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Vincenzo Carrieri; Leonardo Madio and  
Francesco Principe

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# Vaccine Hesitancy and Fake News: Quasi-experimental Evidence from Italy

Vincenzo Carrieri<sup>¶</sup>  
Leonardo Madio<sup>†</sup>  
Francesco Principe<sup>♣</sup>

## Abstract

The spread of fake news and misinformation on social media is blamed to be one of the main causes of vaccine hesitancy, one of the ten threats to global health according to World Health Organization. This paper studies the effect of diffusion of fake news on immunization rates in Italy by exploiting a quasi-experiment occurred in 2012, when the Court of Rimini officially recognized a causal link between MMR vaccine and autism and awarded injury compensation. To this end, we exploit *virality* of fake news following the 2012 Italian Court's ruling along with the intensity in the exposure to non-traditional media driven by regional infrastructural differences in Internet broadband coverage. Using a Difference-in-Difference (DiD) regression on regional panel data, we show that the spread of fake news caused a drop in children immunization rates for all types of vaccines.

**JEL Codes:** I12; I18; L82; L86.

**Keywords:** Fake news; vaccine hesitancy; children immunization rates, social media, Internet.

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<sup>¶</sup> Department of Law, Economics and Sociology, “Magna Graecia” University, Catanzaro, Italy; RWI-Research Network, Essen, Germany; HEDG, University of York, United Kingdom. E-mail: [vincenzo.carrieri@unicz.it](mailto:vincenzo.carrieri@unicz.it)

<sup>†</sup> CORE, Université Catholique de Louvain, Louvain-la-Neuve, Belgium; CESifo Research Network, Munich, Germany; HEDG, University of York, United Kingdom. E-mail: [leonardo.madio@uclouvain.be](mailto:leonardo.madio@uclouvain.be)

<sup>♣</sup> Erasmus School of Economics, Rotterdam, The Netherlands; HEDG, University of York, United Kingdom. E-mail: [principe@ese.eur.nl](mailto:principe@ese.eur.nl) (Corresponding author)

# 1 Introduction

Many countries are experiencing an outbreak of vaccine-preventable diseases like measles and diphtheria. For example, measles cases increased by 30% globally<sup>1</sup>. On 29<sup>th</sup> January 2019, Washington State officially declared the state of emergency for measles epidemic. In Europe, between 1 February 2017 and 31 January 2018, European Surveillance System reported 14 732 cases of measles. Among European countries, Italy (4,978 cases) had the highest incidence just after Romania (5,224 cases) (ECDC, 2019). These worrying statistics led WHO to include *Vaccine hesitancy* - i.e. the reluctance or refusal to vaccinate despite the availability of vaccines - as one of ten threats to global health nowadays.

The spread of fake news and misinformation on social media is blamed to be one of the main causes of this vaccine hesitancy (Smith and Marshall, 2010; Dubè et al., 2015; Jolley and Douglas, 2014; Aquino et al., 2017). This originated from the measles-mumps-rubella (MMR)–autism controversy due to the fake “Andrew Wakefield’s study”. A number of papers found that this controversy had a significant effect on immunization choices. Anderberg et al. (2011) found a significant effect on the take-up of the MMR vaccine in the U.K. dropping by over 5% points in 5 years, before climbing back again. Similarly, Smith et al. (2008) examined MMR uptake and nonreceipt in the United States and found declines in 1999 and 2000 and a return to previous levels of vaccination afterward. More recently, Chang (2018) showed that controversy led to a decline in the MMR immunization rates and negative spillovers onto other vaccines in the US.

This paper complements these existing studies in two important ways. First, it exploits a quasi-experiment occurred in March 2012 in Italy when the Court of Rimini granted compensation to a family recognizing that the MMR vaccine caused their child’s autism. To our knowledge, this was the first time that an official body formally recognized a causal link between MMR vaccine and autism. Following the Court’s decision, people concern around vaccines side-effects proliferated on the web and fake news around vaccines, now supported by a judge, became viral (Aquino et al., 2017). Figure 1 shows that the number of queries on Google search engine massively jumped up after March 2012 and remained quite stable afterwards. Compared to pre-2012, the volume of searches increased by 600%. Indeed, Court’s ruling allows us to establish a more precise timeline for *virality* of fake news and misinformation around vaccines in Italy.

Second, as access to non-traditional media and exposure to fake news is facilitated by Internet availability, we exploit the heterogeneity in regional (NUTS-2 level) broadband coverage across areas of the country. Broadband coverage depends on the historical local infrastructural system and this undergone several structural changes in the period we considered to bridge the long-lasting “Digital Divide” in Italy<sup>2</sup>. Broadband coverage is thus unlikely to be correlated with the demand for high-speed Internet and this provides an exogenous variation in the regional exposure to the

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<sup>1</sup> See WHO, “Ten threats to global health in 2019”, January 2019. Available at: <https://www.who.int/emergencies/ten-threats-to-global-health-in-2019>.

<sup>2</sup> In the period analyzed, broadband coverage in Italy passed from 15% in 2006 to 76% in 2016.

news. Similar identification strategies using discontinuities in broadband coverage have been widely used to estimate the effect of the Internet and media exposure on other relevant outcomes (see e.g., Falck et al., 2014; Gavazza et al., 2018).

We combine both source of variations (i.e. the 2012 Court's ruling and heterogeneity in broadband coverage) in a Differences-in-Differences (DiD) framework. We find that the spread of misinformation around vaccines following the Court's ruling caused a significant reduction in children immunization rates.

[Figure 1 around here]

## 2 Methods and data

We use a unique longitudinal dataset recording regional data on children immunization rates in Italy, matched with information on broadband coverage from 2006 through 2016 for all 21 NUTS-2 areas (19 regions and 2 autonomous provinces). This leads to a total sample of around 215 non-missing observations. Data on regional broadband coverage are made available by EUROSTAT, whereas regional data on vaccines are provided by the Italian Health Ministry.

We set-up a differences-in-differences model as follows:

$$Y_{rt} = \beta_1 Post + \beta_2 BBcoverage_{r,t} + \beta_{12} Post \times BBcoverage_{r,t} + \mu_r + \varepsilon_{rt} \quad (1)$$

Where  $Y_{rt}$  is the yearly regional immunization rate for all types of child vaccines: measles-mumps-rubella (MMR), diphtheria-pertussis-tetanus (DTP), Haemophilus influenzae type B (HIB), Polio (POL3), Hepatitis B (EpB).  $Post$  is the indicator of the post 2012 court decision period, whereas  $BBcoverage$  is our treatment intensity variable and measures the percentage of households that are connectable to broadband fixed and/or mobile connections.<sup>3</sup>  $\mu_r$  accounts for time-invariant differences between regions, whereas  $\varepsilon_{rt}$  is the idiosyncratic error term.

To assess the robustness of our findings, we estimate four additional versions of Equation (1). First, we add a time trend to account for variations over time in the immunization rates. Second, we add region-specific time trends. Third, we include a set of time-varying controls accounting for the socio-economic development of the area, such as regional per-capita disposable income and the share of university graduated individuals in the region. Lastly, following Bertrand et al., (2004), we perform randomization tests by estimating equation (1) using a random selection of a set of different time periods and treatment intensities ( $Year \times BBcoverage$ ) and using these placebo treatments instead of the real one. We then perform a Montecarlo simulation of these estimates with 2,000 repetitions in order to build a distribution of placebo treatment effects. This allows us to assess the credibility of the identification strategy and to check the robustness of our results to different assumptions about the structure of the error distribution.

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<sup>3</sup> Following EUROSTAT definition, broadband coverage at local level is measured as “the percentage of households (with at least one member aged 16 to 74) that are connectable to an exchange that has been converted to support xDSL-technology, to a cable network upgraded for internet traffic, or to other broadband technologies.”

### 3 Results

[Table 1 around here]

In Table 1 we report DiD estimates of equation (1) for all vaccines separately and for an overall measure of average immunization rate. We find a negative average treatment effect on all obligatory vaccines in Italy. Specifically, we find that a 10% increase in local broadband coverage led to a significant reduction of 1.45% in POL3 coverage, 1.32% in DTP coverage, 1.65% in EpB coverage, and 1.39% MMR coverage. For the case of HIB, spread of fake news entailed a negative although not statistically significant effect. The magnitude of our results raises important public health. In fact, this reduction led the immunization rates below the 95%, which is considered the herd immunization threshold. These results are robust also in magnitude to several alternative specifications, that is when including socio-economic controls (row 2), including time-trend (row 3), and region-specific trend (row 4).

[Figure 2 around here]

[Figure 3 around here]

In Figure 2 we perform a graphical inspection of the pre-Court's ruling trend of immunization rates across terciles of the treatment intensity variable. Visual inspection suggests that common trend hypothesis can be credibly maintained. However, to reduce any residual concern about possible violations of common trend assumption, in Figure 3 we present the non-parametric distribution of placebo estimates. As the mean of the distribution is virtually zero, the estimator is unbiased. Moreover, all the average treatment effects we estimate in Table 1 fall in the very extreme left tail of this distribution. This increases the confidence that the effect we estimate is not obtained by chance and provide full support to our identification strategy.

### 4 Conclusions

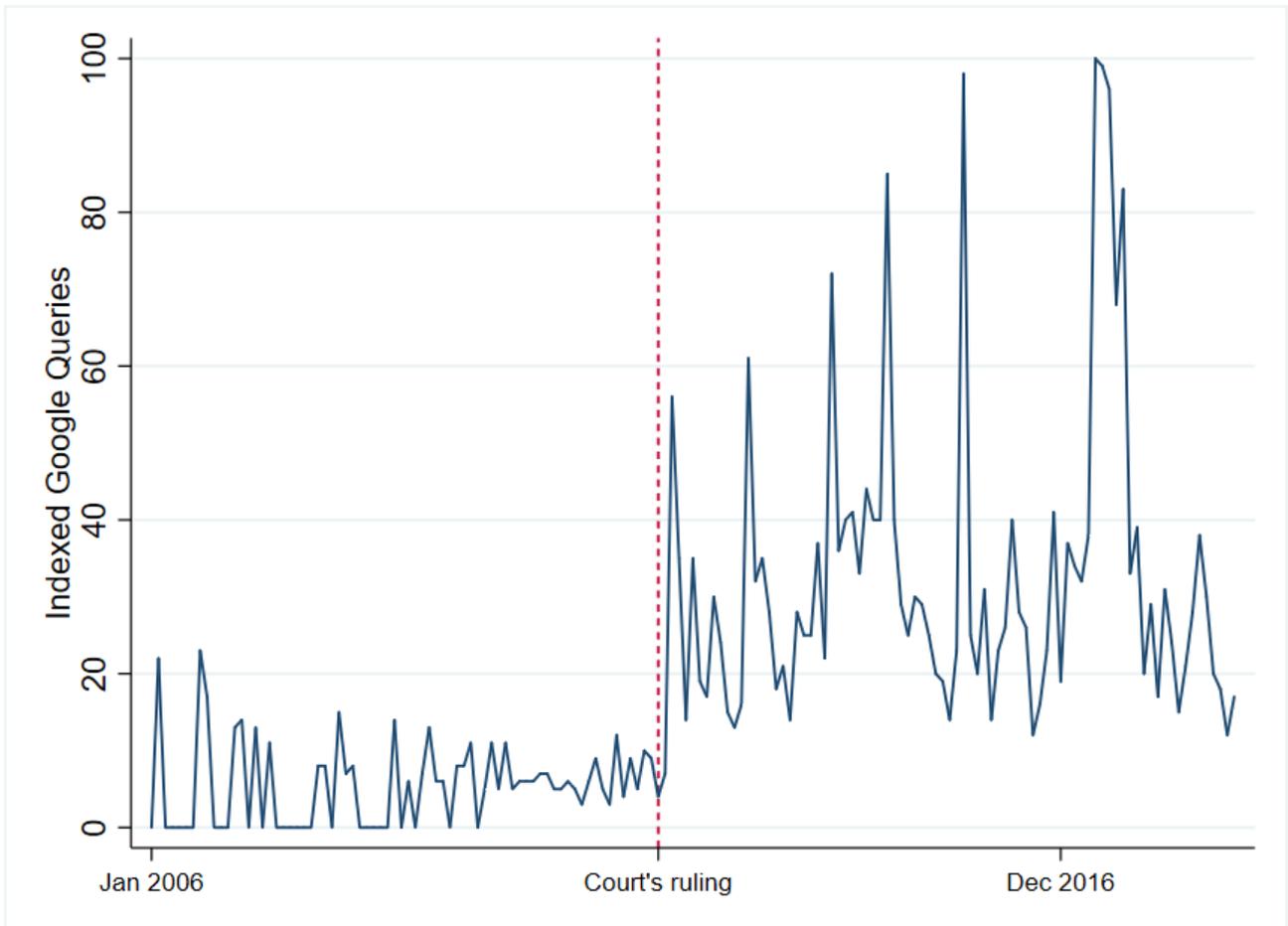
Fake news on social media are often blamed to be the cause of reduction in immunization rates worldwide. Recently, this pressured policy-makers, health authorities, and social media to regulatory interventions (see e.g., Chiou and Tucker, 2018). Our paper aimed at providing causal evidence of the effects of fake news on vaccines immunization rates. We exploit a quasi-experiment occurred in Italy when the Court of Rimini officially recognized a causal link between MMR vaccine and autism and awarded vaccine-injury compensation. After the decision, fake news and misinformation on vaccines became viral on the Web. Building on a growing literature studying the effects of the Internet on real-life outcomes, we find that after the Court's ruling in 2012, larger accessibility to non-traditional media (via broader broadband coverage) led to a reduction in children immunization rates. Interestingly, the negative and significant effect we found encompasses all vaccines and led the immunization rates below the critical threshold of 95%. Our results thus corroborate the thesis that virality of fake news was a dangerous cause of the vaccine hesitancy issue.

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## Figures and Tables

Figure 1. Google trends for “vaccini autismo” (vaccines autism) in Italy, 2006-2018



Own elaboration on Google Trends data.

**Figure 2. Trends in immunization rates within tertiles of the treatment intensity variable (2006-2011)**

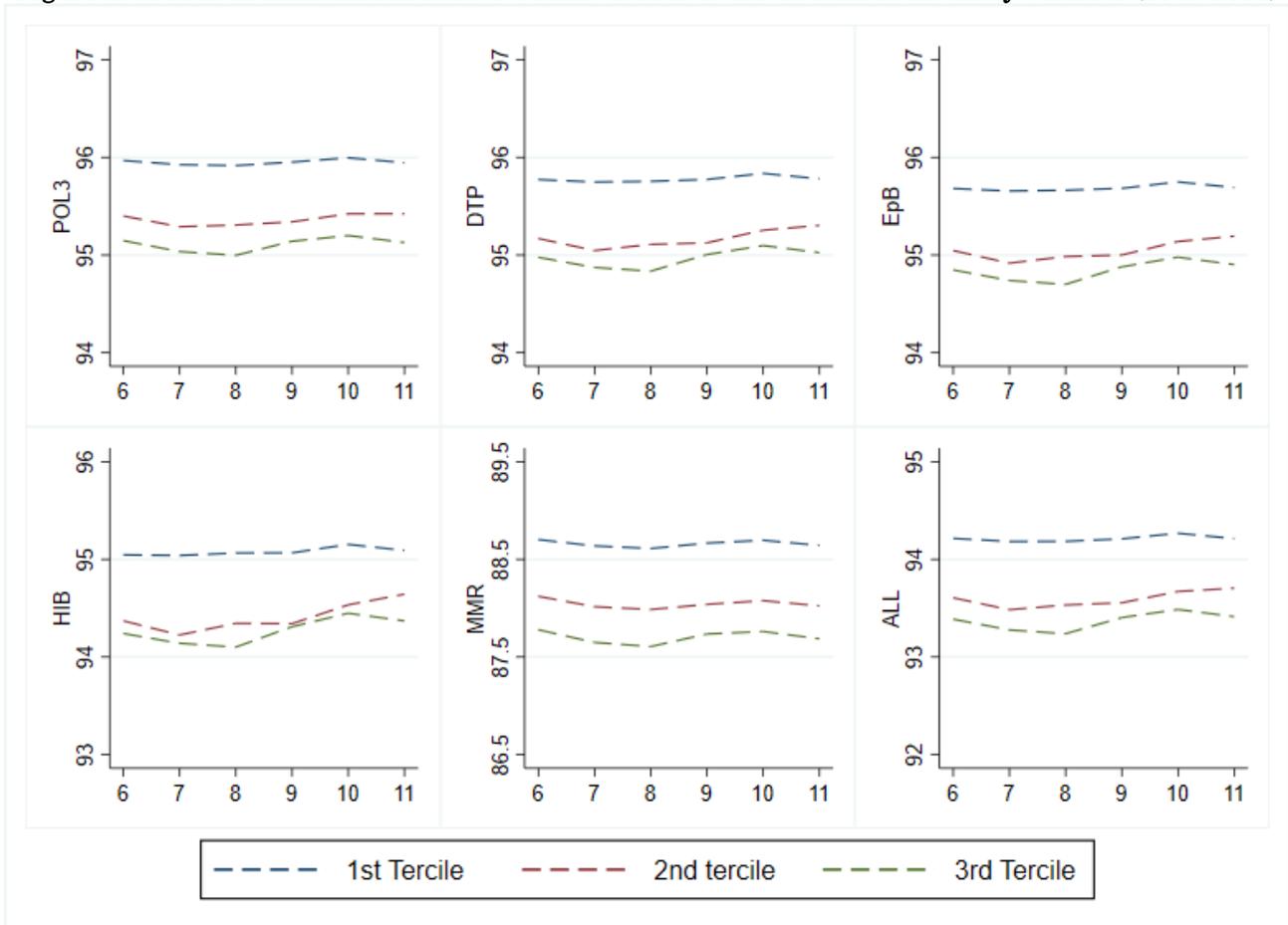
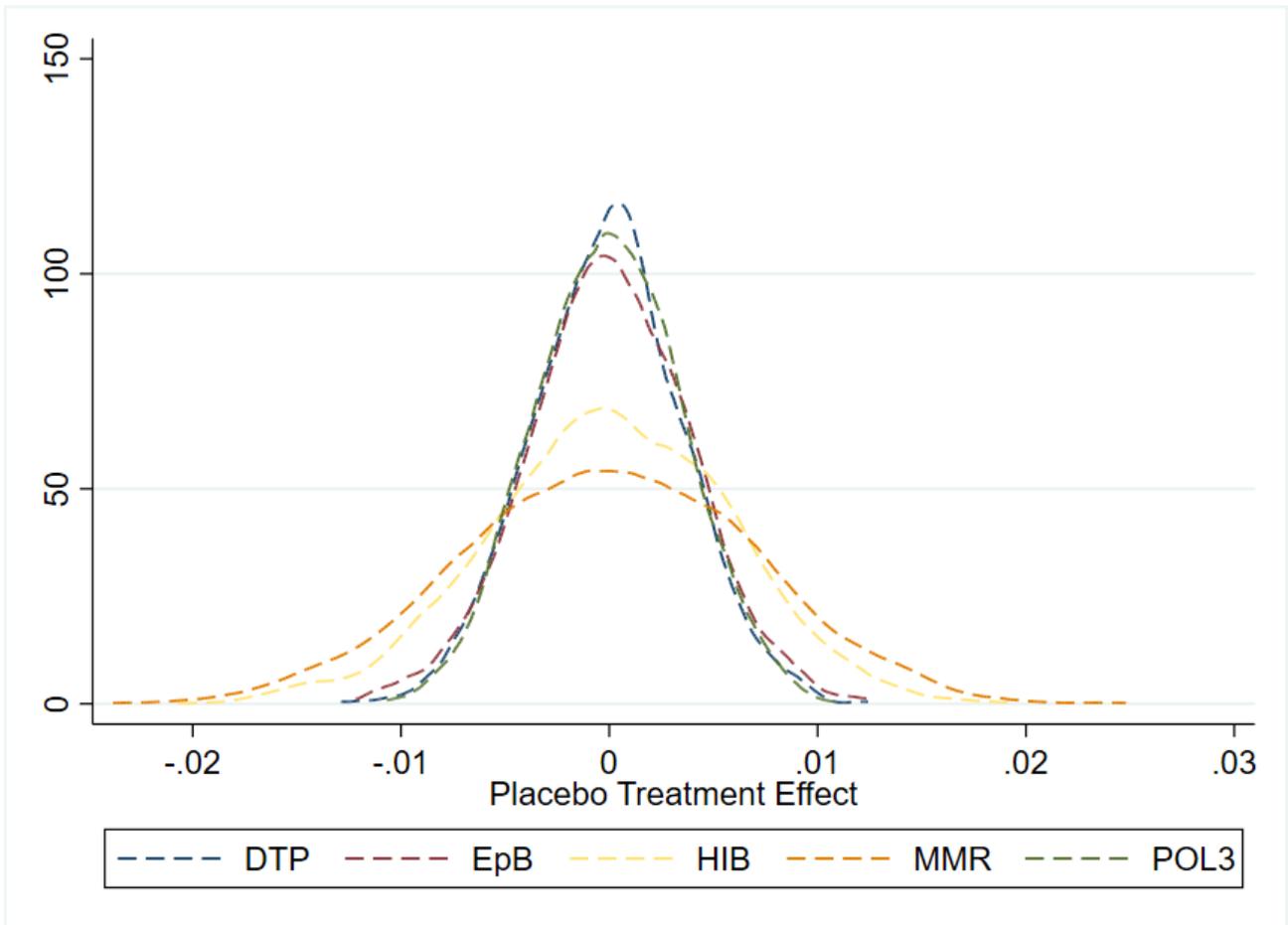


Figure 3. Placebo Estimates



Kernel density distribution of 2000 placebo estimates for all types of vaccines.

**Table 1. Differences-in-Differences Regression**

	POL3 (1)	DTP (2)	EpB (3)	HIB (4)	MMR (5)	All (6)
<i>DiD</i>	-0.145*** <i>0.035</i>	-0.132*** <i>0.036</i>	-0.165*** <i>0.035</i>	-0.067 <i>0.062</i>	-0.139** <i>0.051</i>	-0.130*** <i>0.032</i>
<i>DiD with controls</i>	-0.129*** <i>0.039</i>	-0.119*** <i>0.040</i>	-0.161*** <i>0.039</i>	-0.076 <i>0.057</i>	-0.156*** <i>0.052</i>	-0.128*** <i>0.036</i>
<i>DiD with time trends</i>	-0.133*** <i>0.042</i>	-0.124*** <i>0.042</i>	-0.156*** <i>0.042</i>	-0.067 <i>0.056</i>	-0.125** <i>0.057</i>	-0.122*** <i>0.036</i>
<i>DiD with region-specific trends</i>	-0.101*** <i>0.033</i>	-0.100*** <i>0.030</i>	-0.124*** <i>0.036</i>	-0.023 <i>0.088</i>	-0.172** <i>0.064</i>	-0.104** <i>0.038</i>
Region Fixed Effects	yes	yes	yes	yes	yes	yes
Obs.	216	215	216	216	215	214

DiD coefficients of Fixed Effects estimates of equation (1) according to several specifications. Dependent variables defined as follows: Polio (POL3), diphtheria-pertussis-tetanus (DTP), Haemophilus influenzae type B (HIB), Hepatitis B (EpB), measles-mumps-rubella (MMR). All includes average immunization rates.

Standard errors clustered at regional level in *italics*.

Note: \*\*\*, \*\*, \*, indicate statistical significance at 1%,5% and 10%, respectively.