaccines in Italy

National Plan of Vaccine Prevention (PNPV) establishes vaccine calendar and eligible population which receives the shots free of charge at Local Health Authorities (LHAs)

MANDATORY

polio, diphtheria, tetanus, hepatitis B (combined with HIB and whooping cough as **hexavalent**, or 6-in-1 vaccine)

RECOMMENDED until 2017

MMR, chickenpox, meningo- and pneumococcal

- After 2010 coverage declined and several outbreaks of measles epidemics took place.
- In 2017 PNPV **enforced** and extended **mandatory shots to MMR and the recommended ones** stating that ”*falling uptake was driven by* ***novax sentiment*** *and put in danger not only the eligible but also* ***the fragile”*** (Decree 73, 2017, “Lorenzin’s Law”).

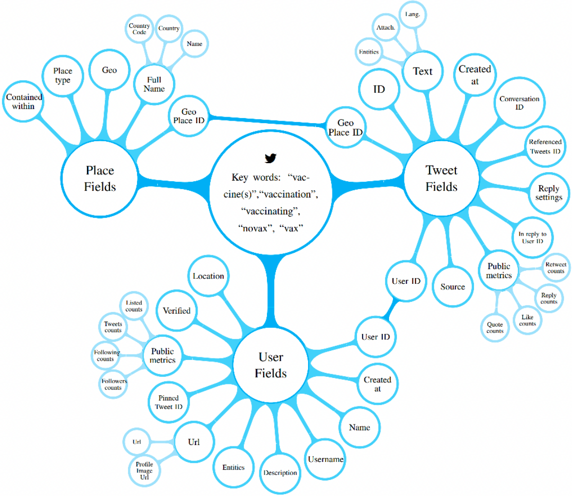
RQ: Does `Twitter` novax activism affect public health?

Understand how the anti-vax movement harms public health endeavors and generates negative spillovers:

- Pair vaccine-related tweets with disease-specific vaccine coverage rates, hospitalizations, and costs due to vaccine-preventable diseases for 2013-2018
- Propose a model of opinion dynamics formation on social networks, to formalize the sources of engodeneity that pervade the relationship between the spread of anti-vax opinions on media and vaccine hesitancy
- Use an IV strategy based on users' ”friends-of-friends” network to identify exogenous variation in anti-vax views (Bramoullé et al., 2009)
- In a Mixed 2SLS (Dhrymes and Lleras-Muney, 2005) estimate the effect of users' anti-vax stances on their municipality level vaccination rates and vaccine preventable hospitalizations
- Policy implications

Scraping data from Twitter

Through Twitter API for academia we collect all publicly available tweets on vaccines (Jan 1, 2013 to Dec 31, 2018) $\rightarrow \approx 2.04$ mln Query.



We map tweets with geolocation data ($\rightarrow$ 830,253 geotagged tweets for 80,471 unique users on 4220 municipalities) Descs. Maps User trend

Sentiment analysis: `VaxBERTo`

Train an anti-vax tweet classifier **`VaxBERTo`** on 2.04mln tweets, using the Italian version of the Natural Language Processing model `BERT` (as in Polignano et al 2019)

- capable of *understanding* the social media atypical language, with all contextual nuances (irony etc.)

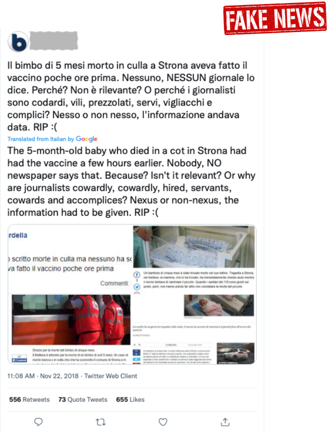
For geeks, please see the Appendix

1 **manually** label (`anti-vax==0/1`) tweets created by media and renowned fake news accounts (48k tweets) (Pierri et al. 2020)

3 the **prediction phase**: the model is evaluated with the small test dataset and the remaining untagged textual data (2mln) are categorized: $l_\tau \in \{0, 1\}$

Identifying users' attitudes

`anti-vax == 1`



`anti-vax == 0`

Consider a user i producing a number of a_i of contents: $C_i = \{c_1, c_2, ...c_{a_i}\}$

The individual anti-vax stance is defined as the **share of anti-vax tweets in all their vax-related tweets** in year t:

$$s_{it} \equiv \frac{\sum_{\tau=1}^{a_{it}} c_\tau}{a_{it}} \times 100$$

Health data

Vaccination rates Descriptive statistics.

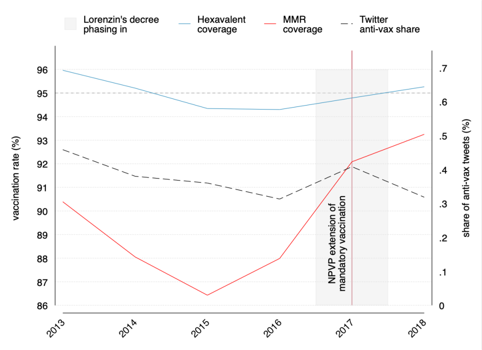
- Disease specific vaccination rates in the target pediatric population at municipality yearly level provided by LHAs, for the period 2013-2018

Hospitalization data Descriptive statistics.

- Hospital Discharge Data (SDO) on the **universe** of Italian hospital admissions for the period 2013-2016.
- focus on the diagnosis of vaccine-preventable diseases in:
  - vaccine-target population (children aged between 1 and 10 y.o.)
  - fragile population not-targeted by the vaccines: newborns, pregnant women, and patients with immunosuppressing conditions (based on ICD-09)
- Construct hospitalization **rates and costs** per 100k residents at municipality yearly level.

Twitter stances and vaccination rate

Figure 1: (b) Vaccination rate and share of tweets anti-vax geolocated



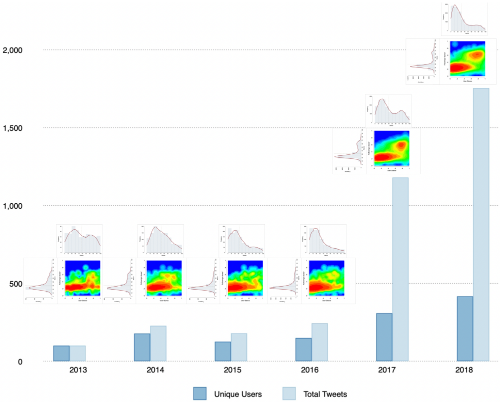
- Progressive decline in coverage until 2015, when the Rimini Court sentence was reversed by the Bologna Appeal Court
- Coverage rates (MMR in particular) started to rise from 2016, when extension and enforcement of mandatory vaccines was debated, and reinforced by National Law 117,2017.

The model of Opinion Dynamics and Network formation

Rationalize the evolution of social media anti-vax stances in Italy based on a model of social networks opinion dynamics proposed by Baumann et al, 2020: Details. Simulations.

- *exposure effect*: exposure to extreme-stances influences users' stance
- *link formation effect*: the controversialness of a vaccine-related topic endogenously exacerbates polarization by influencing the network formation process

Figure 2: Dynamics of Twitter activity on vaccination (2013-2018)



IV strategy

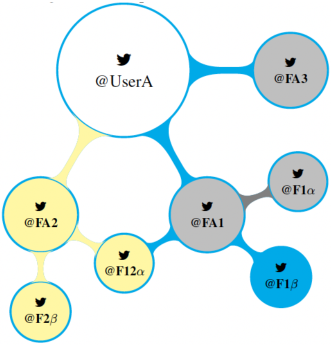
Exogenous variation in novax views of `Twitter` $\rightarrow$ peer effects of the users' networks (Bramoullé et al., 2009)

LANGUAGE

friend $=$ a user I follow
friend of friend $=$ a user that my friend follows
follower $=$ a user that follows me

- To overcome the link formation effect we exploit **intransitivity** in network connections - when **user's friends of friends** are not direct friends of the user, they have an impact on user's outcomes only through their effect on direct friends, providing a valid instrument

Friends-of-friends network



For each geotagged initial user we define a 2-step neighborhood:

1. *friends*
   - ~~*active*~~
   - *passive* ($\sim$ 48,2mln nodes for $\sim$ 8mln unique friends)
2. *friends of friends*
   - *active* ($\sim$ 103,3mln nodes for $\sim$ 222k unique friends lag2)
   - ~~*passive*~~

IV variable: each initial user's i in time t features an indirect exposure to their N *friends of friends* novax stances as the **group-specific average anti-vax stances**:

$$ffs_{it} \equiv \frac{\sum_{\tau=1}^{N} s_\tau}{N_{it}} \times 100$$

Mixed 2SLS

We adopt M2SLS for estimation with grouped data (Dhrymes and Lleras-Muney, 2005):

- endogenous regressor s_{it} (*novax stance*) at the individual level i
- dependent variables $\overline{V}_{mt}$ (*vaccination rates/hospitalization rates/hospitalization costs*) at the municipality level m

First stage - (individual/year level)

$$s_{it} = \alpha + \beta f\bar{f} s_{it}^{ind} + \mathbf{T}'_{mt}\zeta + \mathbf{C}'_{mt}\phi + \gamma_m + \rho_r \times t + \theta_t + \varepsilon_{it} \qquad (1)$$

Second stage - (municipality/year level)

$$V_{mt} = \alpha + \lambda\bar{\hat{s}}_{mt} + \overline{\mathbf{T}}'_{mt}\xi + \mathbf{C}'_{mt}\phi + \gamma_m + \rho_r \times t + \theta_t + \eta_{mt} \qquad (2)$$

Second stage - vaccine coverage

Table 1: Results of the OLS and the Second stage of the Mixed 2SLS - Vaccination rates

	(1) OLS V_{mt}	(2) Mixed 2SLS V_{mt}
Panel a: Hexavalent (94.06)		
s_{mt}	-0.0005	-0.002
	[0.002]	[0.015]
	7239	7239
Panel b: MMR (89.53)		
s_{mt}	-0.005	**-0.043****
	[0.003]	[0.022]
	7238	7238
Panel c: Menigococcal (81.32)		
s_{mt}	-0.006	-0.008
	[0.007]	[0.055]
	7074	7074
Panel d: Pneumococcal (82.64)		
s_{mt}	-0.0001	-0.029
	[0.007]	[0.054]
	7066	7066
CONTROL (Twitter)	✓	✓
CONTROL (socioeconomics)	✓	✓
CITY and YEAR FE	✓	✓
Reg Year	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
$Notes$: All estimates include city and year fixed effects as well as region specific time trends. Standard errors (in brackets) are clustered at the municipality level. Estimates as well as averages of V_{mt} is weighted by the municipality population size.

First stage.

Second stage - hospitalizations and costs

Table 2: Results of the OLS and the Second stage of the Mixed 2SLS - Hospitalizations .

	(1) OLS V_{mt} non-target pop.	(2) Mixed 2SLS V_{mt} non-target pop.	(3) OLS V_{mt} non-target pop.(MMR)	(4) Mixed 2SLS V_{mt} non-target pop.(MMR)	(5) OLS V_{mt} Children age 1-10 (MMR)	(6) Mixed 2SLS V_{mt} Children age 1-10 (MMR)
Panel a: Hopitalizations						
s_{mt}	0.0211	**0.213***	0.0182**	**0.234*****	0.00712	**0.145****
	[0.0159]	[0.113]	[0.00841]	[0.0601]	[0.00780]	[0.0650]
Panel b: Healthcare costs						
s_{mt}	129.8*	**731.1****	71.96**	**722.1*****	47.13*	**366.9****
	[66.39]	[353.8]	[30.92]	[243.1]	[25.95]	[161.1]
N	3331	3331	3331	3331	3331	3331
CONTROL (Twitter)	✓	✓	✓	✓	✓	✓
CONTROL (socioec.)	✓	✓	✓	✓	✓	✓
CITY and YEAR FE	✓	✓	✓	✓	✓	✓
Reg Year	✓	✓	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
$Notes$: All estimates include city and year fixed effects as well as region specific time trends. Standard errors (in brackets) are clustered at the municipality level. Estimates are weighted by the municipality population size.

A 10pp increase in the municipality level novax stance → 2 additional hospitalization every 100k residents, and 7311 euro additional expenditure, which is a + 11% increase. Second stage (Mandatory).

Robustness checks - Second stage Vaccination rate

Table 3: Mixed 2SLS Individual - Second stage (Vaccination rate.

	(1) Main	(2) Twitter algortithm	(3) Emilia Romagna Law	(4) Populist party	(5) Network distance
	s_{it} (30.33)	s_{it} (30.33)	s_{it} (30.33)	s_{it} (30.33)	s_{it} (30.33)
$f\bar{f}s_{it}^{ind}$	0.704***	0.528***	0.706***	0.691***	0.611***
	[0.017]	[0.035]	[0.017]	[0.022]	[0.021]
$f\bar{f}s_{it}^{ind} \times$ TWalg		0.251***			
		[0.039]			
$f\bar{f}s_{it}^{ind} \times$ ER			0.005		
			[0.0742]		
$f\bar{f}s_{it}^{ind} \times$ PP				0.048	
				[0.043]	
N	127,754	127,754	127,754	127,754	127,754
CONTROLs	✓	✓	✓	✓	✓
CITY and YEAR FE	✓	✓	✓	✓	✓
REG year	✓	✓	✓	✓	✓
F-stat	1757.86	998.690	870.815	943.98	875.82

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$Notes$: The numbers refer to an initial sample of 830,253 tweets to a population of 80,471 unique users across 4220 municipalities. All estimates include city, region and year fixed effects and region-specific time trends fixed effects. Standard errors (in brackets) are clustered at the municipality level. Mean values of s_{it} in parentheses are weighted by population size.

second stage checks Hospitalizations second stage vaccination rate

Non-linear effects and policy implications

Table 4: Mixed 2SLS for pro-vax vs. anti-vax users - First stage.

	(1)	(2)
	Pro_{it}	$Anti_{it}$
	(0.495)	(0.204)
$f\bar{f}s_{it}^{ind}$ (28.77)	-0.0076 ***	0 .0046***
	[0 .0003]	[0.0001]
N	127754	127754
CONTROLs	✓	✓
CITY and YEAR FE	✓	✓
Reg Year	✓	✓
F-stat	1765.22	1763.52

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Mixed 2SLS for pro-vax vs. anti-vax users - Second stage Vaccination rates

	(1)	(2)
	Pro_{mt}	$Anti_{mt}$
	V_{mt}	V_{mt}
Panel b: MMR (89.53)		
	3.9086*	-6.6162*
	[2.1978]	[3.5315]
	7238	7238
CONTROLs	✓	✓
CITY and YEAR FE	✓	✓
Reg Year	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The role of online debates' topics

Table 6: User exposure to friends-of-friends stances and the role of online debates' topics.

	(1)	(2)	(2)
	s_{it}	Pro_{it}	$Anti_{it}$
	(30.31)	(0.495)	(0.204)
$f\bar{f}s_{it}^{ind}$	0.2884***	-0.3309***	0.2295***
	[0.0693]	[0.0757]	[0.0728]
$f\bar{f}s_{it}^{ind} \times Efficacy$	-0.3425	0.3765	-0.3548
	[0.2724]	[0.2754]	[0.2961]
$f\bar{f}s_{it}^{ind} \times TrustfulSource$	-0.3136***	0.2656**	-0.3805***
	[0.0992]	[0.1127]	[0.1057]
$f\bar{f}s_{it}^{ind} \times PoliticsandMandate$	-0.1749***	0.0660	-0.3899***
	[0.0530]	[0.0408]	[0.0589]
$f\bar{f}s_{it}^{ind} \times VaccinesUnsafe$	-0.0697	0.1369	-0.0387
	[0.2292]	[0.2442]	[0.2495]
N	531352	531352	531352
User FE	✓	✓	✓
Daily date FE	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$Notes$: The numbers refer to an initial sample of 830,253 tweets to a population of 80,471 unique users across 4220 municipalities. All estimates include individual and daily date fixed effects. Standard errors (in brackets) are clustered at the individual. Mean values of s_{it}, $ffsPro_{it}$, and $ffsAnti_{it}$ in parentheses are weighted by population size.

Conclusions

- Novax propaganda in social media is **contagious** among users
- In the absence of vaccination mandate, local exposure to novax propaganda causes a reduction in vaccination rates
- Novax propaganda has economically relevant negative spillovers, where hospitalizations of patients non-targeted by the vaccines for vaccine-preventable disease are more frequent and impose extra costs on society.
- Controversial vaccination mandates (e.g. enforced on school enrollment) have the potential to **backfire**
- Policy makers should invest in raising awareness, especially using trustful sources in order to mitigate the impact of vaccine skeptic social media campaigns

APPENDIX

Scraping data from Twitter

We run the query based on very general keywords related to vaccines - more specifically, we focus on all tweets in Italian which include the translation of “vaccine(s)”,“vaccination”, “vaccinating”, “novax”, “vax”, but for those (mainly ads) referring to mozzarella or cow milk (“latte vaccino” in Italian). The current version of the dataset was downloaded on April 23rd, 2021.

```
query = "(vaccino OR vaccini OR vaccinazione OR vaccinazioni
OR vaccinarsi OR vaccinato OR vaccinata OR novax OR vax
-latte vaccino) lang:it"
start_date = "01-01-2013T00:00"
end_date = "01-01-2019T00:00"
```

Scraping.

Descriptive statistics of `Twitter` data

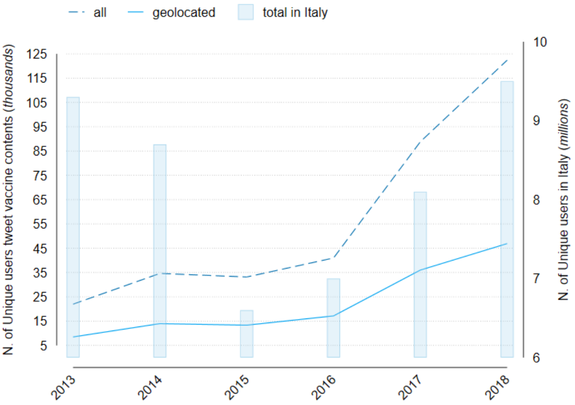
	median	mean	sd	min	max
(a) User characteristics					
Tweets about vaccine	1.00	6.24	32.82	1.00	3,720
Total *tweets*	5,586.00	19,793.54	50,699.13	1.00	1,825,203
Total *followers*	335.00	3,692.14	51,951.40	0.00	3,262,940
Total *friends*	462.00	970.31	2,759.93	0.00	189,582
Account's date of creation		2012	2.49	2006	2018
Verified accounts		0.007	0.084	0	1
(b) Tweets' characteristics					
Length of the tweet (number of characters)		102.42	42.05	0	306
Number of words		16.13	6.96	0	62
Retweets (%)		0.60	0.49	0	1
Replies (%)		0.10	0.30	0	1
(c) Tweets' popularity					
Retweet count		2.59	35.85	0.00	6696
Reply count		0.73	7.10	0.00	1106
Quote count		0.06	1.31	0.00	341
Like count		5.71	90.44	0.00	14188

$Notes$: *(a)*: summary statistics of 80,471 geotagged unique users tweeting on vaccines (2013-2018); *(b)*: summary statistics of 830,253 geotagged tweets cleaned by hashtag, "RT @", "@", url and emoji; *(c)*: Tweet-related popularity metrics of 328,879 original tweets.

Scraping data.

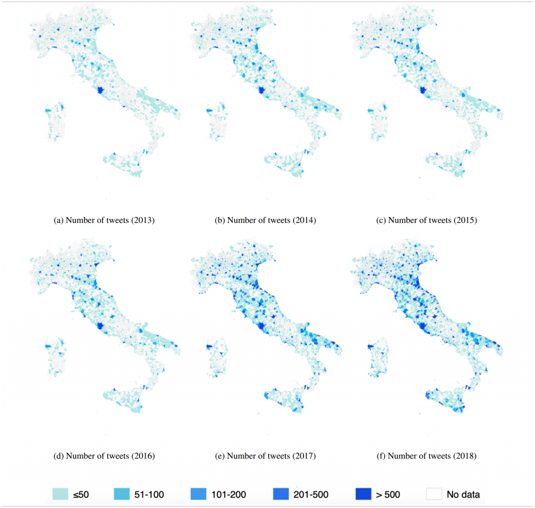
Number of unique users

Figure 3: Number of unique users



Scraping data.

Tweets mapping



Scraping data.

Descriptive statistics of vaccination rates (2013-2018

		Median	Mean	SD	Min	Max	N
Hexavalent	Diphteria*	94.97	94.29	3.15	54.69	100.00	44,750
	Hephatitis B*	94.80	94.15	3.19	54.69	100.00	44,750
	Polio*	95.00	94.31	3.14	54.69	100.00	44,750
	Tetanus*	95.00	94.38	3.13	54.69	100.00	44,777
	Pertussis**	94.94	94.29	3.14	54.69	100.00	44,750
	HIB**	94.64	94.04	3.17	54.69	100.00	44,749
Hexavalent		94.88	94.24	3.14	54.69	100.00	44,779
MMR	Measles**	91.05	89.52	5.97	10.72	100.00	44,750
	Rubella**	91.00	89.50	5.97	10.72	100.00	44,750
	Mumps**	91.00	89.48	5.96	10.72	100.00	44,750
MMR		91.02	89.50	5.97	10.72	100.00	44,752
Meningococcus		87.32	81.22	15.86	0.17	99.61	43,219
Pneumococcus		91.46	87.26	11.94	.17	100	43,167

Notes: exavalent and MMR vaccination rates across 7,929 Italian municipalities for the period 2013-2018. Average values are weighted by the municipality population size. * marks 2013-2017 set of compulsory vaccinations, ** indicates additional mandatory shots introduced by the 2017 Law Decree 73.

Health data.

Descriptive statistics of hospitalization due to vaccine-preventable diseases (2013-2016)

	Median	Mean	sd	Min	Max	N
Panel a: Hopitalizations						
non-target population	14.71	22.21	30.95	0.00	3,202.85	31,760
non-target population (MMR)	0.00	4.99	17.58	0.00	2,846.98	31,760
non-target population (Hexav.)	10.40	16.99	22.02	0.00	355.87	31,760
non-target population (Meningo.)	0.00	0.02	0.26	0.00	29.02	31,760
non-target population (Pneumo.)	0.00	0.88	2.25	0.00	155.04	31,760
Children age 1-10 (MMR)	0.00	2.96	6.87	0.00	1,617.25	31,760
Children age 1-10 (Hexav.)	0.00	1.27	2.70	0.00	152.44	31,760
Children age 1-10 (Meningo.)	0.00	0.04	0.41	0.00	26.21	31,760
Children age 1-10 (Pneumo.)	0.00	0.50	1.76	0.00	132.04	31,760
Panel b: Healthcare costs						
non-target population	38,581.69	66,477.60	116,320.65	0.00	59,880,842.11	31,760
non-target population (MMR)	0.00	15,381.55	96,931.58	0.00	59,880,842.11	31,760
non-target population (Hexav.)	46,275.59	83,151.57	119,925.38	0.00	14,819,697.72	31,760
non-target population (Meningo.)	0.00	150.92	3,976.38	0.00	411,341.22	31,760
non-target population (Pneumo.)	0.00	2,332.30	9,004.03	0.00	1,941,927.83	31,760
Children age 1-10 (MMR)	0.00	4,749.99	25,506.58	0.00	2,274,286.39	31,760
Children age 1-10 (Hexav.)	0.00	2,545.85	9,407.74	0.00	759,286.31	31,760
Children age 1-10 (Meningo.)	0.00	190.58	3,185.72	0.00	409,748.10	31,760
Children age 1-10 (Pneumo.)	0.00	1,255.36	5,365.51	0.00	259,504.65	31,760

Notes: The statistics refer to 7,940 municipalities for the time period between 2013-2016 and are weighted by the municipality population size.

Health data.

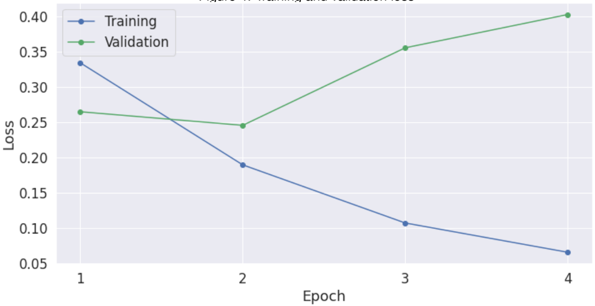
Training phase

Table 7: vaxBERTo last layer training

epoch	Training Loss	Valid. Loss	Valid. Accur.	Training Time	Validation Time
1	0.3342	0.2650	0.8885	0:05:50	0:00:13
2	0.1897	0.2456	0.9072	0:05:47	0:00:13
3	0.1074	0.3554	0.9023	0:05:47	0:00:13
4	0.0660	0.4025	0.9055	0:05:46	0:00:13

Notes: training and validation losses (columns 2 and 3), accuracy (4) and computing time (5 and 6) for each vaxBERTo training epoch.

Figure 4: Training and validation loss



How it works

Conceptual Framework

$$\dot{s}_i = -s_i + \mathbb{I} \sum_{j=1}^{N} W_{ij}(t) tanh(\alpha s_j) \qquad (3)$$

- $\mathbb{I}$ measures the strength of the interaction among users of the platform
- $W(t)$ is a time-varying spatial contiguity matrix, whose i^{th}, j^{th} elements represent every link between individuals in the network
- $tanh(\cdot)$ is the hyperbolic tangent function, which provides a sigmoidal influence function of peers on individuals' stances.
- α captures the degree of *controversialness* of the topic

The contiguity matrix $W(t)$ evolves according to an activity-driven (AD) temporal network (Perra et al 2012), where each agent is characterized by the propensity to interact with a share $\omega_i \in [\epsilon, 1]$ of other agents, and the probability of an interaction is driven by homophily (Bessi et al 2016) $\longrightarrow$individuals are more likely to interact with like-minded peers, and we model it as a decreasing function of the (absolute) distance between i and j's opinions, $p_{ij}(t) = \frac{|s_i(t)-s_j|^{-\beta}}{\sum_j |x_i - x_j|^{-\beta}}$.

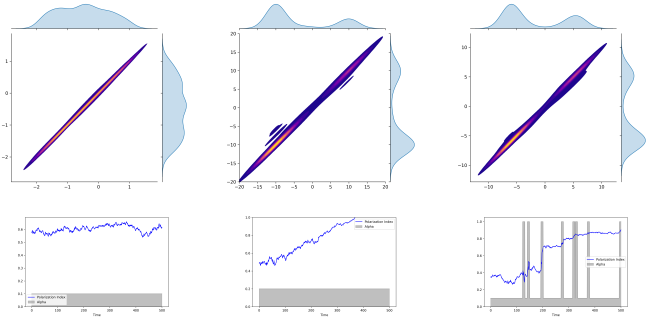
Conceptual framerwork

Simulated distribution of stances

Simulations →Micro-interactions of users on **controversial** topics give rise to transitions from a relative consensus to polarization

Figure 5: Simulated distribution of stances

(a) Low controversialness (b) High controversialness (c) Time-varying controversialness



Notes: user (x-axis) and average friends' (y-axis) distribution of stances in a simulated model with low - (a), $\alpha = .1$ - high - (b), $\alpha = .2$ - and low with exogenous, short-term outbursts controversialness - (c). In all models, the number of individuals is $N = 500$ and the periods are $T = 5$ - divided in 100 subperiods. We also set $\beta = 2$, $K = 3$ and $a = .2$. Initial values (s_0) are randomly drawn from a gaussian distribution with $\mu = -0.2$ and $\sigma = 0.5$ to match the asymmetry of the initial opinions in the data.

Conceptual framework.

Descriptive statistics of ego network

	Median	Mean	sd	Min	Max
Friends	469	973.46	2,717.55	1.00	189,433
Friends of friends (fof)	7,687	12,556.24	14,078.73	1.00	139,508
Total fof tweets with vaccine contents	59,535.50	142,261.09	186,460.83	1.00	1,685,355

Notes: The statistics refer to 80,471 geotagged unique users tweeting on vaccines (2013-2018) for 132,190 observations.

Friend-of-friends network

First stage

Table 8: Mixed 2SLS Individual - First stage.

	(1)	(2)	(3)	(4)
	s_{it}	s_{it}	s_{it}	s_{it}
	(30.31)	(30.31)	(30.31)	(30.31)
$f\bar{f}s_{it}^{ind}$ (28.77)	0.703^{***}	0.703^{***}	0.704^{***}	0.704^{***}
	[0.017]	[0.017]	[0.017]	[0.017]
N	127754	127754	127754	127754
CONTROL (Twitter)		✓		✓
CONTROL (socioeconomics)			✓	✓
CITY and YEAR FE	✓	✓	✓	✓
Reg Year	✓	✓	✓	✓
F-stat	1765.22	1763.52	1755.84	1757.86

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
$Notes$: The numbers refer to an initial sample of 830,253 tweets to a population of 80,471 unique users across 4220 municipalities. All estimates include city, region and year fixed effects and region specific time trends fixed effect. Standard errors (in brackets) are clustered on municipalities level. Mean values of s_{it} and $f\bar{f}s_{it}^{ind}$ in parentheses is weighted by population size.

In a set of balance tests we rule out potential non-random assignment of our IV with respect to contextual features of municipalities where the users reside.

Second stage. Balance test.

Balance Test

Is our IV randomly assigned with respect to contextual features of municipalities where the users reside?

Variation in novax stances of friends of friends should be unrelated to predetermined characteristics of the municipalities after controlling for municipality and year fixed effects First stage.

Table 9: Balance test

	(1) Health public cost per capita	(2) Income per capita	(3) Lower secondary school att. (%)	(4) Avg. mother's age at birth	(5) Birth rate	(6) Populist party
Panel a: geolocated in the same user's municipality						
$f\bar{f}s_{it}^{ind}$	-0.0211	-0.403	0.0001	0.0001	-0.0002	0.0002
	[0.0246]	[0.442]	[0.0002]	[0.0001]	[0.0002]	[0.0002]
	110639	110639	110639	110589	110639	110639
Panel b: geolocated in municipalities different from the user's municipality						
$f\bar{f}s_{it}^{ind}$	-0.0001	-0.447	-0.0001	-0.0001	-0.00002	0.0001
	[0.0126]	[0.337]	[0.0004]	[0.0001]	[0.0001]	[0.0001]
	131003	131003	131003	130817	131003	131003
Panel c: not geolocated						
$f\bar{f}s_{it}^{ind}$	0.0037	1.001	-0.00004	-0.00001	0.0001	0.0002
	[0.0121]	[0.912]	[0.0002]	[0.00003]	[0.0001]	[0.0002]
	130977	130977	130977	130791	130977	130977
CITY and YEAR FE	✓	✓	✓	✓	✓	✓

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.
$Notes$: Figures in parentheses are standard errors robust to clustering at the municipality level.

Second stage - vaccine coverage (MANDATORY)

Table 10: Results of the OLS and the Second stage of the Mixed 2SLS - Hospitalizations.

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Mixed 2SLS	OLS	Mixed 2SLS	OLS	Mixed 2SLS
	V_{mt} (Hexav.)	V_{mt} (Hexav.)	V_{mt} (Meningo.)	V_{mt} (Meningo.)	V_{mt} (Pneumo.)	V_{mt} (Pneumo.)
	Non-target population					
Panel a: Hopitalizations						
s_{mt}	0.009	0.025	-0.0001	-0.0003	-0.0006	-0.021
	[0.012]	[0.092]	[0.0002]	[0.0009]	[0.002]	[0.015]
Panel b: Healthcare costs						
s_{mt}	102.0	-628.4	-4.756	-20.81	-10.53*	-46.519
	[100.6]	[700.3]	[3.976]	[16.46]	[6.103]	[37.26]
	Children age 1-10					
Panel a: Hopitalizations						
s_{mt}	-0.00007	0.002	0.00005	0.0003	-0.002	0.009
	[0.003]	[0.016]	[0.0006]	[0.004]	[0.002]	[0.011]
Panel b: Healthcare costs						
s_{mt}	12.74	-66.18	-0.528	10.36	-3.788	-37.99
	[18.45]	[49.21]	[2.887]	[14.90]	[6.229]	[42.28]
N	3331	3331	3331	3331	3331	3331
CONTROL (Twitter)	✓	✓	✓	✓	✓	✓
CONTROL (socioeconomics)	✓	✓	✓	✓	✓	✓
CITY and YEAR FE	✓	✓	✓	✓	✓	✓
Reg Year	✓	✓	✓	✓	✓	✓

$^{*}\ p < 0.10, ^{**}\ p < 0.05, ^{***}\ p < 0.01.$

$Notes$: All estimates include city and year fixed effects and region-specific time trends. Standard errors (in brackets) are clustered at the municipality level. Estimates are weighted by the municipality population size.

Second stage.

Robustness checks - Second stage vaccination rate

Table 11: Mixed 2SLS Individual - Second stage (Vaccination rate).

	(1) Main	(2) Twitter algortithm	(3) Emilia Romagna Law	(4) Populist Party Law	(5) Network distance
	V_{mt}	V_{mt}	V_{mt}	V_{mt}	V_{mt}
Panel a: Hexavalent (94.06)					
s_{mt}	-0.001	-0.001	-0.003	-0.00393	-0.001
	[0.014]	[0.017]	[0.014]	[0.0157]	[0.014]
	7239	7239	7239	7239	7239
Panel b: MMR (89.53)					
s_{mt}	-0.041**	-0.039*	-0.043*	-0.0440*	-0.028*
	[0.019]	[0.024]	[0.025]	[0.0236]	[0.013]
	7238	7238	7238	7238	7238
Panel c: Menigococcus (81.32)					
s_{mt}	-0.040	-0.0113	-0.0109	-0.0127	-0.035
	[0.043]	[0.057]	[0.058]	[0.0552]	[0.039]
	7074	7074	7074	7074	7074
Panel d: Pneumococcus (82.64)					
s_{mt}	-0.010	-0.010	-0.018	-0.0386	-0.008
	[0.018]	[0.019]	[0.021]	[0.0594]	[0.010]
	7079	7079	7079	7079	7079
CONTROL (Twitter)	✓	✓	✓	✓	✓
CONTROL (socioeconomics)	✓	✓	✓	✓	✓
CITY and YEAR FE	✓	✓	✓	✓	✓
Reg Year	✓	✓	✓	✓	✓

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.
$Notes$: All estimates include city and year fixed effects and region-specific time trends. Standard errors (in brackets) are clustered at the municipality level. Estimates, as well as averages of V_{mt}, are weighted by the municipality population size.

Robustness checks

Robustness checks - Second stage hospitalizations

Table 12: Mixed 2SLS Individual - Second stage (Hospitalizations).

	(1) Main	(2) Twitter algortithm	(3) Emilia Romagna Law	(4) Populist party	(5) Network distance
	V_{mt}	V_{mt}	V_{mt}	V_{mt}	V_{mt}
			Non-target population		
Panel a: Hopitalizations					
	0.213*	0.231*	0.204*	0.215*	0.220*
	[0.113]	[0.121]	[0.112]	[0.112]	[0.115]
Panel b: Healthcare costs					
	731.1**	821.3**	712.8**	746.5*	794.0**
	[409.8]	[434.7]	[406.6]	[412.2]	[411.0]
			Non-target population (MMR)		
Panel c: Hopitalizations					
	0.234***	0.256***	0.233***	0.231***	0.242***
	[0.0601]	[0.0675]	[0.0596]	[0.0603]	[0.0621]
Panel d: Healthcare costs					
	722.1***	716.7***	725.1***	734.0***	743.7***
	[243.1]	[250.6]	[242.8]	[247.7]	[247.1]
			Children age 1-10 (MMR)		
Panel e: Hopitalizations					
	0.145**	0.150**	0.145**	0.146**	0.142**
	[0.0650]	[0.0664]	[0.0651]	[0.0653]	[0.0659]
Panel f: Healthcare costs					
	366.9**	428.7**	366.5**	363.6**	390.2**
	[161.1]	[171.8]	[160.9]	[163.9]	[163.7]
	3331	3331	3331	3331	3331
CONTROLs	✓	✓	✓	✓	✓
CITY and YEAR FE	✓	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
$Notes$: All estimates include city and year fixed effects and region-specific time trends. Standard errors (in brackets) are clustered at the municipality level. Estimates are weighted by the municipality population size.