Three essays on the economic perspectives of false information

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Contents

Summary

This thesis covers the debate about the political implications of false information online. The increasing scholarly and public attention to this topic has been prompted by the suspicion that false information might have influenced the outcomes of several recent ballots, such as the 2016 American presidential election and the UK Brexit referendum. In addition, false information may cause public alarm, decrease citizens' trust in national and supranational institutions, harm public health and hamper citizens' ability to take informed decisions. In a nutshell, it represents a threat to democracy.

The aim of this work is to study the political outcomes of false information. Throughout the thesis the term false information is used to indicate misleading contents that are produced either intentionally or unintentionally.

The dissertation is composed of three articles. The first article sets the theoretical basis for the empirical analysis and covers the false information issue by taking an interdisciplinary perspective. The analysis aims to provide the reader with a systematic conceptualization of the problem across social sciences. This essay contributes to the literature on false information by proposing a cross-disciplinary classification of studies in the field. After providing some definitions of key concepts and a taxonomy of the category of false information, we cover studies examining the cognitive mechanisms underlying individuals' information processing that may lead to biased beliefs. We then discuss studies on debunking and automatic detection of false information online. Last, we address the literature on the political outcomes of false information.

The second article investigates how the exposure to false information online may have impacted the 2018 Italian political elections. Italy is an interesting case study as two populist and anti-establishment parties took the lead of the country. We explore how the exposure to misleading contents relates to the performance of the main Italian parties across provinces. As some authors argue that social media facilitate the spread of false information, the measure of exposure to misleading contents is built on social media data. We build a unique and novel dataset combining false information data with electoral data and other province-level information. The analysis builds on Twitter data for three reasons. First, this Social Networking Site makes available a larger amount of information for researchers. Second, if closely compared with other social networking sites, it is used by individuals to retrieve information rather than for bridging social relationships. Third, it is a tool exploited by politicians for political communication and propaganda. The detection of misleading tweets follows two steps. In a first phase, a sample of geotagged tweets is extracted from the universe of real-time publicly available tweets for a period before the election regardless of the topic. In a second phase, we detect misleading tweets according to specific identification criteria: interactions with disinformation accounts, keywords related to debunked false stories, links to misleading articles, photos and

videos. The geolocation parameter is crucial for this methodology as it allows to combine Twitter data with other local information. Finally, the analysis was also restricted to politically charged disinformation. Results suggest the presence of a strong and positive correlation between the exposure to false information on Twitter and the performance of the Five Star Movement (FSM). Moreover, results from the Multinomial Logistic regression report a positive association with the probability to win both for the FSM and the center-left coalition. This finding might be interpreted in two ways: on the one hand, both FSM and center-left supporters might be sensible to false information. On the other hand, we might suspect the presence of two different stances: one fostering and the other countering false information. To disentangle the positions of Democratic Party (DP) - which is the main center-left party - and FSM supporters for false information, we select a subsample of pro-disinformation tweets by excluding from the analysis such tweets containing the word/s "fake news" or "hoax". Results show a positive and significant correlation with the vote share for FSM and a negative and significant correlation with the performance of the DP. This finding, in conjunction with previous evidence showing that FSM voters are more vulnerable to conspiracy theories (Mancosu et al., 2017) is suggestive of the presence of two echo-chambers (one in favor and one against false information).

We conclude arguing that false information may advantage or disadvantage political parties at different levels. Due to the availability of data, we are unable to straightforwardly disentangle the stances of the two parties in a rigorous way. Nevertheless, we can suggest an interpretation that should be taken with all due caution. The hypothesis of the presence of online polarization is useful to interpret the relationship found with vote shares of the two parties, suggesting that supporters of different parties form distinct online polarized clusters with the respect to the false information. This interpretation is consistent with previous studies on the spread of misinformation online, which argue that it spreads in polarized cluster of like-minded people. The polarization of the online discourse is supposed to be fostered by confirmation bias and motivated reasoning, two cognitive mechanisms that drive our information filtering, favoring the acquisition of attitude-congruent information.

The third article exploits the occurrence of the 2019 European elections to assess whether findings emerged for the political election also held for other types of election. Again, the focus is on Italy. Data collection and false information detection follow the same methodology. In the first part of the article, we perform a cross-sectional analysis at the province-level to analyze how false information online relates to the performances of the main Italian parties. Firstly, we find no association of voter turnout with exposure to false information. We suggest that false claims are unrelated to voter turnout because they do not affect people's trust in the political system. We expect that a mechanism similar to that of online hate speech apply to fake news (Antoci et al., 2019). Misleading contents positively correlate with the two parties that are more sensitive both to the spreading of false information and online activity of the previous article as we find presence of a positive and statistically significant correlation between the exposure to malicious contents on Twitter and Five Star Movement and Democratic Party vote shares. Hence, the hypothesis of polarization of these online communities acquires further evidence. In the second part of the article, we implement a First Difference analysis exploiting data collected on the occasion of the 2018 political election. This empirical strategy allows to eliminate biases from unobserved time-invariant factors. Results confirm the relationship found for the Five Star Movement but not for the Democratic Party. This result is in line with results from Mancosu et al., (2017): if FSM voters are more likely to believe in conspiracy theories, than it is not surprising to find that false information consumption correlates with FSM voting.

Overall, results emerged from the analyses of the second and third essay reveal that false information played a role in the Italian political debate. We contribute to the literature on false information in three substantive ways. First, we present one of the first exploration of the impact of false information on parties' vote shares, and the first exploration of how false information relates to voter turnout. Second, we present a novel dataset combining social media data with other local variables. Third, we propose a novel methodology to detect false information online.

Findings presented in this dissertation should be interpreted with caution. First, the endogeneity problems (both in terms of cofounding factors and reverse causality) hamper the possibility to claim a causal relationship. Second, we are unable to rigorously disentangle the supporters' stances for false information in our data. Future works should account for the sentiment of the tweet for identifying pro vs. against false information tweets or the political affiliation of the user. However, this task would require the exploitation of automatic classification techniques, i.e. machine learning, which is not easy and straight to implement. Last, we underestimate the level of false information spreading online for two reasons. First, we limit the analysis on Twitter, while a consistent amount of false information circulates on Facebook or other social media. Second, we focus on geotagged tweets that represent a low incidence of the overall tweeting.

Chapter 1: False information in the digital ecosystem

Abstract

In this paper we examine several aspects of the concept of false information, with the aim to make a systematic conceptualization of the problem. In this multidisciplinary analysis, we first define some types of false information and suggest a classification. We then classify studies in the field according to their research question, presenting investigations over: 1) diffusion patterns of false information; 2) cognitive mechanisms intervening in the selection of the information to consume; 3) debunking and detection strategies; 4) political outcomes of false information. Most of the fields of research here covered show certain levels of contradictoriness, sometimes presenting opposite and conflicting result.

1 Introduction

After the 2016 US presidential election and the EU referendum in UK, fake news became a central topic in the public and scientific debate. The recent spread of new information and communication technologies has increased the possibility for individuals to select information from a wider set of informative sources, either official or unofficial. New media have indeed revolutionized communication and information habits both from the provider and the consumer point of view. However, the new features of the digital ecosystem may favor the diffusion of inaccurate information. First, the market asks journalists to accelerate their activity, perhaps and sometimes to the detriment of the originality and quality of the supply (Bakir and McStay, 2018). Second, the shift from a one-to-many to a many-to-many communication (Stevens, 1981) - where the information is no more unidirectional - entails that the reader is no more a passive spectator of the information, but actively contributes to its spreading both as sharer and producer. Lastly, the disintermediation of news production, i.e. the lack of peer control on the released materials, has undermined the accuracy of the produced information (Westerman et al., 2012). Social media, for their part, have exacerbated the problem as they play an important role both in the interactions with our social network and in our news diet (Gottfried and Shaerer, 2017; Fletcher and Nielsen, 2018).

This work aims to provide the reader with a comprehensive presentation of studies that have examined different aspects of false information across social sciences. We believe that an interdisciplinary approach is helpful to understand and analyze the issue. We first define some types of false information, suggesting a classification based on the intention underlying the action. We then present studies exploring the diffusion patterns of false information, with particular attention to differences in spreading patterns between real and false news. We further cover studies examining the cognitive mechanisms underlying individuals' information processing that may lead to biased beliefs. We then discuss two strands of the literature aiming to counteract the diffusion of false information, i.e. debunking and detection studies. Last, we report studies exploring the political impact of false information. To the best of our knowledge, this is the first work addressing the study of false information from several perspectives and accounting for different research questions. While we do not adopt a critical assessment of the reviewed studies, this work contributes to the literature by providing a cross-disciplinary classification and dissertation of studies on false information.

We identify three main limits in the literature. First, there are several types of false information (from inaccurate to totally fabricated contents) and scholars should put great attention to the focus of their studies in order to guarantee a comparability of results. Second, measures of false information are necessarily approximate as it is tough to reconstruct individual exposure levels. Third, despite the relevance of the problem, we still lack a clear assessment of the impact of false information on society. This is due to problems related to the selection of an identification strategy to estimate the causal effect of false information on some economic and political outcomes.

The remainder of this paper is organized as follows: section 2 defines the concepts of disinformation, misinformation and fake news; section 3 presents the online transmission mechanisms and diffusion patterns of false information; section 4 lists the cognitive mechanisms that lead to a successful deception; section 5 discloses studies on debunking and fact-checking; section 6 outlines detection studies; section 7 discusses whether and how false information may represent a threat to democracy; section 8 concludes.

2 Definitions

False claims have been labelled in different ways. Misinformation, disinformation and fake news are only some of the most frequent words used to indicate false information. We suggest a classification of false information based on the intention underlying the action. Incorrect information may arise by mistake, e.g. mistakes made by journalists, or on purpose, e.g. fabricated false news. False information arising by mistake are considered as misinformation, whereas false claims created on purpose fall within the category of disinformation. Hereafter we discuss these concepts, focusing on a specific type of disinformation, i.e. fake news, by presenting some definitions and abstracting the key elements that allow to distinguish one concept from the other.

Misinformation. One of the first author to examine the concept of misinformation was the information philosopher Christopher Fox. In his text 'Information and misinformation' (1983) the author simply defines misinformation as information that is false. An opposite thesis is supported by Fred Dretske, which states that «False information, misinformation, and (grimace!) disinformation are not varieties of information» (1983:57). Nevertheless, these definitions are not necessarily antithetic if we assign to information a more general connotation and separate it from the concept of truth (Fallis, 2016). On this respect Floridi (2011), starting from his definition of information as semantic content, defines misinformation as semantic content that is false. Finally, other authors have defined misinformation as inaccurate (Hernon, 1995) or misleading (Skyrms, 2010) information.

The definitions we presented insofar do not consider the reasons why misinformation is produced. Instead latest contributions stress this point as pivotal in the distinction of misinformation from disinformation. In this regard, we report the contribute of Søe, which defines misinformation as «unintended false, inaccurate, or misleading information» (2017:321).

Disinformation. As far as we know, one of the first definition of disinformation is provided by Floridi (1996) that states that disinformation «arises whenever the process of information is defective». However, Fallis (2015) stresses that this definition is too general because it includes both intentional and unintentional false claims. In fact, this definition would encompass also the misinformation, which is unintentionally false.
From the surveyed literature, we have identified three specific features of disinformation: content falseness (1); intention to mislead (2); large scale dissemination (3). Whenever a claim has these three elements it can be considered as disinformation. We consider the intention to mislead to be the main distinctive feature of disinformation. Fallis captures this aspect when he defines disinformation as «misleading information that has the function to mislead» (2015: 625). Fetzer also underlines this point when arguing that «while "misinformation" can be simply defined as false, mistaken, or misleading information, "disinformation" entails the distribution, assertion, or dissemination of false, mistaken, or misleading information in an intentional, deliberate, or purposeful effort to mislead, deceive, or confuse» (2014:231).
We finally propose the definition of the European Commission that defines disinformation as «false, inaccurate, or misleading information designed, presented and promoted to intentionally cause public harm or for profit»[1].

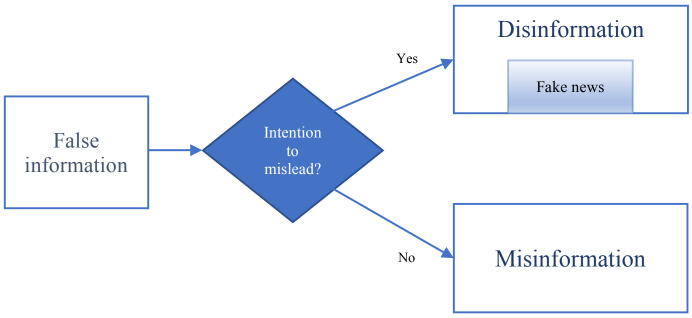
Fake news. The term fake news has only recently become a buzzword and sometimes it is overused and misused. This is not limited to the agenda setting, but also at political level there have been politicians accusing competitors and mainstream media to spread fake news, threatening in turn citizens' trust in institutions. The overuse of this term, took some researcher to claim its unreliability for research classification (Vosoughi et al., 2018).
We consider fake news to be partially or totally manipulated contents that are intended to be false and are presented under the guise of news, which can be disseminated both online and offline and have the intention to mislead the reader.
Fake news is a kind of disinformation and hence it presents the same characteristics. It has totally (Paskin, 2018) or partially (Bakir and McStay, 2018) false content, is intentionally misleading (McGonagle, 2017), and is widely disseminated either online (Klein and Wueller, 2017) or offline (Paskin, 2018). What distinguishes fake news from other kinds of disinformation is the fact to be presented under the guise of news. This point emerges from several definitions in literature: Gelfert states that fake news is «the deliberate presentation of (typically) false or misleading claims as news, where the claims are misleading by design» (2018:108); Allcott and Gentzkow (2017) define fake news as

[1] Report of the independent high-level group on fake news and online disinformation, 2018, p.11.

«news articles that are intentionally and verifiably false, and could mislead readers». (Allcott and Gentzkow 2017:213). Last, Lazer et al. consider «fake news to be fabricated information that mimics news media content in form but not in organizational process or intent» (2018:1094).

The presented studies have showed that the terms misinformation, disinformation, and fake news identify different types of false information. In conclusion, we consider the intention to mislead the key element that allows to distinguish misinformation from disinformation. On their part, fake news is a specific type of disinformation having as distinctive feature the imitation of real news articles. In this work, we will indistinctively use the expression false claims and false information to indicate false or inaccurate contents. Figure 1 illustrates the relation between these concepts.

Figure 1: Classification of false information.



3 Diffusion patterns

The new features of the digital ecosystem have fostered the spreading of false information. Concerns about the societal implications of false claims especially arises as a consequence of the diffusion of Social Networking Sites (SNSs). As false or misleading claims predominantly circulate on SNSs (Allcott and Gentzkow, 2017; Jang and Kim, 2018), a large number of scholars has been interested in studying their online diffusion patterns. In the following subsections, we examine the concepts of cascades and echo chambers to understand how false information spreads. We then delve into the concepts of homophily and polarization as they are pivotal in the creation of echo chambers and, hence, for the circulation of these contents.

Real and false information spreading. False information spread through cascades, which occur «when a group of early movers, sometimes called bellwethers, say or do something and other people follow their signal» (Sunstein, 2009:22).
The identification of the elements that distinguish false from real information cascades has been object of some studies. Overall, the two types of information produce independent cascades that present different characteristics. First, false claims are more viral and can potentially reach a larger audience. Vosoughi et al. (2018) compare the cascades generated by true and false claims spreading on Twitter from 2006 to 2017. The authors find that misleading information spread «farther, faster, deeper and more broadly than the truth in all category of information» (2018: 1147). The authors also find that false news is newer and expresses more negative sentiments than real one. False claims and real facts also differ for cascades evolutionary dynamics. Shin et al. (2018), in their study on cascades dynamics of true and false news on Twitter before the 2012 American election, find that 11 out of the 13 rumors in their sample have been shared multiple times, whereas real news appears only once. Moreover, authors observe that these 'comeback rumors' have been particularly frequent as we go closer to the election day. Del Vicario et al. (2016a) show how two different narratives, i.e. science and conspiracy theories, originate different cascades that differ for the lifetime, when the latter is considered as a function of the cascade size. Users in the conspiracy theories cascade present a slower assimilation of contents and the message lifetime is positively associated with the cascade size. Other authors wondered whether the features of the message may somehow affect the diffusion patterns. Lee et al. (2015) investigate differences in rumor and non-rumor related tweets during extreme events. They find that the number of followers is positively associated with the diffusion of rumors, which is in turn negatively associated both with the presence of hashtags and with the reaction time of the retweet action for both types of contents.
Even if cascades differ, the consumption behavior of users interacting with real and false claims are very similar. Mocanu et al. (2015) examine the interactions of Facebook users with three kinds of news pages, i.e. mainstream news, alternative news and political activists, during the 2013 Italian general election. The authors get to the following conclusions: there is no difference in the consumption behavior of users interacting with different pages; some of these users interact with two out of the three page categories; the lifetime of true and false claims cascades is similar. Last, Bessi (2016) finds that users interacting with science and conspiracy theories narratives on Facebook present the same psychological traits and that the prevalent personality model is the same in both groups.

Echo chambers. A cascade presenting high levels of polarization and homophily is also called "echo chamber". In other words, echo chambers are homogeneous clusters of like-minded individuals presenting high level of information polarization (del Vicario et al., 2016a; Bessi et al., 2015). Empirical studies have demonstrated that false claims spread in online echo chambers (Del Vicario et al., 2016b) and, at the same time, the presence of echo chambers contributes to the spread of misinformation (Törnberg, 2018). Nevertheless, Vaccari et al. (2016), in their study about political polarization and echo chambers on Twitter, argue that even if individuals are more inclined to engage in online situations sharing congruent opinions, situations where heterogeneity is still present are not so rare. They conclude that the level of polarization and ideological segregation rather depend on personal characteristics such as the political use of social media and the structure of the offline network.

Filter bubbles and polarization. Even if new information and communication technologies may increase the consumption of cross-cutting contents, they also entail the danger for individuals to be differently exposed to information. The possibility for people to choose the information to consume may lead to ideological segregation and polarization. In this regard, evidence from previous studies is uneven. If a strand of the literature upholds that new technologies have increased the likelihood for people to inadvertently encounter other opinions (Boxell et al., 2017; Wojcieszak and Mutz, 2009; Messing and Westwood, 2012), other studies point out their role in the polarization of public speech online (Del Vicario et al., 2016b; Sunstein 2002, 2009; Grömping, 2014). In this regard, Flaxman et al. (2016) find that people mainly seek information from news sources that are ideologically aligned with their beliefs. Their results also suggest that the level of segregation is higher on SNSs and that the stronger is someone’s belief, the most he or she is polarized in news consumption behavior. The level of polarization on social media also depends on the level of endorsement that an action entails. In their study on the exposure to ideologically diverse contents on Facebook, Bakshy et al. (2015) find that the exposure to counter opinions is indeed cross-cutting, but the engagement of people with respect to these contents is more polarized. Furthermore, the polarization appears to be stronger when we come to politics (Colleoni et al., 2014; Stroud, 2010).
Studies presented insofar show how the consumption of ideologically aligned contents may increase social polarization. However, the Internet play a relevant role in the selective exposure to information. In this regard, Pariser (2011) argues that new algorithms create some filter bubbles, where a filter bubble is a «unique universe of information for each of us that fundamentally alters the way we encounter ideas and information» (2011:30). The increasing contents personalization made by the Internet and social media algorithms entails that the individual is presented with contents that are in line with his or her previous behavior. Therefore, filter bubbles increase the level of online ideological polarization to the extent that they provide users only with contents one is more likely to appreciate.

Homophily. It has been demonstrated that individuals with similar characteristics are more likely to connect in networks (e.g. Currarini et al., 2016). Centola (2011) studies the contagion behavior through an experiment in the health field. He finds that homophily significantly improves the contagion of health behavior even between subjects that have different characteristics, and it increases the likelihood for someone to adopt a behavior across dyadic ties. In another study, the author takes also into account the network topology in the analysis of behavior contagion and diffusion (Centola, 2010). In an experimental approach and social network analysis tools, he finds that the network topology has a significant role in the behavior spreading, and that networks with a high clustering level and degree are more effective in social contagion.

4 Psychological reasons of false information

In previous sections, we defined three types of false information and discussed their diffusion patterns. Now we are willing to go through the reasons why it spreads. Indeed, it is critical to understand which are the individual-level and contextual-level factors that foster the spreading of misleading contents. In the first part of the section, we briefly report the reasons why fake news are produced. We further discuss the cognitive mechanisms intervening in our information processing as well as the individual-level characteristics that have been found to be positively correlated with the vulnerability to false information. Figure 2 illustrates the relations between cognitive mechanisms and vulnerability to false information.

Motivations for the production of false information. The providers of false information may have ideological or economic reasons (Allcott and Gentzkow, 2017). People may be inclined to produce and share disinformation for political reasons, with the aim of discrediting political competitors and rising consensus for the preferred party. At the same time, malicious providers may release false articles with sensationalistic headlines to attract more audience and increase revenues. Bakir and McStay (2018) offer an interesting interpretation of the economic drivers of fake news production. They argue that «the fake news problem concerns the economics of emotion» (p. 155). Their thesis relies on the fact that contemporary media have become "emphatic media" with the ability to extract sentiments from our online footprints, which are then exploited to capture audience attention. They also manifest the concern about the exploitation of "empathically optimized automated fake news" (Bakir and McStay, 2018:155).

Cognitive mechanisms. There are two main theses in the literature accounting for the sensitivity to false information.

The most accredited theory traces the cause in a series of cognitive mechanism related to information processing. Individuals constantly attempt to make sense of reality and of the world surrounding them. To achieve this goal people do not simply act as passive consumers of information, but are also active in information seeking. Psychologists have studied the mechanisms driving our way to process information, either true or false. From the consumers' perspective, several cognitive processes may intervene. According to some authors, the mechanisms at the basis of misinformation spreading are selective attention and confirmation bias (Del Vicario et al., 2016a; Zollo et al., 2017). The selective attention was introduced by Cherry in 1953 to denote the process that, in situation of stimulus concurrence, brings our mind to select some stimulus rather than others. The confirmation bias was introduced in 1960 by the psychologist Wason and it is defined as the individuals' inclination to seek and assimilate only information in line with prior beliefs. These two mechanisms are not mutually exclusive: indeed, selective attention can be activated to reach only convenient information. Likewise, Flynn et al. (2017) identify in the motivated reasoning the underlying mechanism for misinformation roots, which is the tendency of individuals to: seek information that are in line with their previous beliefs (confirmation bias); refuse information that contradict their beliefs (disconfirmation bias); perceive confirmative information to be more convincing than the counterpart ones. Furthermore, individuals may also incur in what Festinger (1957) defined cognitive dissonance. Cognitive dissonance is onerous for our analytical thinking because it poses a threat to our beliefs and requires an adjustment in light of new information, in addition to producing a sense of personal failure.
A second theory ascribes the sensitivity to false information to the analytical thinking. A recent study of Pennycook and Rand (2019) finds that individuals with higher levels of analytical reasoning are more effective in recognizing false from real news regardless of the ideological alignment. In other words, people fall for false information because «they fail to think» (Pennycook and Rand, 2019:47) rather than for their partisanship or ideology.

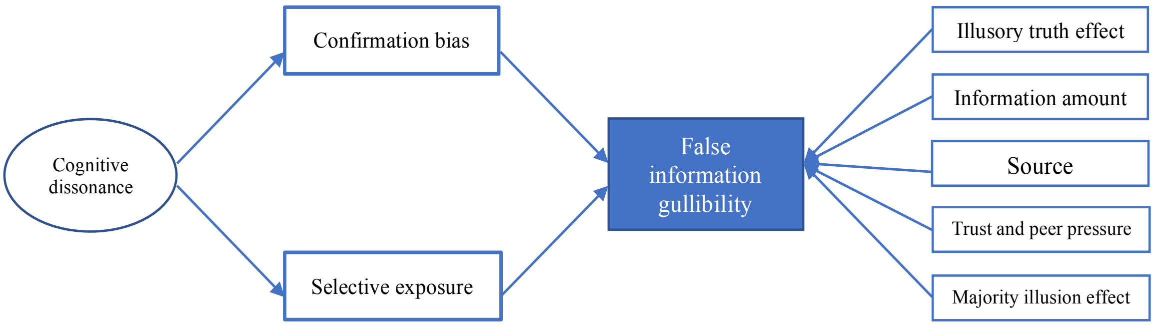
Factors increasing false information efficacy. There are at least five elements that increase the likelihood for people to believe in false claims: the illusory truth effect, which is triggered both by repetition and prior exposure; information amount; information source; majority illusion effect; trust in peer and peer pressure.

- *Illusory truth effect*. It indicates the wrong perception of a false statement to be true. This effect can derive from:
    - Prior exposure. An individual is more likely to believe that an information is accurate if he/she has already been exposed to that information more than once (Pennycook et al., 2018);

- Stimulus repetition. The more someone is exposed to a stimulus, the more the probability to believe it. Knapp (1944), in his study on wartime rumors, find a significant relation between repetition and beliefs. Other evidence to this mechanism can be find, for instance, in Hasher et al. (1977) and DiFonzo and Bordia (2007).

- *Information amount*. The more the information is detailed the less individuals are misled by false claims (Levy and Gvili, 2015; Peters et al., 1997). Paskin (2018) find a positive correlation between amount of information provided and the ability for individuals to correctly identify false news.
- *Information source*. DiFonzo and Bordia (2007) argue that the credibility of a rumor increases if the source is considered trustworthy.
- *Trust and peer pressure*. Trust in people around us and peer pressure increase the likelihood for a news to be shared if it has been previously shared by one or more elements in our network (Asch, 1958; Latane and Darley, 1968).
- *Majority illusion effect*. Individuals are not aware of the real size of their online social network. This results in an overestimation of the number of people that have adopted a given behavior. This bias increases the effect of the information endorsement on the web (Lerman et al., 2016).

Figure 2: The psychology of false information



Who is misled by false information? After having described which are the underlying psychological mechanisms intervening in the definition of our news processing, which in turn increase the risk to engage with false contents, we now want to discuss individual-level features that may increase the likelihood of believing in false information.

The Functional illiteracy appears to increase the likelihood of believing in false claims (Zollo et al., 2017). The OECD defines a functionally illiterate person as someone «who cannot engage in all those activities in which literacy is required for effective functioning of his group and community and also for enabling him to continue to use reading, writing and calculation for his own and the community's development». This feature may increase individuals' gullibility to the extent that they are unable to distinguish false from correct claims.

From the surveyed literature, the inclination to consume or being exposed to misleading contents appears to be associated with a few individual-level characteristics. Allcott and Gentzkow (2017) find that high educational levels, more time spent on media, and being older are good predictors for the ability of American voters to correctly identify headlines. However, Guess et al. (2019) and Grinberg et al. (2019) find that people over 65 are more likely to engage with false contents. They also agree that political slant is influential for the probability to be exposed to misleading contents. Authors find that conservative Americans are more inclined to interact with this kind of information.

Conversely, cognitive features appear to be more influent in people's exposure to misleading contents. The study of Pennycook and Rand (2019) inspects the cognitive profile of people who believe in fake news finding a positive correlation between analytical thinking and the ability to distinguish false from real news, concluding that people with high level of analytical thinking are less inclined to share fake articles. Bessi (2016) investigate the personality traits of individuals involved in Facebook echo chambers, measured according to five dimensions that are known as Big Five. The author compares the typology of persons participating in two different echo chambers, i.e. scientific and conspiracy theories, finding that even if personality traits are determinant in the choice to engage with echo chambers, they are not determinant in the choice of which echo chamber to engage with. These results suggest that the personality traits of individuals in both echo chambers are similar[2].

Recent studies agree on the key role played by few super-spreaders in misinformation circulation (Shao et al., 2018; Grinberg et al., 2019; Guess et al., 2019), but whether or not these users are human or bots is uneven. Shao et al. (2018), analyzing 14 million messages spreading 400 thousand articles during and following the 2016 US presidential campaign on Twitter, find evidence of the key role played by bots in the spreading of low-credibility contents. First, they argue that bots act in the early few seconds after the article has been posted in order to make it go viral, while the main responsible for its retweets are humans. Second, bots mention influential users when linking to a false content in order to increase its visibility and perceived accuracy. Conversely, Vosoughi et al. (2018) find that bots are equally responsible for the diffusion of either real and false news on Twitter, with humans playing a pivotal role in the spreading of false contents.

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[2] Individuals embedded in the two echo chambers show low extraversion, agreeableness and conscientiousness, and high openness.

5 Fact-checking and debunking

Scholars have paid great attention to the identification of possible strategies able to stem the spread of unsubstantiated claims. So far, the political and journalistic debate has suggested two possible solutions: fact-checking (the verification of the truthfulness of the claim) and debunking (the response to a false claim with the relative true one).

Most of the studies document the inefficacy of debunking and fact-checking activities. Nyhan and Reifler (2010) test the efficacy of corrections to political misperceptions in an experimental setting. The frame of the experiment consists in providing participants with fake articles covering different topics (American weapons found in Iraq; taxes cuts; stem cells) followed by the related real article in a second time. Results suggest that, regardless the argument, corrections are not effective in the adjustment of previously stored information if misperceptions are ideologically relevant. Indeed, authors find differences in the response of liberals and conservatives where the latter are more likely to fail in responding to corrections. Nyhan et al. (2014) testing the effects of debunking on vaccine misperceptions, confirm previous insights even finding stronger evidence of the so-called *backfire effect*, which consists in a cognitive mechanism that strengthen our beliefs when they are contradicted. If applied to misperceptions, this process results in a consolidation of prior biased perceptions when we are presented with corrections. Zollo et al. (2017) corroborate this thesis by investigating how users of scientific and conspiracy echo chambers interact with debunking posts on Facebook through a sentiment analysis, showing a predominantly negative sentiment of posts in reply to debunking activity. Conversely, a recent experimental study of Wood and Porter (2019) involving 8,100 participants and covering 36 topics of claims made by politicians gets to opposite results. Authors find no evidence of the backfire effect even when participants were presented with arguments that were supposed to trigger it.

Focusing on political outcomes, Barrera et al. (2020) examine the effect of fact-checking on voting intentions. In an online experiment involving 2,480 French eligible voters, the authors investigate the effectiveness of fact-checking on three outcomes: beliefs about the fact, policy impressions and voting intentions. They find that fact-checking on political false statements can correct biases in factual knowledge, but it does not change voting intention expressed by participants. Authors hypothesize that a ready and short time debunking activity may be effective on correcting biases.

The research on the topic does not depict a negative picture as one might think. Recent studies find that corrections may be successful if applied wisely. One factor that seems to be significant for a good outcome is timing (Kuklinski et al., 2000), that is, if a correction is presented immediately after the presentation of the fake news it may be effective. The source is determinant too: if the correction comes from sources that are aligned with individual ideology, the failure decreases (Berinsky, 2017). Bode and Vraga (2015) test the efficacy of the Facebook function "related stories", i.e. the suggestion of links to debunking articles on the same topic of the malicious content, for correcting false beliefs. Authors find that presenting users with debunking stories succeed to correct false beliefs. In addition, presenting corrections through a counterfactual increase the likelihood that people adjust previous misinformed-based beliefs. Nyhan and Reifler, (2015) document a positive response of politicians when alerted about reputational risks of spreading misinformation. Looking at individual cognitive characteristics that may influence the effectiveness of the fact-checking, De Keersmaecker and Roets (2017) in an experimental study find that people with higher levels of cognitive ability are more likely to accept corrections.

Even though a successful strategy has not been found yet, advances in this field are opening to optimistic perspectives. Nevertheless, this approach presents some criticalities. First, even if third-party independent websites fact-checking represent a trustworthy strategy as it relies on human reasoning, it is not a scalable solution. In addition, it is impossible to manually check every information that circulates on the web, both because of the amount and for the velocity that characterizes the computer-mediated communication. On the other part, we cannot rely on individual self-fact-checking due to the aforementioned cognitive mechanisms (section 4). At the light of these considerations, the necessity of automatic detection techniques arose and recently a large body of works has been committed to this purpose.

6 Detection studies

In the previous section, we have covered the field of research that attempts to find an ex post solution to false claims after that the instance has already become viral and reached the audience. What if we turn the point of view and think about the possibility to stem misinformation and disinformation before they become viral and usable? This is what the strand of research on detection strategies attempts to do. We propose a classification of the studies based on three information features: content, propagation, and user solutions.

Content-based. These studies focus on the syntactic (e.g. frequency of words, number of sentences), lexical (e.g. use of nouns, pronouns, predicates), and sematic (emotions and opinions) features of the message. All these features may also be enclosed in a unique methodology called Linguistic Based Cues (LBC) (Zhou et al., 2004).

Early studies emphasize the analysis of the word as fundamental unit of a sentence. Bag-of-words (single unit) or n-grams (sequence or two or more words) analysis represent the

instances of Natural Language Processing (NLP). For instance, Markowitz and Hancock, (2014) account for the function of a word within the sentence considering both the presence and the frequency of the grammatical units in the phrase. On the other hand, lexical-based studies account for negations, doubt words and vulgar expression as cues of malicious contents. Burgoon et al. (2003) consider semantic features in addition to syntactic and lexical cues. They build an emotiveness index and calculate the percentage of affective terms. A recent study from Gravanis et al. (2019) find that a set of 57 LBC is the best combination for the classification of true and false messages, and that “ensamble methods”, i.e. the combination of two or more simple classification methods, and Supervised-Vector Machines produce best performances.
Not only words, but also images have been object of this field of analysis. Jin et al. (2016) introduce five scores for the identification of fake images that represent accuracy measures of malicious contents.

User-based. These studies rely on users’ characteristics for the detection of false or inaccurate contents. Aspects like user location, account creation date, verified account, number of followers and following are taken into account. Drawing on Twitter data, Chu et al. (2012) attempt to identify humans, bots, and cyborg accounting for the tweeting behavior, the tweet content, and the account properties. Using a random forest classification method, they classify users according to: the time intervals between tweets of the same user; the device from which the tweet has been sent; and the URL ratios. The authors find that human Twitter accounts generally have more followers than following, differently from bots that present the opposite trend. In this regard, they propose an account reputation index that is the incidence of followers on the total of followers and followings, arguing that as we move to 0 the probability to observe a bot is higher. Authors also find that, at a first glance, humans tweets more than bots in the account lifetime. However, they conclude that this result is driven by the different lifetime of the considered users’ typology because bots, on average, have higher hibernation time. If Chu et al. (2012) focus on the Twitter environment, Xu et al. (2019) draw on broader Internet data and focus on the domain reputation to detect malicious accounts. To this purpose they consider website registration patterns, age, domain ranking and popularity.
As social media users tend to connect with like-minded individuals, some studies assumed that features of the news creator network can be a cue for the identification of malicious contents. Overall, these studies attempt to identify any systematic pattern in the circulation of fake news, such as the amount or directions of edges between nodes.

Propagation-based. The last group of studies relies on the environment where these contents spread. The main consideration of this group of studies is that misleading contents can be detected based on the peculiarities of their propagation networks, such as epidemic (Daley and Kendall, 1965; Zhao et al., 2013) and influence model (Wu et al., 2017). One application of these models for the detection of rumors culprits can be found in Shah and Zaman (2011), which develop a strategy for the identification of the false information source in a susceptible-infected network model. Overall, studies falling in this category have focused on diffusion patterns (entity of the propagation network) and evolutionary dynamics for the identification of false information.

Recently, due to the diversity and complexity of online communication, some authors have stressed the necessity to develop detection methods that does not exclusively rely on one identification criterion, rather encouraging the association of more techniques (Zhang and Ghorbani, 2019). Some examples of studies implementing both user and content-related methods are: Gravanis et al. (2019), Chu et al., (2012), Xu et al. (2019).

This field of study is still far from getting to decisive results. One challenge is represented by the lack of big, comprehensive, and labelled datasets on real and false news necessary to train classifiers[3]. A second challenge is represented by the difficulty in coding human behavior.

7 False information: A threat to democracy?

The risk that false information may undermine democracy has been highlighted by several scholars (e.g. Allcott and Gentzkow, 2019; Lazer et al., 2018; Gaughan, 2016). This concern rises from the consideration that democracy relies on well-informed citizens (e.g. Berelson et al., 1954; Delli Carpini and Keeter, 1996). As individuals shape their opinions according to the information they collect, there is the risk that factual beliefs are shaped on both correct and incorrect information.

Studies documenting the relationship between false information exposure and political outcomes can be classified into three groups. One body of research focuses on the exposure to false information before specific political events; the second group investigates the role of false information in shaping political factual beliefs; the third group encompasses studies analyzing the electoral outcomes of false information.

False information exposure. These studies estimate to what extent citizens have been exposed to misleading contents for a period before a specific political event. The exposure to false information may in fact influence opinions and heuristics about the true state of the world. Findings from these studies reveal a low and concentrated exposure to false information of Americans before the last presidential election. Allcott and Gentzkow (2017) suggest that the average American voter read and remembered at least one fake

[3] For a comprehensive review of studies in this field see Bondielli and Marcelloni (2019) and Zhang and Ghorbani (2019).

news in the months before the presidential election. Guess et al. (2018) find that 1 out of 4 Americans have visited a fake news website during the 2016 American electoral campaign. Guess et al. (2019) estimate that the 8.5% of their sample of Americans shared at least one fake news in the same period. In their investigation of the fake news sharing behavior Grinberg et al. (2019) state that the 80% of false contents shared by their sample of Twitter American eligible voters was shared by the 0.1% of the sample. Drawing on a sample of 16,442 panel members, the authors also estimate that the 1.18% of the Twitter personal feed of the average American voter was from fake news sources. Howard et al. (2017) analyze how misinformation spread in a 10 days span before the 2016 US elections collecting tweets that contain specific election-related hashtags. They find evidence that users getting informed on Twitter are more exposed to misinformation and polarized political contents with higher relevance in swing states. On the other hand, Silverman et al. (2016) have shown that fake news articles about the US election had more visibility and a greater impact than real ones on the topic feed on Facebook.
One point of strength of these studies is the good approximation of individuals' exposure to information through the social media considered. However, studies considering more than one SNS would add precision to the estimates.

False information and beliefs. One group of studies document the effect of false information on previous factual beliefs, which may influence citizens' opinions on political issues. Merckelbach et al. (2010) set a laboratory experiment to catch the effect of misinformation on changing people recognition of their (existing or not) clinical symptoms. The empirical results reveal a strong persuasive effect of misinformation on people discerning ability. Authors report that 63% of participants did not recognize misinformation and revised their symptom ratings in its direction. Kuklinski et al. (2000) investigated, under specific assumptions, the possible impact of misinformation on public voice and opinion using the estimated parameter from a structural equation model, having as dependent variable policy preferences and as independent variable a measure for factual beliefs, political orientation and values. The authors then use the estimated parameter in four simulated situations where people could be totally misinformed in pro-welfare direction, totally misinformed in anti-welfare direction, half misinformed in one direction and half in the other, or everyone are in the average level of misinformation, finding evidence that misinformation can affect policy preferences. Misperceptions may influence public support on foreign policies. Kull et al. (2003) investigate the presence of misperceptions about the war in Iraq[4] in a sample of 8,634 American adults. Authors find

[4] The polls considered three misperceptions: the link between Iraq and Al Qaeda; the presence of weapons of mass destruction in Iraq; the world public opinion (and support) about the war.

that misperception was the stronger predictor of the positive attitude of Americans towards the war in Iraq and that the misperceptions about the war was strongly explained by the support for president Bush. Misinformation can be used by politicians to meet approval but also to detriment of the government. This is the case of the study from Huang (2017), which explores the effects of misinformation against the authoritarian Chinese government on the public support. In two online experiments where a total of 1,421 participants have been asked to report whether they read on the Internet some selected rumors and relative rebuttals, the author concludes that being exposed to anti-government misinformation reduces citizens' trust in government.

The political outcomes of false information. Two main studies contribute to this strand. In their seminal paper Allcott and Gentzkow (2017) carry out an online post-election survey to a sample of 1,208 American voters. Respondents were asked to indicate whether they saw and remembered a set of fifteen randomly selected true and false headlines circulating before the 2016 American election. Authors find that the probability to believe in a news – either true or false- is related to the ideological alignment of the headline, even though Republicans are more likely than Democrats to believe pro-Trump news rather than pro-Clinton news. Furthermore, following Spenkuch and Toniatti authors conclude that if fake news was effective as TV campaign ads, vote shares would have changed of hundredth of percentage points.

Weeks and Garrett (2014) analyze how negative political rumors about a candidate may influence the probability to vote for that candidate. Immediately after the 2008 American presidential election, authors interview a sample of 600 American adults, which are presented with a set of rumors either against Obama or McCain. First, authors find that individuals are more likely to believe in rumors against the candidate of the opposite party. Second, believing to a negative false rumor decreases the probability to vote for a candidate, and increases the probability to vote for the preferred one.

Moving from the US to Italy, Cantarella et al. (2019) try to address this question by exploiting the language differences in a particular Italian region, the Trentino-Alto Adige, which presents high incidence of German speakers. They instrument false claims exposure with the incidence of Italian speakers to inspect its causal effect on the vote for populist parties, in a difference-in-differences setting. From the analysis emerges no causal relationship between the variables.

However, many questions still remain unanswered. Indeed, it is still unclear whether and to what extent false information affects voting behavior, and researchers should pose more efforts in the investigation of this relationship.

8 Conclusion

The increased spread of false information in the last years raised some concerns for its potential societal implications. In particular, democracy may be affected by false information if it is able to drive voters' attention and individuals' factual beliefs.
In this paper, we presented the problem of false information, clarifying in the first place the differences between the concepts of misinformation, disinformation, and fake news. The criterion used to distinguish these concepts was the intentionality at the bottom of the action: if misinformation is false or incorrect information created by mistake, disinformation is generated with the intention to mislead. Fake news instead, is a type of disinformation that distinguishes itself for being presented as real news.
We proposed a classification of studies in compliance with their research question. The first strand of the literature investigates the spreading patterns of false information online. Studies in the field have found that false information circulates in echo chambers characterized by high levels of polarization and homophily (Del Vicario et al., 2016a,b). The investigation of the differences between the spread of false and real news online has shown that the former is newer, expresses more negative sentiments and spreads faster and further than real news.
The second group of studies explores the cognitive mechanisms intervening during the information processing. This is important to understand how false information misleads individuals and why individuals may fail in recognizing it. The literature ascribes the failure of individuals in recognizing inaccurate contents to the inclination to accept ideologically-congruent information - and to reject contrarian contents. Hence, false information is accepted and processed when it confirms prior beliefs. While this is a widespread thesis in the literature, a recent study of Pennycook and Rand (2019) find that good levels of analytical thinking and cognitive reflection increases the ability to recognize fake news even when ideologically congruent.
The third group of studies analyses the efficacy of debunking in correcting misperceptions. The most consolidated thesis states that providing the correct information after the exposure to misleading contents fails to update individuals' opinion due to confirmation bias and backfire effect (e.g. Nyhan et al., 2014). However, recent studies found that debunking may be effective if implemented under specific condition (e.g. Bode and Vraga, 2015).
The fourth strand of the literature aims to identify efficient techniques for the automated detection of malicious contents. Several criteria have been used to detect online false information: user-based, propagation-based and content-based. The best results have been obtained by the combination of more criteria. However, the virality of information on social media, the lack of extensive labelled datasets, and the several forms that the news can take (text, images, links), make it tough to assess effective algorithms.

The last group of studies investigates the impact of false information on political outcomes. To date, we lack of systematic evidence in support of this thesis. First, most of the studies evaluate the levels of exposure and circulation of misleading contents on social media before specific political events. Second, evidence concern how misperceptions affect the trust in government (Kull et al., 2003) or policy preferences (Kuklinski et a., 2000) but almost no study establishes a connection with voting behavior. The few studies investigating this aspect fail to find an effect (Cantarella et al., 2019) or estimate it indirectly (Allcott and Gentzkow, 2017).

References

Allcott, H. and Gentzkow M., (2017). Social media and fake news in 2016 election. *Journal of Economic Perspectives*, 31(2), 211-236.

Allcott, H., Gentzkow, M., and Yu, C. (2019). Trends in the diffusion of misinformation on social media. *Research & Politics*, 6(2), 2053168019848554.

Asch, S. E. (1958). Effects of group pressure upon modification and distortion of judgments. In E. E. Maccoby, T. M. Newcomb, and E. L. Hartley (Eds.), Readings in social psychology (3rd ed., pp. 174-183). New York: *Holt, Rinehart & Winston*.

Bakir, V., and McStay, A. (2018). Fake News and The Economy of Emotions. *Digital Journalism*, 6:2, 154-175.

Bakshy, E., Messing, S., and Adamic, L. A. (2015). Exposure to ideologically diverse news and opinion on Facebook, *Science*, 348(6239), 1130-1132.

Barrera, O., Guriev, S., Emeric, H., and Zhuravskaya, E., (2020). Facts, Alternative Facts, and Fact Checking in Times of Post-Truth Politics. *Journal of Public Economics,182,104123, 1-19*.

Berelson, B. R., Lazarsfeld, P. F., McPhee, W. N., and McPhee, W. N. (1954). Voting: A study of opinion formation in a presidential campaign. *University of Chicago Press*.

Berinsky, A. J. (2017). Rumors and health care reform: Experiments in political misinformation. *British Journal of Political Science*, *47*(2), 241-262.

Bessi, A., Coletto, M., Davidescu, G. A., Scala, A., Caldarelli, G., and Quattrociocchi, W. (2015). Science vs conspiracy: Collective narratives in the age of misinformation. *PloS one*, *10*(2), e0118093.

Bessi, A., Petroni, F., Del Vicario, M., Zollo, F., Anagnostopoulos, A., Scala, A., Caldarelli, G., and Quattrociocchi, W. (2016). Homophily and polarization in the age of misinformation. *The European Physical Journal Special Topics,* 225(10), 2047-2059.

Bessi, A. (2016). Personality traits and echo chambers on Facebook. *Computers in human behavior*, 65, 319-324.

Bode, L., and Vraga, E. K. (2015). In related news, that was wrong: The correction of misinformation through related stories functionality in social media. *Journal of Communication*, 65(4), 619-638.

Bondielli, A., and Marcelloni, F. (2019). A survey on fake news and rumour detection techniques. *Information Sciences*, 497, 38-55.

Boxell, L., Gentzkow, M., and Shapiro, J. M. (2017). Greater Internet use is not associated with faster growth in political polarization among US demographic groups. *Proceedings of the National Academy of Sciences*, 114(40), 10612-10617.

Burgoon, J. K., Blair, J. P., Qin, T., and Nunamaker, J. F. (2003). Detecting deception through linguistic analysis. In Chen, H., Miranda, R., Zeng, D. D., Demchak, C., Schroeder, J., and Madhusudan, T. Intelligence and security informatics, Berlin, 91–101, Heidelberg: *Springer Berlin Heidelberg*.

Cantarella, M., Fraccaroli, N., and Volpe, R. (2019). Does Fake News Affect Voting Behaviour?

Centola, D. (2010). The spread of behavior in an online social network experiment. Science 03 Sep 2010: Vol. 329, Issue 5996, 1194-1197.

Centola, D. (2011). An experimental study of homophily in the adoption of health behavior. *Science*, 334(6060), 1269-1272.

Cherry, E. C. (1953). Some experiments on the recognition of speech, with one and with two ears. *The Journal of the acoustical society of America*, 25(5), 975-979.

Chu, Z., Gianvecchio, S., Wang, H., and Jajodia, S. (2012). Detecting automation of twitter accounts: Are you a human, bot, or cyborg? *IEEE Transactions on Dependable and Secure Computing*, 9(6), 811–824.

Colleoni, E., Rozza, A., and Arvidsson, A. (2014). Echo chamber or public sphere? Predicting political orientation and measuring political homophily in Twitter using big data. *Journal of Communication*, 64(2), 317–332.

Currarini, S., Matheson, J., Vega-Redondo, F., (2016). A simple model of homophily in social networks. *European Economic Review*, 90, 18-39.

Daley, DJ, and Kendall, D.G. (1965). Stochastic rumours. *IMA Journal of Applied Mathematics*, 1(1):42–55.

De keersmaecker, J., and Roets, A., (2017). 'Fake news': Incorrect, but hard to correct. The role of cognitive ability on the impact of false information on social impressions. *Intelligence*, 65, 107-110.

Del Vicario, M., Bessi, A., Zollo, F., Petroni, F., Scala, A., Caldarelli, G., Stanley, H.E., Quattrociocchi, W. (2016a). The spreading of misinformation online. *Proceedings of the National Academy of Sciences*, 113(3),554-559.

Del Vicario, M., Vivaldo, G., Bessi, A., Zollo, F., Scala, A., Caldarelli, G., and Quattrociocchi, W. (2016b). Echo chambers: Emotional contagion and group polarization on Facebook. *Scientific reports*, 6, 37825, 1-12.

Delli Carpini, M.X. and Keeter, S. (1996). What Americans Know about Politics and why it Matters. *New Haven: Yale University Press*.

DiFonzo, N., and Bordia, P. (2007). Rumor psychology: Social and organizational approaches. Vol. 750, Washington, DC: American Psychological Association.

Dretske, F. (1983). Precis of Knowledge and the flow of information. *The behavioral and brain sciences*, (1983) 6, 55-90.

Fallis, D. (2015). What is disinformation? *Library trends*, 63(3), 401-426.

Fallis, D. (2016) Mis- and Dis-information (lying, propaganda etc.), in Floridi, L. (2016), The routledge handbook of philosophy of information, *Routledge*.

Festinger, L. (1957). A theory of cognitive dissonance. *Stanford: Stanford University Press*.

Fetzer, J. H. (2004). Information, misinformation, and disinformation. *Minds and machine*, 14 (2):223-229.

Flaxman, S., Goel, S., Rao, J. M. (2016). Filter bubbles, echo chambers, and online news consumption. *Public Opinion Quarterly*, Vol. 80, Special Issue, 298–320.

Fletcher, R., and Nielsen, R. K. (2018). Are people incidentally exposed to news on social media? A comparative analysis. *New media and society*, 20(7), 2450-2468.

Floridi, L. (1996). Brave.net.world: The internet as a disinformation superhighway? *Electronic Library,* 14, 509-14.

Floridi L. (2011). The philosophy of information, Oxford university press.

Flynn, D. J., Nyhan, B., and Reifler, J. (2017). The nature and origins of misperceptions: Understanding false and unsupported beliefs about politics. *Political Psychology*, 38, 127-150.

Fox, C. J. (1983). Information and Misinformation: An Investigation of the Notions of Information, Misinformation, Informing, and Misinforming. *Westport, Conn: Greenwood Press*.

Gaughan, A. J. (2016). Illiberal Democracy: The Toxic Mix of Fake News, Hyperpolarization, and Partisan Election Administration. *Duke Journal of Constitutional Law and Public Policy*, 12, 57.

Gelfert, A. (2018). Fake news: A definition. *Informal Logic*, 38(1), 84-117.

Gottfried, J., and Shearer, E. (2017). Americans' online news use is closing in on TV news use, *Pew Research Center*, 7.

Gravanis, G., Vakali, A., Diamantaras, K., and Karadais, P. (2019). Behind the cues: A benchmarking study for fake news detection. *Expert Systems with Applications*, 128, 201-213.

Grinberg, N., Joseph, K., Friedland, L., Swire-Thompson, B., and Lazer, D. (2019). Fake news on Twitter during the 2016 US presidential election. *Science*, 363(6425), 374-378

Grömping, M. (2014). 'Echo Chambers' Partisan Facebook Groups during the 2014 Thai Election. *Asia Pacific Media Educator*, 24(1), 39-59.

Guess, A., Nyhan, B., and Reifler, J. (2018). Selective exposure to misinformation: Evidence from the consumption of fake news during the 2016 US presidential campaign. *European Research Council*, 9.

Guess, A., Nagler, J., and Tucker, J. (2019). Less than you think: Prevalence and predictors of fake news dissemination on Facebook. *Science advances*, 5(1), eaau4586.

Hasher, L., Goldstein, D., and Toppino, T. (1977). Frequency and the conference of referential validity. *Journal of Verbal Learning and Verbal Behavior*, 16(1), 107–112.

Hernon, P. (1995). Disinformation and misinformation through the Internet: Findings of an exploratory study. *Government Information Quarterly*, 12(2), 133-139.

Howard, P. N., Kollanyi, B., Bradshaw, S., Neudert, L.M. (2017). Social Media, News and Political Information during the US Election: Was Polarizing Content Concentrated in Swing States? *COMPROP DATA MEMO,* 2017.8.

Huang, H. (2017). A war of (mis) information: The political effects of rumors and rumor rebuttals in an authoritarian country. *British Journal of Political Science*, 47(2), 283-311.

Jang, S. M., and Kim, J. K. (2018). Third person effects of fake news: Fake news regulation and media literacy interventions. *Computers in Human Behavior*, 80, 295-302.

Jin, Z., Cao, J., Zhang, Y., Zhou, J., and Tian, Q. (2016). Novel visual and statistical image features for microblogs news verification. *IEEE transactions on multimedia*, 19(3), 598-608.

Klein, D. O., and Wueller J. R. (2017). Fake news: a legal perspective. *Journal of Internet Law*, 20(10), 5-13.

Knapp, R.H. (1944). A psychology of rumor. *Public opinion quarterly*, 8(1):22– 37.

Kuklinski, J. H., Quirk, P. J., Jerit, J., Schwieder, D., and Rich, R. F. (2000). Misinformation and the currency of democratic citizenship. *The Journal of Politics*, 62(3), 790-816.

Kull, S., Ramsay, C., and Lewis, E. (Winter, 2003/2004). Misperceptions, the Media, and the Iraq War. *Political Science Quarterly*, 118(4), 569–598.

Latane, B., and Darley, J.M. (1968). Group inhibition of bystander intervention in emergencies. *Journal of personality and social psychology*, 10(3), 215.

Lazer, D. M., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., Metzger, M. J., Nyhan, B., Pennycook, G., Rothschild, D., Schudson, M., Sloman, S. A., Sunstein C. R., Thorson, E. A., Watts, D. J., and Zittrain, J. L. (2018). The science of fake news. *Science*, 359(6380), 1094-1096.

Lee, J., Agrawal, M., and Rao, H. R. (2015). Message diffusion through social network service: The case of rumor and non-rumor related tweets during Boston bombing 2013. *Information Systems Frontiers*, 17(5), 997-1005.

Lerman, K., Yan, X., and Wu, X. Z. (2016). The" majority illusion" in social networks. *PloS one*, 11(2), e0147617.

Levy, S., and Gvili, Y. (2015). How credible is e-word of mouth across digital-marketing channels? The roles of social capital, information richness, and interactivity. *Journal of Advertising Research*, 55(1), 95-109.

Markowitz, D. M., and Hancock, J. T. (2014). Linguistic traces of a scientific fraud: The case of Diederik Stapel. *PloS one*, *9*(8), e105937.

Merckelbach, H., Jelicic, M., and Pieters, M. (2011). Misinformation increases symptom reporting: a test–retest study. *JRSM short reports*, *2*(10), 1-6.

McGonagle, T. (2017). "Fake news" False fears or real concerns? *Netherlands Quarterly of Human Rights*, 35(4), 203-209.

Messing, S., and Westwood, S. J. (2014). Selective exposure in the age of social media: Endorsements trump partisan source affiliation when selecting news online. *Communication research*, 41(8), 1042-1063.

Mocanu, D., Rossi, L., Zhang, Q., Karsai, M., and Quattrociocchi, W. (2015). Collective attention in the age of (mis)information. *Computers in Human Behavior*, 51, 1198-1204.

Nyhan, B., and Reifler, J. (2010). When corrections fail: The persistence of political misperceptions. *Political Behavior*, 32(2), 303–330.

Nyhan, B., Reifler, J., Richey, S., and Freed, G., (2014). Effective messages in vaccine promotion: a randomized trial. *Pediatrics*, 133(4): e835– e842.

Nyhan, B., and Reifler, J. (2015). The effect of fact-checking on elites: A field experiment on us state legislators. *American Journal of Political Science*, 59(3):628–640.

Pariser, E. (2011). The filter bubble: What the Internet is hiding from you. *Penguin UK*.

Paskin, D. (2018). Real or Fake News: Who Knows? *The Journal of Social Media in Society*, 7(2), 252-273.

Pennycook, G., and Rand, D. G. (2019). Who falls for fake news? The roles of bullshit receptivity, overclaiming, familiarity, and analytic thinking. *Journal of personality*. 00, 1– 16.

Pennycook, G., Cannon T. D., and Rand D. G. (2018). Prior exposure increases perceived accuracy of fake news. *Journal of experimental psychology*, General, 147, 1865-1880.

Peters, R. G., Covello, V. T., and McCallum, D. B. (1997). The Determinants of trust and credibility in environmental risk communication: An empirical study. *Risk Analysis*, 17(1), 43-54.

Shah, D., and Zaman, T. (2011). Rumors in a network: Who's the culprit? *IEEE Transactions on information theory*, 57(8), 5163-5181.

Shao, C., Ciampaglia, G.L., Varol, O., Flammini, A., and Menczer, F. (2018). The spread of low-credibility content by social bots. *Nature communications*, 9(1), 4787.

Shin, J., Jian L., Driscoll, K., and Bar, F. (2018). The diffusion of misinformation on social media: Temporal pattern, message, and source. *Computers in Human Behavior*, 83, 278-287.

Silverman, C., Strapagiel, L., Shaban, H., and Hall, E. (2016). Hyperpartisan Facebook pages are publishing false and misleading information at an alarming rate. Buzzfeed News.

Skyrms, B. (2010). Signals. Evolution, Learning, and Information. *Oxford University Press*.

Stevens, C. H. (1981). Many-to-Many Communication. *Technical Report MIT/Sloan/TR-175 Sloan School of Management*, Massachusetts Institute of Technology.

Stroud, N. J. (2010). Polarization and partisan selective exposure. *Journal of communication*, 60(3), 556-576.

Sunstein, C. R. (2002). The law of group polarization. *Journal of political philosophy*, 10(2), 175-195.

Sunstein, C. R. (2009). On rumors: how falsehoods spread, why we believe them, what can be done. *Farrar, Straus and Giroux*, New York 10011, First edition.

Törnberg, P. (2018). Echo chambers and viral misinformation: Modeling fake news as complex contagion. *PLoS ONE*, 13(9): e0203958.

Vaccari, C., Valeriani, A., Barberá, P., Jost, J. T., Nagler, J., and Tucker, J. A. (2016). Of echo chambers and contrarian clubs: Exposure to political disagreement among german and italian users of twitter. *Social Media+ Society*, 2(3), 2056305116664221.

Vosoughi, S., Roy, D., and Aral, S. (2018). The spread of true and false news online. *Science*, 359(6380), 1146-1151.

Wason, P. C. (1960). On the failure to eliminate hypotheses in a conceptual task. *Quarterly Journal of Experimental Psychology*, 12, 129–140.

Weeks, B. E., and Garrett, R. K. (2014). Electoral consequences of political rumors: Motivated reasoning, candidate rumors, and vote choice during the 2008 US presidential election. *International Journal of Public Opinion Research*, 26(4), 401-422.

Westerman, D., Spence, P. R., and Van Der Heide, B. (2012). A social network as information: The effect of system generated reports of connectedness on credibility on Twitter. *Computers in Human Behavior*, 28(1), 199-206.

Wojcieszak, M.E., and Mutz, D. C. (2009). Online Groups and Political Discourse: Do Online Discussion Spaces Facilitate Exposure to Political Disagreement? *Journal of Communication*, 59(1): 40–56.

Wood, T., and Porter, E. (2019). The elusive backfire effect: Mass attitudes' steadfast factual adherence. *Political Behavior*, 41(1), 135-163.

Wu, h., Arenas, A., and Gomez, S. (2017). Influence of trust in the spreading of information. *Physical Review E*, 95(1):012301.

Xu, K., Wang, F., Wang, H., and Yang, B. (2019). Detecting fake news over online social media via domain reputations and content understanding. *Tsinghua Science and Technology*, 25(1), 20-27.

Zhang, X., and Ghorbani, A. A. (in press). An overview of online fake news: Characterization, detection, and discussion. *Information Processing and Management*. Available online from the 20 March 2019, 102025.

Zhao, L., Qiu, X., Wang, X., and Wang, J. (2013). Rumor spreading model considering forgetting and remembering mechanisms in inhomogeneous networks. *Physica A: Statistical Mechanics and its Applications*, 392(4):987– 994.

Zhou, L., Burgoon, J. K., Nunamaker, J. F., and Twitchell, D. (2004). Automating linguistics-based cues for detecting deception in text-based asynchronous computer-mediated communications. *Group decision and negotiation*, 13(1), 81-106.

Zollo, F., Bessi, A., Del Vicario, M., Scala, A., Caldarelli, G., Shekhtman, L., Havlin, S., Quattrociocchi, W. (2017). Debunking in a world of tribes. *PloS one*, 12(7), e0181821.

Chapter 2: The electoral outcomes of false information: Evidence from Italy [±]

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Abstract

We explore how the exposure to false information relates to the performance of political parties in the 2018 Italian political election. Drawing on unique Twitter geotagged data, we build a measure of the exposure to online misleading contents and merge this information with election data and a set of local level variables. We find that the exposure to misleading contents is significantly and positively associated with the performance of the Five Star Movement and negatively associated with vote shares for the Democratic Party when the analysis is limited to political false information or to a reduced sample of pro false information tweets.

Keywords: False Information, Electoral Outcomes, Social Networking Sites, Political Economy

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1 Introduction

A series of recent political events, such as the 2016 American election and the Brexit referendum in UK, have attracted scholars' attention on the societal and political outcomes of fake news. Some scholars argue that fake news may have influenced some political campaigns (e.g. Groshek and Koc-Michalska, 2017; Benkler et al., 2017), affected public perception of reality (Gu et al., 2017), and made people unable to recognize environmental treats (Flynn et al., 2017). It has also been reported that fake news stories have been shared more than real news in the months before the last American election (Silverman, 2016) and a discussion paper of the European Policy Centre (Butcher, 2019) alleges that fake news may lead disenchanted citizens to lose faith in democracy. Concerns about the electoral outcomes of false information rise from the fact that citizens form political opinions based on information they collect and that an efficient democratic system relies on well-informed citizens (Dalton and Klingemann, 2007; Dennis, 1970; Delli Carpini and Keeter, 1996; Luskin et al., 2002). As Berelson et al. (1954:308) argue «The democratic citizen is expected to be well-informed about political affairs. He is supposed to know what the issues are, what their history is, what the relevant facts are, what alternatives are proposed, what the party stands for, what the likely consequences are». Lastly, studies investigating the media effects on public opinion find that citizens respond more to bad news (Soroka, 2006), and the study from Aragones (1997) shows that negative news are more effective in shaping voting behavior. As false information mainly expresses a negative sentiment (Vosoughi et al., 2018), we also expect it may play a role in influencing public opinion. Yet, empirical evidence of a causal effect of false claims on voting behavior is almost nonexistent (Lazer et al., 2018). In this paper, we aim to contribute to the analysis of the potential effect of false information on voting behavior by investigating whether the exposure to misleading contents is associated with the outcomes of the 2018 Italian political election. Italy is an interesting case study because the Five Star Movement (hereafter FSM) and the Lega, two antiestablishment and populist parties (Inglehart and Norris, 2017; van Kessel, 2015), forged a governmental coalition taking the lead of the country.

Our analysis accounts for both disinformation and misinformation. For this reason, we use the general expression 'false information' to indicate partially or totally manipulated contents regardless of the intention to mislead[1].

[1] The discussion of the different implications of the usage of these terms would require a long digression which exceed the purposes of this paper. For a comprehensive analysis of the term fake news see Gelfert (2018) and Fallis (2009, 2015) for disinformation.

We conduct an aggregate, cross-sectional analysis at province level. For the identification of false information, we collect geotagged data from Twitter for the twenty days before the election. In fact, social media have been found to facilitate the propagation of misleading contents compared with other media (Allcott and Gentzkow, 2017). The selection of misleading tweets can be divided into two steps. First, we scrape tweets according to the unique geolocation parameter and, second, we select misleading tweets fitting specific identification criteria. The geolocation of the tweet is a key element for our analysis as it allows to assign the message to a specific geographic area. A tweet is labelled as misleading if it meets at least one of the following criteria: it is the result of an interaction with malicious accounts; it contains keywords related to debunked stories or well-known scientific disinformation; it links to incorrect or fake articles; it has attached photos or video with false contents. In order to detect malicious websites and false information we rely on third-party independent fact-checking websites. We collected 473,729 geotagged tweets where 4,118 contained misleading contents. Data are aggregated at province level based on the geographic information attached to the tweet. We build two indexes of false information: a broad false information index including all the selected false or misleading claims regardless of the topic, and a political false information index considering only political disinformation stories. This information is matched with electoral data provided by the Italian Ministry of the Interior, and other information collected by the National Bureau of Statistics and the Italian Authority for Communications Guarantees (AGCOM).

Overall, our estimates suggest that being exposed to misleading contents on Twitter is a significant predictor of the vote for the FSM across Italian provinces. This finding is robust to different specifications and to the addition of regional fixed effects. We also find a negative but not robust correlation of the vote share for right parties and a positive association with the probability to vote for the center-left coalition, only when implementing a multinomial logit model. However, this result may be utterance of two underlying mechanisms: on the one hand both FSM and Democratic Party (hereafter DP) supporters may be sensitive to false information; on the other hand, there might be two opposite clusters, one supporting and one contrasting the spread of false information. To discern the nature of users' engagement, we select only pro disinformation tweets from our sample. The selection has been carried out by labelling as 'against' all tweets containing the word/s 'fake news' or 'hoax'. The reduced sample has been used to build a new index of 'pro' false information. The resulting analysis shows a positive correlation of the index with the vote share for the FSM and a negative correlation with the vote shares for the DP. This adds little evidence that perhaps the two groups of supporters embrace opposite points of view toward false information.

The analysis of the heterogeneity by demographic structure suggests that provinces with high shares of young individuals and false information report higher vote shares for the

FSM and the Lega. Furthermore, vote shares for the Lega positively correlate with the interaction term of elderlies and political false information. Conversely, estimates show an opposite picture for the DP, reporting the same statistically significant correlations of Lega and FSM but with negative signs. Lastly, the heterogeneity of false information by unemployment rate reveals positive and statistically significant correlation with the performance of the FSM.

Even if results pass robustness checks, the cross-sectional nature of the data prevents the possibility to infer a causal relationship. In the first place, it is difficult to discern the effect of false information from that of other factors that may influence voting behavior. To address this issue, we control for several sets of local level characteristics that may bias voting behavior. Besides, there might exist other factors that we cannot include in our equation that correlate both with the voting behavior and the selection of inaccurate news. Last, we cannot ignore the presence of reverse causality: a party may also exploit false information to extend its reach and gain followers. Despite these limitations, this paper adds to the literature in two substantive ways. First, we carry out one of the first exploration of how online false information relates to the performance of Italian parties, exploiting a novel and unique database that merge aggregate-level administrative data with online social network information. Second, we propose a new approach to measure the exposure to online false news by exploiting Twitter geotagged data.

Our contribution bridges two strands of the literature. First, we contribute to the recent field of studies aiming to identify the relationship between false information and electoral outcomes. Studies in this strand mainly explore the amount of false information spreading online before an election, most of them focusing on the US case study (Grinberg et al., 2019; Guess et al., 2019; Howard et al., 2017), or estimate the number of fake news stories read before the election and to what extent people trusted them (Allcott and Gentzkow, 2017). In a recent study Grossman and Helpman (2019) model parties' behavior through the probabilistic voting model of Lindbeck and Weibull and find that fake news can have real effects in such situations where parties are partially constrained in the truthfulness of their statement and the effect of fake news consists in the divergence of party's positions about a policy with respect to the socially desirable benchmark. We also contribute to the growing literature about persuasive communication in economics, by investigating how this specific type of (dis-)information affects electoral outcomes. Indeed, media are of great importance in citizens' opinion shaping and a field of economics has posed attention on the impact of different media such as radio (Strömberg, 2004), television (e.g. Gentzkow, 2006; Enikolopov et al., 2011; DellaVigna and Kaplan, 2007), broadband (e.g. Campante et al., 2018; Falck et al., 2014), and social networking sites (Petrova et al., forthcoming) on political outcomes.

To the best of our knowledge, this is one of the first exploration of the relation between false information and voting outcomes in Italy. Our main contributions lie in the usage of

a novel and unique dataset of geotagged disinformation as well as in the proposal of a new methodology for the detection of inaccurate contents.
The reminder of the paper is organized as follows: section 2 discusses related literature; section 3 depicts the Italian political background; section 4 presents methodology and empirical strategy; section 5 reports descriptive statistics and describes our sample; section 6 presents results; in section 7 we carry out robustness checks and placebo test; section 8 concludes.

2 Related literature

Even if the term fake news has only recently become popular, scholars already posed attention upon the problem of false information[2]. To the best of our knowledge, studies measuring the political outcomes of false information have rarely accounted for electoral results. Political scientists have documented that misperceptions and misinformation can affect collective preferences (Kuklinski et al., 2000), citizens' opinion about political economic issues (Kull et al., 2003), and harm trust in government (Huang, 2017). However, it is still unclear whether and how false information may affect voting behavior. The study of Weeks and Garrett (2014) makes a first step in this direction by investigating how negative political rumors affect voting behavior. Authors carry out a random-digital-dial telephone survey to 600 Americans representative of the US population for the two weeks following the 2008 American election. Respondents were asked to state whether they heard ten selected stories (eight false and two true) either against Obama or McCain, as well as the relative rebuttal. Authors observe that, on average, the exposure to rumors was low (respondents reported hearing less than three out of the ten rumors proposed) and conclude that believing in a rumor mainly depends on motivated reasoning. Indeed, they find that the probability to vote for Obama decreases as participants believed to negative rumors about the president both for Democrats and Republicans, even if the latter are much more likely to believe in negative rumors about Obama (and vice versa).
Political engagement appears to be one leading factor for the exposure to fake news. On this respect Allcott and Gentzkow (2017) find that both Democrats and Republicans are more likely to believe to ideologically aligned articles, either true or false. In their study upon the impact of fake news on the 2016 American election, the authors carry out a post-election survey to a representative sample of 1,208 American voters where participants were asked to allege whether they read and remembered a set of 15 news headlines that could be true, false, or placebo. The authors estimate that the average American voter read and remembered one or perhaps several fake news headlines before the election.

[2] Early studies on rumors appear during the second world war, see for instance Knapp (1944).

However, the authors argue that how much this affected electoral results depends on the effectiveness of fake news to change one's belief. They conclude that, if fake news was effective as a TV campaign ad, false stories would have changed vote shares of hundredths of a percentage point[3]. Even if the vulnerability to false information may relate individuals regardless of their party affiliation, it appears that, at least for the American case study, some are more likely than others to share and believe in misleading contents. According to Grinberg et al. (2019) individuals more likely to share fake news are older, more engaged with political news, and conservative leaning. Analyzing the Twitter newsfeed of 16,442 American voters, the authors estimate that, on average, the 1.18% of the political URLS were from malicious sources. Even if conservatives were more likely than liberals to share fake news, supporters of both parties show no significant differences in the probability to share an article conditional on the ideological alignment of the information source. Again, this finding confirms the role of confirmation bias and motivated reasoning in the exposure to misleading information. Likewise, Guess et al. (2019) find that conservatives were more likely to share fake news on Facebook during the 2016 presidential campaign and contribute to measure the spread of false information online by estimating that only the 8.5% of their sample shared at least one fake news.
Moving to Italy, Cantarella et al. (2019), exploit the differences in spoken language of the Italian region Trentino-Alto Adige to instrument false information exposure in a difference-in-differences setting, assuming that German-speaking population should have been less exposed to Italian disinformation. They conclude that there is no causal effect between exposure to false information on Facebook and the change in populist parties' vote shares between 2018-2013.
Overall, these studies suggest that being highly engaged with politics -regardless of party affiliation- increases the probability to encounter and believe in false information. This is mainly due to motivated reasoning that is responsible for our information filtering. Given that citizens take voting decisions based on political information they collect and that most of the times they are not able to discern true from false news, it is essential to acknowledge how misleading information affects electoral results.

3 Political background

Until the 2013 election, the political supply in Italy was mainly (even though not exclusively) represented by two main coalitions: the center-right and the center-left. The second republic rose in a particular situation, where old parties have been accused of corruption (the scandal of Tangentopoli and Mani Pulite), and new political actors

[3] The authors rely on results from Spenkuch and Toniatti which state that one unit increase in exposure to TV campaign ads changed vote share by 0.02 percentage points.

presented themselves as a novel alternative to the previous leading class. President Silvio Berlusconi, with his party Forza Italia, has dominated the political scene from 1994 when first entered in politics also profiting from the support of his Television channels (Durante and Knight, 2012). Mr. Berlusconi led the center-right coalition for 24 years. The coalition was composed of several and mutable parties such as the Northern League and the Democratic Centre, whereas the center-left embedded parties like the Left DP, the communist party, and the socialist party. Even if the end of the second republic is a controversial topic in literature, the 2013 election appears to be a turning point in the Italian republic. Indeed, a new political figure, the FSM, burst onto the political scene interrupting this dualism. The FSM becomes a political party in the 2009 but its origins go behind to the 2005 when the Italian comedian Beppe Grillo, which was politically active since 1989, created its own blog (www.beppegrillo.it) and encouraged citizens to use the online platform Meetup to organize collective actions. Beppe Grillo realized the new and strategic role of the Internet in political communication. Like Forza Italia, this movement rises to the political scene in a situation of political and economic crisis. The FSM has exploited this situation by devising its rhetoric and narrative upon these topics and fostering the discontent of some fringes of the population.

The electoral outcomes of the last election ultimately confirm the increasing support for this political actor. The last 2018 election was regulated by a novel electoral law based on a mixed system consisting of a one-third majority and a two-third proportional part. During this election, the center-right coalition was composed of three moderate parties (*Forza Italia; Fratelli d'Italia; Noi con l'Italia*) along with the *Lega*, which was born as separatist party and changes its guise under the new leader Matteo Salvini. The center-left coalition was led by Matteo Renzi of the incumbent DP and other newborn parties *(+Europa; Civica Popolare; Italia Europa Insieme*). The third main political actor running in this election was indeed the FSM, which was the most voted party running alone both to the 2013 and 2018 elections, a singular performance for a new political actor. We also register an additional decrease of the voter turnout with respect to the previous election (in line with a trend started from the 1970s) that equals the 72,93% for the Chamber of Deputies and to the 72,99% for the Senate. Final results see the center-right as winner of the elections, followed by the FSM, the center-left and *Liberi e Uguali*. Despite the higher number of votes has been obtained by the center-right coalition, the percentage of votes and the in-between-party dynamics prevented the possibility for the center-right to form a solid government alone or new political coalitions. The burden to form the government was finally assigned to the Lega and the FSM, two anti-establishment parties that based their political campaign against European Institutions and national corrupted politicians and exploited new communication technologies as their political arena.

4 Data and methods

The purpose of this paper is to analyze the impact of false information spreading online on the outcomes of the 2018 Italian political election. In order to measure how exposure to online disinformation correlates with the performance of the main political parties, we collect data from Twitter for the twenty-days before elections (from the February 13th to the March 04th). We use Twitter data because, compared with other social networking sites, this platform makes available a high amount of data for researchers. In addition, the features of this social media make it a privileged field of analysis for the purposes of our research for two reasons. First, the focus of this study is false information and, as Gruzd and Roy (2014) argue, Twitter is particularly used as source of information rather than for bridging social relations. Second, we study the effect of false information on political outcomes. As «Nowadays, Twitter is used by journalists as the online media of choice to propagate information, and accordingly most of the political debates take place on this social network» (Caldarelli et al., 2014:1), individuals may shape their political opinions based on the information here retrieved and the platform may be used by politicians to spread propaganda.

However, this choice entails some considerations. First, the streaming Application Programming Interface (API) returns a sample of the overall tweets corresponding to the declared parameters[4]. The strategy followed for the extraction of the sample is not revealed by Twitter, but it states that it represents at most the one percent of the overall global public traffic. This may pose some issues about its representativeness. Nonetheless, it has been demonstrated that the sample is representative at different levels and for several features of the overall activity on the platform (e.g. Wang et al., 2015). The suitability of these data to predict social outcomes is also corroborated by their usage to forecast box office revenues (Vujić et al., 2018), social protests (Steinert-Threlkeld et al., 2015; Cadena et al., 2015), the stock market (Bollen et al., 2011; Zhang et al., 2011), and political outcomes such as election results (e.g. Caldarelli et al., 2014). Second, one could warn that Twitter users may not be representative of the overall Italian population as they are, on average, younger and more educated. According to the Pew Research Center, American Twitter users are representative of the overall population for gender and race, but not for age (Twitter users are younger), education (more educated), average income (higher), and political slant (left-oriented)[5]. Looking at Italy, the 32% of the population between 16 and 64 years old has a Twitter account and most of them are women[6]. The distributions by gender and age of the Italian social media users compared

[4] See the next section for more details about the implemented strategy to scrape data from Twitter.
[5] Pew Research Center (Apr. 24th 2019), *Sizing Up Twitter Users.*
[6] Digital 2019 report, We Are Social.

with the total population is shown in the Appendix table A1. We can see that the remarks presented for the US also apply to the Italian case.
The key point of the analysis is the identification of the tweet location in order to assign it to a specific province. We then combine this information with other aggregate-level data. The analysis is carried out at the provincial level because the National Bureau of Statistics provides more updated and comprehensive information at this level.
We consider our outcome variables to be a vector of the vote shares of the main political parties in the Italian landscape, while keeping other parties' performances as checks. We estimate a binomial Generalized Linear Model having the vote share for party *p* as dependent variable and an index of the exposure to false information online as main explicative variable. The selection of this econometric model follows Papke and Wooldridge (1996), which find that Bernoulli quasi-likelihood methods returns more robust estimation for fractional respond variables models. A separate regression is run for each party. As we shall see more in detail below, we account for two indexes of false information exposure: the 'Broad False Information' index (BFI), which encompasses all types of false information (e.g. politics, science, conspiracy theories) and the 'Political False Information' index (PFI), which considers only political related contents.

4.1 Detecting false information on Twitter

In this section we describe the criteria followed to build our false information sample. Twitter allows to retrieve data through its Application Programming Interface (API). We called the streaming API that filters publicly available real-time tweets and allows different input parameters for the selection of the information to obtain[7]. For the purposes of this paper, we use the unique parameter of the geolocation. It has been demonstrated that the sample of tweets selected through streaming API truthfully reflect the daily and hourly activity patterns as well as the scaling behavior of the overall Twitter users, and reproduce the relative importance of the arguments (Wang et al., 2015). Sampling tweets according to the only constraint of the geolocation entails several advantages. First, we do not need to a priori define specific hashtags or keywords in order to collect data, allowing a more comprehensive and reasoned selection of these parameters at the end of the collecting period. Second, this gives us a measure of the trending topic of conversation on this SNS, including topics unrelated with false information. Last, if the assumption that malicious accounts have the geolocation disabled is reliable, the presence of bots and disinformation accounts' posts should be limited in this environment.

[7] https://developer.twitter.com/en/docs/tweets/filter-realtime/api-reference/post-statuses-filter

In the sample of geotagged tweets, any tweet matching at least one of the following criteria has been labelled as misleading:

1. Direct interaction with disinformation accounts (replies and quoted tweets).
2. Keywords identifying false information.
3. Link sharing.
4. Photos and videos.

Our starting point for identifying of disinformation websites and fake news stories is a list of untrustworthy sites compiled by the independent fact-checkers website BUTAC, following a consolidated strategy in related studies (Zollo et al., 2017; Fletcher and Nielsen, 2018). The blacklist of BUTAC encompasses websites, Facebook pages, YouTube channels that publish news with no scientific base (pseudoscience), biased and unverified news (pseudo-journalism), pseudo-satire, conspiracy theories, hoaxes, and viral news[8]. We then manually verified the existence of Twitter accounts for the listed websites, successfully identifying 53 accounts, as reported in the Appendix Table A2. All users' interactions with these entities are included in our sample. In addition, we consider domains of all the websites and blogs listed by fact-checkers, searching them throughout the database of geotagged tweets. With this approach, we identify such messages that directly link to external deceptive news sources even in absence of a direct interaction with the disinformation account. We rely on fact-checking websites also for identifying the most popular false stories spreading before the election for a total number of 61 stories. We then search these stories within our geotagged database by means of keywords that could univocally detect them. Table A3 in the Appendix presents some examples of false stories and related keywords. We also accounted for scientific and well-known hoaxes like vaccine and autism or chemtrails (see Appendix table A4). Last, starting from media attached to these tweets we searched for other tweets having the same media attached.

These tweets represent our base for the calculation of the Broad False Information index (BFI). The index is computed by dividing the number of selected false information tweets by the total number of geotagged tweets in the area[9]:

$$\mathrm{BFI}_i = \mathrm{m}_i / \mathrm{t}_i \qquad (1)$$

[8] We did not include Facebook pages, YouTube channels, and viral news websites in our analysis.

[9] In a robustness test, we use an alternative index obtained by dividing the number of users that interact with online misleading contents by the total numbers of Twitter users in the province. Results are shown in table 13.

where i indexes provinces, t_i represents the total number of tweets in province i and m_i is the total amount of false information tweets in the province.
At a second stage of the analysis we consider only political-related disinformation. To this purpose, within the subsample of general disinformation, we select only misleading tweets on political issues responding to at least one of the following conditions:

- Misleading tweets containing a direct reference to political issues;
- Misleading tweets covering controversial topics discussed in the electoral campaign (e.g. vaccines, immigration);
- Misleading tweets resulting from an interaction with political disinformation accounts;
- Misleading tweets about immigration, considered as a subcategory of politics.

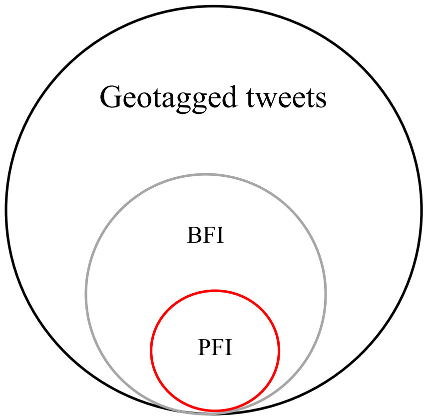
As for the BFI, we create a measure of the exposure to Political False Information (PFI) by dividing the number of selected political false information tweets by the total number of geotagged tweets in the area.

$$PFI_i = p_i / t_i \quad (2)$$

Where i indexes provinces, t_i represents the total number of tweets in province i and p_i is the total amount of political false information tweets in the province. Figure 1 illustrates the composition of our Twitter data.
We do not account for the sentiment of the tweet, which results in a coexistence of both negative and positive stances. We do not distinguish for from against tweets for a few reasons. First, automated detection techniques (i.e. machine learning) necessitate of a considerable amount of labelled data in addition to a good command of the various classification algorithms. Considering the amount of data available, all the dataset should be manually coded. Second, the identification of the tweet sentiment is not straightforward: the peculiar shortness of the tweet makes it tricky to automatically or manually detect the message attitude. Last, under the assumption that a tweet countering a false information is a cue of the presence of a misleading tweet, we believe that this strategy allows a more comprehensive detection of false information. We thus assume that also a tweet against a false claim is useful for the purposes of the analysis as it works as signal and amplifier of the news itself.
Broadly speaking, the sample of misleading tweets encompasses: users' replies or quotation from common users to disinformation accounts' messages; users' spreading of misleading stories on the Twittersphere, and the Twitter conversation about misleading stories and news. In this setting, the presence of common users' response to false information should be highly heartened, whereas the presence of native tweets from malicious users is supposed to be discouraged. However, this strategy inherits some

limitations. Managing geotagged tweets prevents us from the possibility to consider retweets as they are never geotagged. Nevertheless, we are able to detect native tweets, quoted tweets and replies.

Figure 1: composition of Twitter data



4.2 Data

Twitter data. This study takes advantage of a novel and unique database. We collect 473,729 publicly available geotagged tweets for the 20 days before the political elections. We construct our indexes of the incidence of false information across Italian provinces based on the GPS coordinates of the tweets, following the methodology describes in the previous section. The resulting general false information sample is made of 4,188 tweets produced by 1,814 distinct users, whereas the political subsample is composed of 2,577 tweets, produced by 829 distinct users. We then combine this information with electoral data collected by the Ministry of the Interior, and with a battery of control variables collected by the Ministry of Economy and Finance (MEF), the National Bureau of Statistics (hereafter ISTAT), and AGCOM.

Electoral data. In order to construct our vector of dependent variables, we use data provided by the Italian Ministry of the Interior, including information about the total number of votes, voters (split for gender), eligible voters (split for genders) at the ward level. The vote shares of the political parties are computed by dividing the number of votes for the party on the total number of votes[10]. We exclude from the analysis the Aosta

[10] In a robustness check we also repeat the analysis with an alternative computation of the dependent variable where the number of party's votes is divided by the total number of eligible voters in province *i*, and results do not change.

province as the voting was regulated by a First-Past-the-Post system, differently from the rest of Italy that used a Mixed-Member proportional system. We also compute the same variables for the previous general election of the 2013 for parties that matched both elections, which are included as control variables.

Control variables. Our battery of province-level control variables is drawn from several sources. Data on gender, migrant share, age, population, employment, education, level of urbanization, topological structure, tourism rate, and firms per capita, are taken from ISTAT[11]. Data on income are taken from the Italian Ministry of Economy and Finance (2017), data on broadband coverage are elaborated on AGCOM data, whereas data on the incumbency at province-level have been scraped from the website www.tuttitalia.it. Last, data on the local total public expenditure have been accessed through a governmental platform served to the ease consultation of expenses made by the Public Administration[12]. Table 1 lists all the control variables.

Table 1. Control variables

	Set	Variables	Computation
1	Demographics	Male	N. of male on the total of the population
		Migrants share	N. of regularly resident migrants on the total of the population
		Employment share	Incidence of employees per sector: primary sector, secondary, buildings, services, hotel and catering
		Unemployment rate	N. of unemployed people on the total of population 18-65 years
		Age	Share of population on the total, split into six classes starting from the minimum voting age: 18-24;25-34;35-44;45-54;55-64; 65 and more
		Education	N. of people with high school or university diploma on the total of the population
2	Economic controls	Local public expenditure	Log of total local expenditure
		Taxable income	Log of the aggregate taxable income
		Firms	Firms per capita

[11] All these variables are at the 01/01/2018 with the exception of the Tourism rate (01/01/2017) that is computed as number of presence days (Italians and foreigners) in tourism facilities per inhabitant.
[12] http://soldipubblici.gov.it/it/homegeo.

3	Political controls	Votes share (2013)	Vote share of the party at the previous Italian general election (2013)
		Incumbency	A dummy for each political party, which equals 1 if the party was an incumbent in that province, 0 otherwise
4	Other	Urbanization	Mean of the urbanization level of the municipalities as measured by the Italian National Institute of Statistics. It varies by 1 (densely urbanized) to 3 (scarcely urbanized)
		Tourism rate	Days of permanence in touristic facilities (Italian and not)
		Broadband supply	Incidence of households (theoretically expected) served with speed in range 30-100 Mbps
		Mountains	Number of totally mountain municipalities on the total number of municipalities

4.3 The model

In order to explore how our measure of online exposure to false information correlates with electoral outcomes we implement a generalized linear regression model of the following type:

$$\text{Vote\_share}_{ip} = \alpha_0 + \beta FI_1 + \gamma X_i + \eta_i + \varepsilon_{ip} \quad (3)$$

where *i* indexes provinces and *p* the political party. Vote_share_{ip} is a vector of outcome variables for the vote shares of selected parties, FI is a generic acronym for both broad and political online false information exposure in the province *i*, X is a vector of aggregate-level control variables, η_i indicates regional fixed effects, and ε_{ip} is the error term. The β coefficient thus captures how the performance of each political party reacts to false information, as proxied by the indexes. The inclusion of regional fixed effects accounts for any unobserved time-invariant characteristics that may affect the vote and may also correlate with the exposure to false information. The vector of control variables X_i encompasses several sets of aggregate-level characteristics: demographics, economics, politics and supplementary controls accounting for the topology and economic wealth of the province, that are progressively added in order to test the robustness of our estimates. Following the main specifications in the literature, we account for a set a socio-demographic characteristic that include: gender; age (partitioned into 5 classes); population; the share of population with higher education; unemployment rate; migrants rate; share of employee in the secondary and tertiary sector. Moreover, in political science it has been demonstrated that the vote can be explained by economic (Erikson and Wlezien, 1996; Lewis-Beck, 1982, 1986, 2006) social (Lijphart, 1979; Rose and Urwin, 1969) and ideological (Campbell et al., 1980) factors. To control for political confounding factors, we add indicators measuring the vote share in previous election[13] and a set of dummies capturing the provincial administrative government holding at the moment of the elections, i.e. the incumbency, which is also crucial in voting models[14]. As economic factors also affect voting behavior we include a set of economic variables including the average taxable income, firms per capita, and total public expenditure. The last set of controls encompasses the average level of urbanization of the municipalities within the province, tourism rate, broadband coverage, and share of totally flat municipalities on the total number of municipalities of the province. The level of urbanization of the area may affect voting behavior as it proxies for other factors that may influence the vote, such as the wealth of the area, the job market structure, and the availability of services. We control for the broadband coverage as the focus of the analysis is about online disinformation and consequently being exposed to false information depends on the presence and quality of the Internet coverage. Furthermore, as the broadband access correlates with topological features of the region (Campante et al., 2018), we also consider the level of "mountainousness" in our model. Table 2 reports the summary statistics for the variables included in the model.

Table 2. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
		Panel A: Independent variables			
BFI	106	0.955	0.654	0	4.105
PFI	106	0.569	0.628	0	3.739
		Panel B: Dependent variables			
The Lega	106	16.626	8.998	2.800	37.784

[13] The loss aversion theory of Kahneman and Tversky (1979) suggests that when taking decisions the dissatisfaction deriving from the loss of any fixed amount is greater than the gratification coming from the gaining of the same amount. Alesina and Passarelli (2015) apply this theory to a voting model where the reference point is the status quo. Authors find that voters tend to prefer the status quo even when their preferences in other conditions would be different and would possibly prefer others status quo. We proxy this aversion to change as well as the persistency of voting behavior by including in the equation the vote shares of the previous election.

[14] Evidence on the incumbency advantage is conflicting. Even if early studies find no advantage for the incumbent party (or candidate), recent studies find incumbency positively affecting the electoral performance. Results confirm the main role of district-level feature (Carey et al., 2000), professionalism (Hogan, 2004), as well as institutional features and historical strength (Berry et al., 2000) on the re-election prospects of incumbents.

Forward Italy	106	13.324	3.743	4.559	22.957
Brothers of italy	106	4.040	1.018	1.549	8.425
Us with Italy	106	1.294	0.966	0	5.839
Democratic Party	106	17.071	5.262	7.467	34.847
+Europe	106	2.114	0.900	0.550	4.770
Popular Civic List	106	0.643	0.617	0.187	4.5
Italy Europe Together	106	0.646	0.448	0.183	3.9
Free and equals	106	3.155	0.950	1.861	6.998
Five Star Movement	106	31.853	10.004	12.681	54.115
Panel C: control variables					
Male	106	49.003	0.490	47.477	50.467
Migrants	106	7.955	3.386	1.853	17.467
Unemployment	106	11.923	6.031	3.1	27.6
Age: 18-24	105	6.785	0.865	5.216	8.802
Age: 25-34	105	10.908	1.108	8.789	13.554
Age: 35-44	105	13.959	0.663	12.293	15.419
Age: 45-54	105	16.014	0.640	14.434	17.206
Age: 55-64	105	13.269	0.619	11.963	15.196
Elderly	106	15.035	2.132	10.323	23.346
Population	106	569412,9	618892	85237	4355725
Employment: primary	105	5.337	4.175	0.037	20.211
Employment: secondary	106	19.834	8.830	6.10	42.449
Employment: buildings	106	6.520	1.662	3.713	11.078
Employment: services	106	47.304	6.490	31.545	67.690
People with HS or univ. dip.	106	59.688	7.671	40.4	83.57
Taxable income	106	7562074557.93	9544482570.85	890821974	65777892346
Firms per capita	104	8.505	1.475	1.998	13.614
Public expenditure	106	3075,632	6153,777	0	41.618
Democratic Party 2013	106	18.765	7.516	0.172	58.375
Forward Italy 2013	106	15.299	4.091	0.211	33.079
Brothers of Italy 2013	105	1.541	1.092	0	7.049
The Lega 2013	106	2.944	4.122	3.133	15.559

Five Star Movement 2013	106	19.019	4.740	1.934	41.593
Us with Italy 2013	105	1.282	0.829	0	6.171
Tourism rate	105	7.601	9.809	0.2	30.2
Urbanization	106	2.637	0.298	1.417	2.986
Mountain	106	50.070	29.572	0	100
Broadband	106	67.676	10.986	40.140	86.760

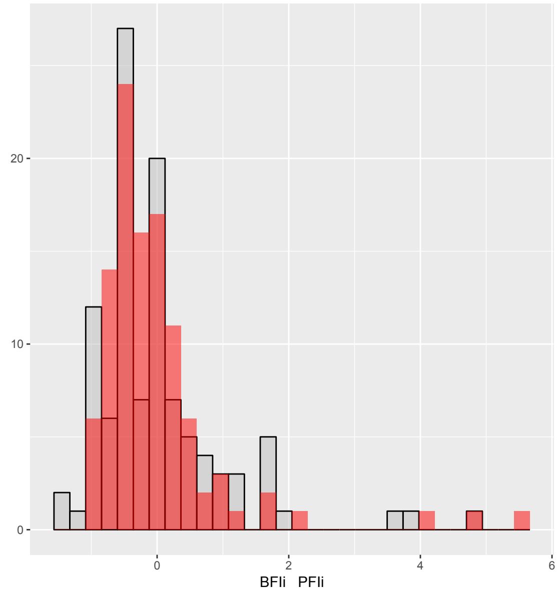
5 Descriptive statistics

In this section we present some descriptive statistics of our false information sample. As shown in table 2, the average level of false information spreading in our Twitter sample is about the 1% of the total geotagged database. Figure 2 illustrates the distributions of both indexes. Compared with the general disinformation, the distribution of the political index is much more concentrated between 0 and 0.1%, thus keeping lower values, whereas the long right tail of both distributions suggests higher level of both indexes in few provinces.

Looking at the composition of our sample, the precise number of fake news stories in our database is not directly measurable due to the heterogeneity of our identification criteria. While on the one hand we are able to quantify the number of stories intercepted through fact-checking websites (61) and those identified as scientific hoaxes (10), on the other hand false information coming from the interaction with disinformation accounts (i.e. quoted tweets, replies, link and media shares) are hard to discern, especially because the tweet usually represents a comment to an article.

In order to identify political tweets and to describe the typologies of disinformation in our sample, we classify tweets into three macro-categories: politics, science, and the residual category ‘other’.

Figure 2: Density of the Broad False Information index (BFI) and Political False Information index (PFI)



Note: the figure plots the density of the broad false information index (grey) and of the political false information index (red).

In order to identify tweet's topic, we rely on the criteria used to detect false information (disinformation accounts, fact-checked stories, images and videos) and label tweets according to one of the following conditions:

- The topic of the selected fact-checked stories;
- The typologies of the disinformation account according to indications provided by the fact-checking website BUTAC;
- Media content.

The combination of these criteria allows us to classify the entire sample. Political tweets have been selected following the identification criteria specified in section 4.1 and represent the computational basis for our Political False Information index, which also encompasses: conspiracy theories; immigration; and science related tweets covering arguments used within the electoral campaign.

Examples of malicious tweets about immigration may be those stating that we are witnessing to an invasion from Africa[15], or the belief that migrants are accommodated in four stars hotels, have smartphones and receive high amount of money from the Italian government. The science category embraces the well-known scientific hoaxes that are listed in table A4 with the exception of the one about the linkage between vaccine and

[15] These were typical topics of the electoral campaign of the Lega, which fed the fear and the insecurity of some fringes of the population.

autism. Indeed, the vaccine-and-autism disinformation may also be political if it is argument of the electoral campaign and parties reflect one or the other faction. As we can see from figure 3, which shows the composition by topic of the false information sample, most of the disinformation tweets are about politics (59.7%). The second larger category is represented by the residual category 'other', which encompasses tweets that are not ascribable to any of the other categories. Most of them concern a hoax about a weather disturbance named Burian that would have caused an ice-cold winter in Italy. The composition of the topics in our sample gives preliminary evidence of the predominant incidence of political-related false information on the total disinformation observed. This evidence is also consistent with the analysis from AGCOM (2018) reporting that 57% of their disinformation sample is about politics and news.

Figure 3: Composition of the sample by main categories

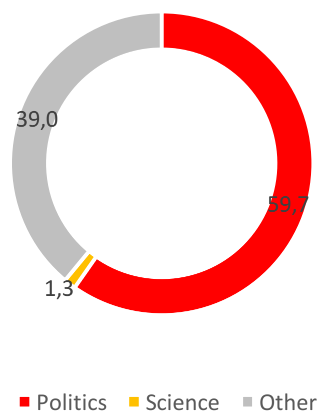
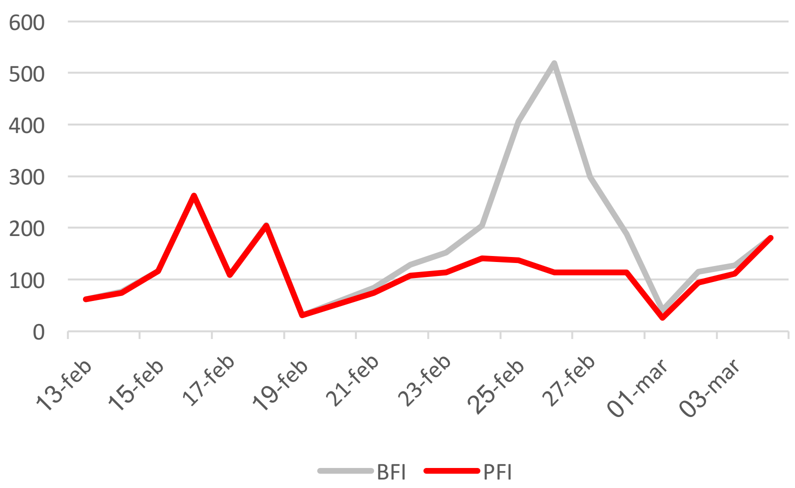


Figure 4 displays the daily evolution of broad (grey line) and political (red line) indexes in the reference period. While in the first week the two indexes follow the same trend, after the 22nd of February the general false information sharply increases whereas the political contents keep values around the mean of the distribution (128.85 tweets per day) and increases again a few days before the election. The big difference between general and political false information in this specified timespan may be ascribable to the snowfall that hit Rome between the 25th and the 26th of February which triggered several disinformation stories.

Figure 4: Time trends of the Broad False Information index (BFI) and of the Political False Information index (PFI)



Note: The x-axis reports days and the y-axis the count of tweets per day.

Aside from temporal trends, we are also and foremost interested in the definition of the geographical distribution of disinformation in Italy. Figure 5 and 6 show the geographical distribution of the broad and political indexes at province level. To a first sight it appears that provinces falling into the highest class of disinformation (dark blue and dark violet) are from the South. In order to provide a statistical measure of the false information incidence across the country, we compute the average level of false information conditional on geographic macro-regions (i.e. North-West, North-East, Center, South, and islands). The average level of exposure to general false information is higher in the South (1.26%), lower in the Islands (0.56%), whereas the North and the Center of Italy are in the average level (1%). Conversely, looking at the political disinformation, we find higher values in the North-East (0.74%) with a substantial difference with the correspondent North-West (0.44%). The Islands confirm the lower level of exposure (0.36%), whereas levels for the South (0.63%) and the Center (0.5%) are nearest to the average value.

Figure 5: Geographical distribution of the overall index (BFI) at province level

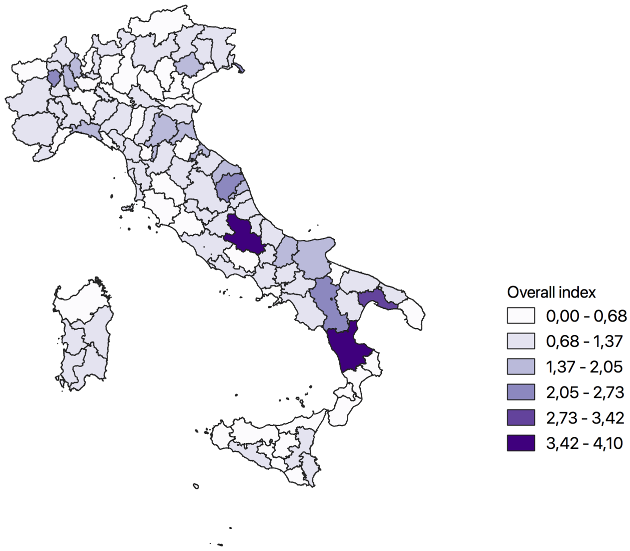
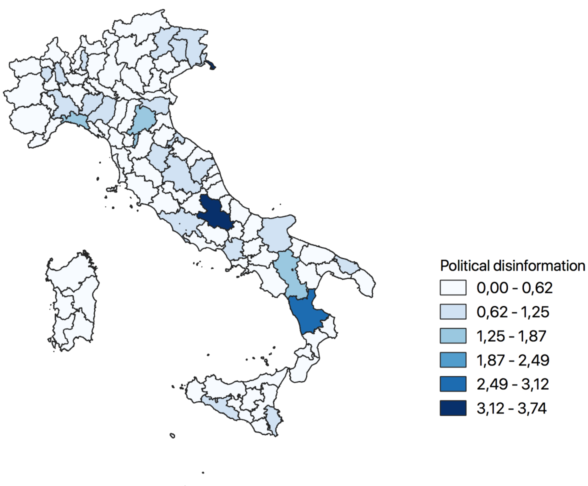
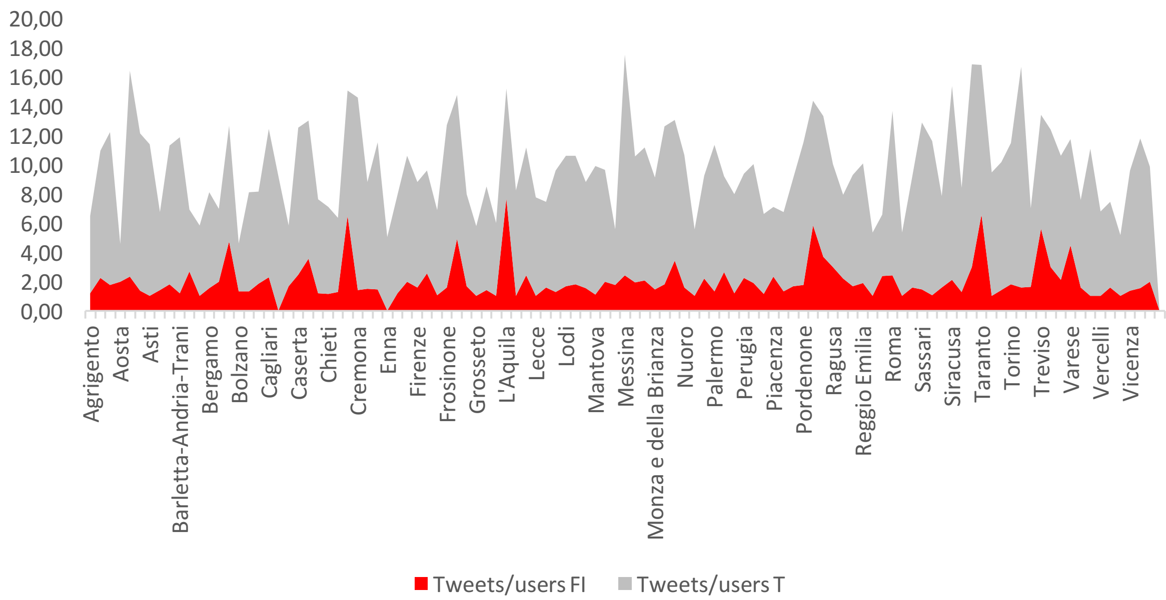


Figure 6: Geographical distribution of the political false information index (PFI) at province level



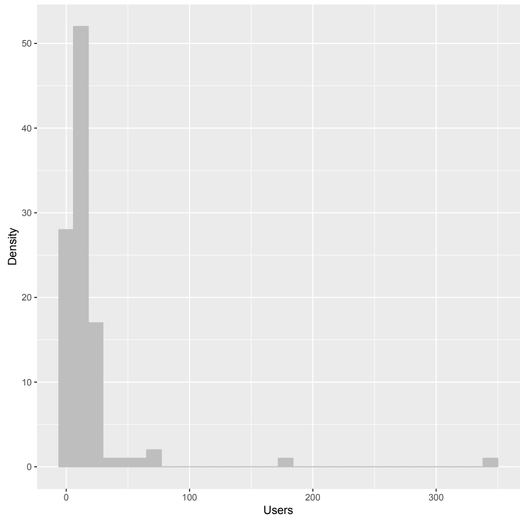
Lastly, we would like to know which is the behavior of users in our sample, how active they are and if all provinces are active the same way. First, in the observation period we register a low average user activity that equals ~2 tweets per user. Figure 7 shows the average number of malicious tweets per user by province compared with the overall geotagged sample. Second, the tweeting intensity may vary by province, as there might be provinces with lots of users twitting less or a few users twitting a lot. In order to address this issue, we compare the level of tweets per user across provinces with the average value. This allows to classify provinces as very active or less active and to tell something about the distribution of the variable. We find that 1 out of 3 province presents values above the mean whereas most of the observation are placed below. This suggests that few users are responsible for most of the disinformation produced, as plotted in figure 8. This evidence is consistent with previous research concluding the presence of few superspreaders in disinformation networks, i.e. few nodes are responsible for a considerable part of the disinformation spreading online (Shao et al., 2018; Grinberg et al., 2019; Guess et al., 2019).

Figure 7. Number of tweets per users by province



Note. The figure plots the number of disinformation tweets per user by province (red) compared with the total activity in the sample (grey). X axis reports provinces, y axis the number of tweets per user.

Figure 8: Tweets per users



6 Results

In this section, we explore the linkage between the exposure to online false information and the performances of main parties: Lega, FSM and DP. We discuss results from GLM regressions as in (3).

Broad false information. Table 3 reports full results for the FSM. Each column adds a set of controls as specified in section 4.3[20]. Overall, we find a positive and statistically significant relation of the vote for the FSM with our broad index of false information in all the specifications of the model. Column 1 presents results from the baseline specification that accounts only for socio-demographic controls.

Table 3. Broad False Information index (BFI) and the performance of the FSM

Dep. Var.: Vote share of the FSM	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
BFI	0.015**	0.021***	0.023***	0.025***	0.016**
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
Male	-0.026*	-0.009	-0.007	0.008	0.000
	(0.012)	(0.011)	(0.009)	(0.009)	(0.012)
Migrants share	-0.008***	-0.010***	-0.009***	-0.009***	-0.005*
	(0.197)	(0.198)	(0.157)	(0.161)	(0.218)

[20] Column 1 = socio-demographic controls; Column 2 = socio-demographic + economic controls; Column 3 = socio-demographic + economic + political controls; Column 4 = socio-demographic + economic + political + other controls; Column 5 = socio-demographic + economic + political + other controls + regional fixed effects.

Age:25_34	0.023	0.013	0.029**	0.029**	-0.003
	(0.014)	(0.013)	(0.010)	(0.009)	(0.009)
Age:35_44	0.017	0.014	0.008	-0.002	0.013
	(0.009)	(0.010)	(0.007)	(0.008)	(0.008)
Age:45_54	0.004	-0.013	0.009	0.009	0.003
	(0.014)	(0.016)	(0.001)	(0.011)	(0.009)
Age:55_64	-0.003	-0.010	-0.008	0.000	0.002
	(0.032)	(0.030)	(0.010)	(0.010)	(0.008)
Elderly	0.031	-0.084	0.176	0.076	-0.160
	(0.329)	(0.266)	(0.239)	(0.195)	(0.160)
Log population	-0.008	-0.026*	-0.011	-0.011	-0.008
	(0.007)	(0.012)	(0.011)	(0.010)	(0.008)
High level education	0.034	0.076	0.059	0.165**	0.056
	(0.066)	(0.064)	(0.054)	(0.052)	(0.064)
Unemployment rate	0.791***	0.784***	0.703***	0.719***	0.437***
	(0.186)	(0.192)	(0.149)	(0.130)	(0.097)
Secondary	-0.173	-0.194	-0.100	-0.073	-0.021
	(0.116)	(0.112)	(0.092)	(0.092)	(0.066)
Buildings	-0.373	-0.535	-0.229	0.047	0.075
	(0.360)	(0.340)	(0.328)	(0.300)	(0.246)
Services	-0.208	-0.258*	-0.217*	-0.230**	-0.207**
	(0.117)	(0.119)	(0.0930)	(0.0879)	(0.0766)
Firms per capita		0.012***	0.012***	0.012***	0.000**
		(0.003)	(0.003)	(0.003)	(0.000)
Income		0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Total public expenditure		0.005	0.003	0.001	0.001
		(0.003)	(0.002)	(0.003)	(0.002)
Previous election			0.416***	0.310**	0.061
			(0.112)	(0.103)	(0.079)
Incumbent: center-left			0.005	0.011	0.008
			(0.010)	(0.011)	(0.008)
Incumbent: Extr. comm.			0.044***	0.043**	0.035**
			(0.013)	(0.015)	(0.012)
Incumbent: Civic list			0.009	0.009	0.011
			(0.012)	(0.011)	(0.008)
Incumbent: FSM			0.065*	0.084***	0.051*
			(0.026)	(0.019)	(0.021)
Urbanization				-0.007	-0.015

				(0.015)	(0.011)
Tourism				-0.039	0.017
				(0.082)	(0.075)
Broadband				-0.158***	-0.060
				(0.039)	(0.033)
Mountainousness				0.045**	0.034**
				(0.016)	(0.012)
Regional fixed effects					✓
Observations	**105**	**103**	**103**	**103**	**103**

Notes. Table presents Average Partial Effects of regression results from the generalized linear model of the vote share of the FSM on the BFI. Reference category for incumbency: center-right; reference category for employment sectors: primary; reference category for gender: female; reference category for age: 18-24. Robust standard errors clustered by provinces in parenthesis. * p<0.1, ** p<0.05, *** p<0.01

In this model, the coefficient is significant at the 5 percent level and suggests that to an increase of 100 false information tweets, the vote for the FSM increases by 0.016 points on average[21]. The size of the coefficient increases as we add indicators of the economic well-being of the province (column 2), with an increase of the magnitude of the coefficient by 0.006. However, the coefficient is quite stable in models 2,3, and 4. Estimates are robust to the addition of the set of political controls, which accounts for the incumbency and the votes obtained by the FSM in the 2013 election (column 3). The positive correlation between the vote share in 2018 and 2013 is consistent with the literature on incumbent preferences due to loss aversion (Alesina and Passarelli, 2015). Our estimates are robust also when controlling for the average level of urbanization, tourism and broadband access, with a slight increase in the magnitude of the coefficient (column 4). Looking at column 5, where fixed effects are added, the coefficient returns to the initial value.

The coefficients of our control variables reveal interesting information. Results suggest that provinces with higher number of firms as well as higher levels of unemployment, young people (25-34), and broadband access are more likely to vote for the FSM. These results are in line with previous individual-level analysis showing that the electorate of this party is mainly composed of unemployed and young people, especially if facing the vote for the first time (Biorcio, 2014), whereas the positive correlation of the vote with high level of broadband access is consistent with findings from Campante et al. (2018). The positive correlation with the number of firms per capita may be due to the role played by the enterprises microcredit fund in the party's electoral campaign. Estimates also

[21] The size of the effect is computed as: $\hat{\beta}\hat{\phi}(\hat{\beta}'x)$.

suggest that the probability to vote for the FSM is negatively associated with high levels of employees in the tertiary sectors and with the migrants share.

Moving our attention to the Lega, the negative sign of the coefficient in all the specifications of the model suggests that false information has lowered the vote for this party (table 4). Yet, the coefficient is significant only in the second model and not robust to the addition of the sets of political and supplementary controls as well as regional fixed effects, suggesting that these variables affect the outcome or intervene in the relation between false information and the vote share for the Lega. Looking at the significance of controls, the choice to vote for this party appears to increase as the incidence of individuals aged 45-64 years old go higher. Positive associations are also observable for provinces with high levels of migrants share, employees in the secondary and tertiary sectors and population size.

Table 4. Broad False Information index (BFI) and the performance of the Lega

Dep. Var.: Vote share of the Lega	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
BFI	-0.006	-0.012**	-0.006	-0.009	-0.004
	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)
Male	0.042***	0.029**	0.013	0.004	0.012
	(0.011)	(0.011)	(0.010)	(0.009)	(0.010)
Migrants share	0.006**	0.008***	0.008***	0.008***	0.002
	(0.0019)	(0.002)	(0.001)	(0.002)	(0.002)
Age:25_34	-0.038**	-0.030**	-0.027**	-0.030**	0.003
	(0.012)	(0.011)	(0.009)	(0.009)	(0.008)
Age:35_44	-0.007	-0.009	-0.001	0.004	-0.013
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Age:45_54	0.015	0.024	0.017	0.016	0.021**
	(0.013)	(0.013)	(0.012)	(0.011)	(0.008)
Age:55_64	0.021*	0.024**	0.021***	0.016*	0.013*
	(0.008)	(0.008)	(0.006)	(0.008)	(0.006)
Elderly	-0.476	-0.394	-0.217	-0.228	-0.0194
	(0.326)	(0.269)	(0.191)	(0.194)	(0.116)
Log population	0.004	0.026*	0.015	0.016	0.020**
	(0.007)	(0.013)	(0.010)	(0.010)	(0.007)
High level education	-0.029	-0.087	-0.029	-0.077	-0.102*
	(0.068)	(0.060)	(0.059)	(0.056)	(0.041)
Unemployment rate	-0.340*	-0.371*	-0.195	-0.247	-0.181*
	(0.172)	(0.170)	(0.135)	(0.136)	(0.083)
Secondary	0.396***	0.437***	0.268**	0.183*	-0.093
	(0.089)	(0.082)	(0.093)	(0.0873)	(0.056)

Buildings	0.524*	0.655**	0.496*	0.310	0.035
	(0.257)	(0.245)	(0.251)	(0.252)	(0.158)
Services	0.230*	0.325***	0.246**	0.202*	0.065
	(0.096)	(0.089)	(0.087)	(0.094)	(0.065)
Firms per capita		-1.134***	-0.484	-0.504	-0.192
		(0.242)	(0.268)	(0.273)	(0.187)
Income		0.000	0.000*	0.000	0.000**
		(0.000)	(0.000)	(0.000)	(0.000)
Total public expenditure		-0.005*	-0.004*	-0.002	-0.002
		(0.002)	(0.002)	(0.002)	(0.001)
Previous election			0.588**	0.537**	0.520***
			(0.188)	(0.179)	(0.139)
Incumbent: center-left			-0.015	-0.020*	-0.006
			(0.009)	(0.010)	(0.008)
Incumbent: Extr. comm.			-0.024*	-0.029*	-0.025*
			(0.012)	(0.013)	(0.011)
Incumbent: Civic list			-0.004	-0.004	-0.002
			(0.010)	(0.010)	(0.007)
Incumbent: FSM			-0.023	-0.042*	-0.017
			(0.017)	(0.020)	(0.012)
Urbanization				0.012	0.010
				(0.015)	(0.011)
Tourism				-0.0677	-0.122**
				(0.047)	(0.041)
Broadband				0.079	0.036
				(0.041)	(0.034)
Mountainousness				-0.028	-0.007
				(0.015)	(0.011)
Regional fixed effects					✓
Observations	**105**	**103**	**103**	**103**	**103**

Notes: Table presents Average Partial Effects of regression results of the vote share of the Lega on the BFI. Reference category for incumbency: center-right; reference category for employment sectors: primary; reference category for gender: female; reference category for age: 18-24. Robust standard errors clustered by provinces in parenthesis. * p<0.1, ** p<0.05, *** p<0.01

Conversely, no statistically significant correlation holds between the vote for the DP and exposure to misleading contents, as shown in table 5. Strong predictors of the vote for this party are gender (provinces with higher incidence of male present low levels of vote shares), migrants share, education, and 2013 vote share (positive association), people aged between 45-55 years old (negative association).

Table 5. Broad False Information index (BFI) and the performance of the DP

Dep. Var.: Vote share of the DP	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
BFI	-0.004	-0.003	-0.002	-0.003	-0.003
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Male	-0.032***	-0.030**	-0.016*	-0.026**	-0.016
	(0.009)	(0.010)	(0.008)	(0.008)	(0.010)
Migrants share	0.005***	0.005**	0.004**	0.005***	0.005**
	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
Age:25_34	-0.018*	-0.020*	-0.015*	-0.012*	-0.013
	(0.008)	(0.008)	(0.006)	(0.005)	(0.008)
Age:35_44	0.031***	0.031***	0.015**	0.017**	0.015
	(0.006)	(0.006)	(0.005)	(0.006)	(0.008)
Age:45_54	-0.022*	-0.025**	-0.020**	-0.027***	-0.017*
	(0.009)	(0.009)	(0.007)	(0.007)	(0.008)
Age:55_64	-0.461	-0.489	-0.576	-0.114	-0.332
	(0.654)	(0.671)	(0.732)	(0.728)	(0.660)
Elderly	0.308	0.295	0.189	0.156	0.139
	(0.179)	(0.177)	(0.104)	(0.108)	(0.105)
Log population	-0.007	-0.010	-0.001	-0.003	-0.011
	(0.004)	(0.009)	(0.008)	(0.007)	(0.006)
High level education	0.067	0.083*	0.041	0.027	0.104**
	(0.042)	(0.040)	(0.044)	(0.043)	(0.034)
Unemployment rate	-0.093	-0.078	-0.095	-0.148	-0.093
	(0.109)	(0.109)	(0.089)	(0.078)	(0.073)
Secondary	0.0306	0.030	0.080	-0.007	0.120*
	(0.063)	(0.067)	(0.057)	(0.055)	(0.049)
Buildings	0.419*	0.428*	0.373	0.177	0.286
	(0.195)	(0.197)	(0.201)	(0.180)	(0.163)
Services	0.0136	0.008	0.044	-0.027	0.0395
	(0.064)	(0.079)	(0.072)	(0.065)	(0.057)
Firms per capita		0.166	0.132	0.193	-0.175
		(0.206)	(0.166)	(0.168)	(0.173)
Income		0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Total public expenditure		-0.001	-0.002	0.001	0.001
		(0.002)	(0.002)	(0.001)	(0.001)
Previous election			0.235**	0.246**	0.193*

			(0.084)	(0.079)	(0.075)
Incumbent: center-left			0.009	0.006	0.008
			(0.005)	(0.006)	(0.005)
Incumbent: Extr. comm.			0.008	0.010	0.001
			(0.007)	(0.008)	(0.007)
Incumbent: Civic list			-0.001	-0.001	-0.001
			(0.005)	(0.006)	(0.005)
Incumbent: FSM			0.019	0.046	0.0319
			(0.030)	(0.035)	(0.021)
Urbanization				-0.032**	-0.013
				(0.011)	(0.011)
Tourism				-0.021	0.003
				(0.042)	(0.0375)
Broadband				0.097***	0.040
				(0.029)	(0.029)
Mountainousness				-0.019*	-0.019
				(0.009)	(0.010)
Regional fixed effects					✓
Observations	105	103	103	103	103

Notes: Table presents Average Partial Effects of regression results of the vote share of the Democratic Party on the BFI. Reference category for incumbency: center-right; reference category for employment sectors: primary; reference category for gender: female; reference category for age: 18-24. Robust standard errors clustered by provinces in parenthesis. * p<0.1, ** p<0.05, *** p<0.01

In order to test whether the relation exists only the FSM, we regress vote shares of other parties on our index of false information, providing additional evidence for results presented insofar. Table 6 shows results for parties of the center-right (Forward Italy, Brothers of Italy and Us with Italy) and the center-left coalition (Popular Civic List, and Italy Europe Together). Each row represents a different regression referring to the specified party, whereas columns follow the same specification of previous estimations. Each cell reports the magnitude and standard error of the BFI clustered by provinces. While the estimates for center-left parties are not statistically significant in all the specifications, they are negative for two parties of the center-right coalition (Brothers of Italy and Us with Italy), suggesting that these parties have been disadvantaged by voters' exposure to false information. The coefficients though have very low magnitude suggesting a very marginal effect of false information on performances of these parties.

Table 6. Broad False Information index (BFI) and the performances of other parties

Dep. Var. : Vote share of various parties	(1)	(2)	(3)	(4)	(5)
Fratelli d'Italia (Brothers	-0.001	0.001	0.001	0.001	-0.002*
of Italy)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Noi con l'Italia	0.000	0.000	-0.001	-0.001	-0.002***
(Us with Italy)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Forza Italia (Forward	-0.002	-0.003	-0.004	-0.006**	0.000
Italy)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)
+*Europa*	0.001	0.001	0.001	0.000	-0.001
(+Europe)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Civica Popolare (Popular	-0.001	-0.001	0.001	-0.001	-0.001
Civic List)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Italia Europa Insieme	-0.001	-0.001	-0.001	-0.001	-0.001
(Italy Europe Together)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Demographics	✓	✓	✓	✓	✓
Economic controls		✓	✓	✓	✓
Politic controls			✓	✓	✓
Other				✓	✓
Regional fixed effects					✓
Observations	**105**	**103**	**103**	**103**	**103**

Notes: Table presents Average Partial Effects from GLM regressions of the vote share of center-right and center-left coalitions on the BFI. Model specifications are the same as in table 1. Reference category for incumbency: center-right; reference category for employment sectors: primary; reference category for gender: female; reference category for age: 18-24. The political set in the regressions for +Europe, Popular Civic List and Italy Europe Together incudes only the incumbency dummies as these parties have been formed close at the 2018 election. Robust standard errors clustered by provinces in parenthesis. * p<0.1, ** p<0.05, *** p<0.01

To account for the possibility that our measure of false information may capture other factors, such as the general local usage of Twitter or other web features, we include the number of total tweets per capita in our model to control for the overall level of tweeting in the province. In fact, one may posit that to same levels of the index there might be different individuals exposed to disinformation. Table 7 presents results for main parties in the complete model.

Table 7. Broad False Information index (BFI) and the performances of main parties

Dep. Var. : Vote share of various parties	Lega	FSM	DP
BFI	-0.009	0.024***	-0.003
	(0.005)	(0.005)	(0.003)
Tweets pc	-0.002	0.003	0.003*

	(0.001)	(0.002)	(0.001)
Demographics	✓	✓	✓
Economic controls	✓	✓	✓
Political controls	✓	✓	✓
Other	✓	✓	✓
Regional fixed effects	✓	✓	✓
Observations	**103**	**103**	**103**

Notes: Table presents Average Partial Effects from GLM regressions of the vote share of main parties on the BFI with the addition of the tweet-per-capita control. Tweets pc=total tweets/population. Model specifications are the same as in table 1. Reference category for incumbency: center-right; reference category for employment sectors: primary; reference category for gender: female; reference category for age: 18-24. Robust standard errors clustered by provinces in parenthesis. * p<0.10 ** p<0.05, *** p<0.01

The coefficient of the relation between false information and vote share for the FSM increases both in magnitude and statistical significance, adding robustness and precision to our estimates. Moreover, the level of tweeting in the province appears to be predictive of the DP performance, suggesting that the usage of Twitter positively correlates with vote shares for this party.

The political index. A related question in our study is whether electoral results are affected by political false information rather than the false information per se. To answer this question, we repeat estimates with the political index from the reduced sample of tweets as described in section 4.1. Estimates for main parties (panel A), center-right (panel B) and center-left (panel C) are presented in table 8.

Results show a decrease in the statistical significance of the FSM to the 10% level even if the magnitude of the coefficient is the same as for the general false information (0.016). Interestingly, a negative and significant correlation between PFI and the vote shares of the DP appears, suggesting that for a 100-tweets increase in political false information exposure corresponds a decline in DP vote share by 0.013 points on average. While no substantial differences emerge for other parties, the correlations found for the Lega and Brother of Italy disappear.

Overall, these results suggest that being exposed to political misleading contents advantages the FSM and penalizes the DP and the right-wing *Us with Italy*. However, we do not expect the relation between false information and electoral outcomes to be the same for all provinces.

Table 8. Political False Information (PFI) index and performances of various parties

Dep. Var.:	(1)	(2)	(3)	(4)	(5)
			Panel A		
FSM	0.010	0.021*	0.016*	0.021**	0.016*
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)
Lega	-0.001	-0.012	-0.006	-0.010	-0.003
	(0.011)	(0.010)	(0.008)	(0.007)	(0.006)
DP	-0.008	-0.001	-0.001	-0.008	-0.013**
	(0.034)	(0.010)	(0.005)	(0.007)	(0.006)
			Panel B		
Forward Italy	-0.003	-0.006	-0.006	-0.011*	-0.010
	(0.007)	(0.007)	(0.006)	(0.006)	(0.025)
Brothers of Italy	0.001	0.101	0.002	0.001	-0.001
	(0.002)	(0.121)	(0.002)	(0.002)	(0.002)
Us with Italy	0.000	0.000	0.000	0.001	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
			Panel C		
+ Europe	0.001	0.001	0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Popular Civic List	0.000	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Italy Europe Together	0.000	0.001	0.001	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Demographics	✓	✓	✓	✓	✓
Economic controls		✓	✓	✓	✓
Political controls			✓	✓	✓
Other				✓	✓
Regional fixed effects					✓
Observations	**105**	**103**	**103**	**103**	**103**

Notes: this table presents Average Partial Effects from GLM estimation for the political false information index. Columns represent different specifications of the model and rows represent different regressions for the party specified. Each cell reports the coefficient for the index and the relative standard error. Model specifications are the same as in table 1. Reference category for incumbency: center-right; reference category for employment sectors: primary; reference category for gender: female; reference category for age: 18-24. Robust standard errors clustered by provinces in parenthesis. Controls include tweets per capita. * p<0.10 ** p<0.05, *** p<0.01

6.1 Heterogeneity of false information

Here we discuss the heterogeneous effect of online false information on the vote share for the FSM, the Lega, and the DP. The analysis is performed considering the demographic structure, levels of unemployment and income. There are a few reasons to suspect that these features may influence the exposure to alternative contents. First, young individuals spend more time on SNSs while ritired and unemployed have more time available that might be committed to online activities. Second, disadvantageous economic conditions – i.e. having low income or being unemployed – may increase the sensitivity to alternative facts especially when targeting institutions. The heterogeneity by age is computed by interacting both indexes of exposure to false information with a set of five age groups variables. We discretize all the interactions' components by creating a set of dummy variables that equals 1 if the observation presents values above the mean of the distribution and 0 otherwise. We add to the equation (3) the interaction terms keeping everything else equal.

Five Star Movement. Overall, estimates using the binary index add new and stronger evidence of the positive association between the vote for the FSM and the exposure to false information. Indeed, the coefficient is always significant at the 0.1 percent level and it suggests that provinces with levels of false information above the mean present vote shares 0.018 points higher than provinces with low values of disinformation in the complete specification of the model (column 5, panel A of table 9). Looking at the interaction terms of the dummy with age classes we notice that the correlation of the vote with the general false information appears to be stronger for young people aged 25-34 or 45-54 as the estimated coefficients are positive and highly significant in the complete specification of the model (panel A of table 9). We also observe a positive and significant correlation for elderlies though disappearing when accounting for regional fixed effects.
A meaningful result occurs with the interaction terms between false information and unemployment. Estimates suggest that provinces with high levels of both features register vote shares for the FSM 0.033 points higher than provinces with low levels of unemployment and false information. Looking at the political disinformation results yield for unemployment and the percentage of people aged 25-34 years old.
Overall, these results suggest that, on average, provinces with higher share of young individuals (in the class 25-34) and unemployed are more sensitive to the exposure of online false information and are more likely to support the FSM.

Table 9. Heterogeneity of false information and vote share for FSM

Dep. Var.: Vote share of the FSM	(1)	(2)	(3)	(4)	(5)
Panel A: Index of exposure to broad false information					
BFIDummy	0.023***	0.024***	0.022**	0.020**	0.018***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.005)
BFIDummy* Aged 25_34	0.036*	0.037**	0.029*	0.021	0.004***
	(0.017)	(0.015)	(0.014)	(0.011)	(0.010)

BFIDummy*Aged 35_44	0.018	0.032**	0.027*	0.024*	-0.006
	(0.015)	(0.013)	(0.012)	(0.012)	(0.008)
BFIDummy*Aged 45_54	0.025	0.023	-0.020	-0.013	0.025***
	(0.013)	(0.013)	(0.011)	(0.010)	(0.007)
BFIDummy*Aged 55_64	0.018	0.025	0.024	0.023*	0.005
	(0.015)	(0.012)	(0.013)	(0.012)	(0.010)
BFIDummy*Elderly	0.027***	0.042**	0.032**	0.027*	0.011
	(0.007)	(0.013)	(0.013)	(0.012)	(0.008)
BFIDummy*unemp	0.029**	0.034**	0.033**	0.027**	. 0.033**
	(0.013)	(0.013)	(0.010)	(0.010)	(0.010)
BFIDummy*income	0.021**	-0.035	0.017*	0.014	0.010
	(0.008)	(0.058)	(0.008)	(0.007)	(0 .007)
Panel B: Index of exposure to political false information					
PFIDummy	0.011	0.013	0.008	0.010	0.005
	(0.008)	(0.008)	(0.006)	(0.007)	(0.005)
PFIDummy*Aged 25-34	0.022	0.037**	0.025*	0.022 *	0.014*
	(0.016)	(0.013)	(0.012)	(0.011)	(0.007)
PFIDummy*Aged 35_44	0.001	0.013	0.016	-0.022	-0.006
	(0.013)	(0.012)	(0.010)	(0.012)	(0.009)
PFIDummy*Aged 45_54	0.019	0.024*	0.007	0.001	0.001
	(0.013)	(0.011)	(0.011)	(0.009)	(0.006)
PFIDummy*Aged 55_64	0.002	00.014	0.016	0.023*	0.006
	(0.015)	(0.012)	(0.011)	(0.011)	(0.012)
PFIDummy*Elderly	0.010	0.022	0.016	0.014	0.001
	(0.015)	(0.013)	(0.012)	(0.012)	(0.009)
PFIDummy*Unemployment	0.014	0.017	0.014*	0.017	0.022*
	(0.015)	(0.011)	(0.007)	(0.017)	(0.009)
PFIDummy*Income	0.008	0.012	0.004	-0.002	-0.004
	(0.010)	(0.009)	(0.010)	(0.009)	(0.007)
Demographics	✓	✓	✓	✓	✓
Economic controls		✓	✓	✓	✓
Political controls			✓	✓	✓
Other				✓	✓
Regional fixed effects					✓
Observations	**105**	**103**	**103**	**103**	**103**

Notes. The table reports Average Partial Effects from GLM estimations of the vote share for the FSM on BFI (panel A) and PFI (panel B) interacted with demographic structure, income and unemployment. BFIDummy, PFIDummy, income, employment and the five age classes are dummies which equals 1 if the province registers values higher than the mean of the distribution, and 0 otherwise. Control variables are the same as in table 1. Robust standard errors clustered by provinces in parenthesis. * p<0.10 ** p<0.05, *** p<0.01

Lega. The binary index coefficients are never statistically significant (table 10). Focusing on the broad index, the heterogeneity of the relation between false information and vote shares for the Lega by demographic structure shows a negative but not robust correlation between voting outcomes and high levels of false information as well as people aged 55-64 years old. Moving to the political index, the interaction terms of young (25-34) and elderly individuals is positive and statistically different from zero, suggesting that as the index and the incidence of young or elderly people move from the mean to the maximum provinces register high shares of vote for the Lega. Finally, no significant association emerges between the economic features and the vote shares for this party.

Table 10. Heterogeneity of false information and vote share for the Lega

Dep. Var.: Vote share of the Lega	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Panel A: Index of exposure to broad false information					
BFI dummy	-0.008	-0.010	-0.010	-0.009	0.001
	(0.008)	(0.007)	(0.006)	(0.006)	(0.004)
BFIDummy*Aged 25_34	-0.19	-0.022	-0.023	-0.021	-0.014
	(0.015)	(0.015)	(0.014)	(0.014)	(0.008)
BFIDummy*Aged 35_44	-0.013	-0.025	-0.018	-0.013	-0.001
	(0.014)	(0.012)	(0.012)	(0.012)	(0.007)
BFIDummy*Aged 45_54	-0.015	-0.016	-0.016	-0.015	-0.003
	(0.014)	(0.011)	(0.008)	(0.008)	(0.006)
BFIDummy*Aged 55_64	-0.018	-0.031**	-0.032**	-0.029*	-0.005
	(0.015)	(0.012)	(0.014)	(0.013)	(0.007)
BFIDummy*Elderly	-0.010	-0.008	-0.001	-0.002	-0.007
	(0.013)	(0.012)	(0.012)	(0.011)	(0.007)
BFIDummy	-0.009	-0.010	-0.007	-0.007	0.000
	(0.007)	(0.007)	(0.006)	(0.005)	(0.004)
BFIDummy*unemp	-0.011	-0.019	-0.018	-0.015	-0.005
	(0.013)	(0.013)	(0.014)	(0.013)	(0.008)
BFIDummy*income	0.017	-0.008	-0.004	-0.004	-0.001
	(0.050)	(0.009)	(0.007)	(0.006)	(0.005)
Panel B: Index of exposure to political false information					
PFIDummy	-0.003	-0.007	-0.002	-0.001	0.004
	(0.007)	(0.007)	(0.007)	(0.007)	(0.004)
PFIDummy*Aged 25-34	-0.001	-0.009	0.004	0.010	0.033**
	(0.015)	(0.016)	(0.016)	(0.016)	(0.011)
PFIDummy*Aged 35_44	0.009	-0.021	0.008	-0.007	0.010
	(0.011)	(0.012)	(0.012)	(0.013)	(0.008)
PFIDummy*Aged 45_54	-0.008	-0.013	-0.006	-0.002	0.004
	(0.011)	(0.010)	(0.009)	(0.009)	(0.006)

PFIDummy*Aged 55_64	-0.008	-0.020	-0.006	-0.006	0.012
	(0.011)	(0.011)	(0.011)	(0.011)	(0.009)
PFIDummy*Elderly	-0.001	-0.005	0.004	0.008	0.023**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.007)
PFIDummy*Unemployment	0.024	0.012	0.015	0.011	0.000
	(0.014)	(0.015)	(0.013)	(0.012)	(0.008)
PFIDummy*Income	-0.015	-0.020**	-0.011	-0.009	0.002
	(0.009)	(0.008)	(0.008)	(0.007)	(0.005)
Demographics	✓	✓	✓	✓	✓
Economic controls		✓	✓	✓	✓
Political controls			✓	✓	✓
Other				✓	✓
Regional fixed effects					✓
Observations	**105**	**103**	**103**	**103**	**103**

Notes. The table reports Average Partial Effects from GLM estimations of the vote share for the Lega on BFI (panel A) and PFI (panel B) interacted with demographic structure, income and unemployment. BFIDummy, PFIDummy, income, employment and the five age classes are dummies which equals 1 if the province registers values higher than the mean of the distribution, and 0 otherwise. Control variables are the same as in table 1. Robust standard errors clustered by provinces in parenthesis.
* p<0.10 ** p<0.05, *** p<0.01

Democratic Party. While the absence of correlation between BFI and PD vote shares is here confirmed, the interaction terms of PFI with the interested variables reveal interesting results. The binary PFI index coefficient suggests that provinces with higher portions of false tweets exposure (above the mean of the distribution) report vote shares for DP 0.012 points lower than provinces with lower values (column 5, panel B of table 11). Looking at the interaction terms, estimates suggest that, on average, provinces with higher shares of individuals aged 25-34, 45-54 or elderlies and high levels of political false information, present vote shares respectively 0.020, 0.018, and 0.016 points lower than provinces with high levels of disinformation spreading. These estimates are in line with results for the other parties, where we observe the same significant correlations but with opposite signs.

Table 11. Heterogeneity of false information and vote share for the DP

Dep. Var.: Vote share of DP	(1)	(2)	(3)	(4)	(5)
Panel A: Index of exposure to broad false information					
BFIDummy	-0.009	-0.006	-0.005	-0.003	-0.002
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
BFIDummy*Aged 25-34	0.004	0.010	-0.003	-0.002	-0.001

	(0.011)	(0.011)	(0.010)	(0.010)	(0.007)
BFIDummy*Aged 35_44	-0.014	-0.009	-0.008	-0.006	-0.007
	(0.009)	(0.008)	(0.006)	(0.006)	(0.007)
BFIDummy*Aged 45_54	-0.003	-0.001	-0.004	-0.003	-0.004
	(0.008)	(0.009)	(0.008)	(0.008)	(0.006)
BFIDummy*Aged 55_64	-0.013	-0.010	-0.004	-0.004	-0.006
	(0.009)	(0.009)	(0.006)	(0.007)	(0.007)
BFIDummy*Elderly	-0.007	0.001	-0.001	0.002	0.004
	(0.010)	(0.007)	(0.009)	(0.009)	(0.006)
BFIDummy	-0.006	-0.004	-0.005	-0.003	0.000
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
BFIDummy*unemp	-0.004	-0.001	-0.005	-0.001	-0.001
	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)
BFIDummy*income	-0.007	-0.006	-0.006	-0.002	0.001
	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)
Panel B: Index of exposure to political false information					
PFIDummy	-0.012**	-0.012*	-0.013**	-0.013**	-0.012**
	(0.006)	(0.06)	(0.005)	(0.005)	(0.004)
PFIDummy*Aged 25-34	0.003	0.005	-0.015	-0.017	-0.020***
	(0.011)	(0.013)	(0.010)	(0.010)	(0.006)
PFIDummy*Aged 35_44	-0.014	-0.011	0.009	0.008	-0.004
	(0.008)	(0.010)	(0.006)	(0.007)	(0.007)
PFIDummy*Aged 45_54	-0.005	-0.005	-0.016*	-0.015	-0.018***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.004)
PFIDummy*Aged 55_64	-0.022	-0.021*	-0.018*	-0.018	-0.014
	(0.010)	(0.012)	(0.008)	(0.008)	(0.008)
PFIDummy*Elderly	0.007	0.010	0.009	-0.009	-0.016**
	(0.010)	(0.013)	(0.009)	(0.009)	(0.005)
PFIDummy*Unemployment	-0.014	-0.011	-0.011	-0.014	-0.007
	(0.010)	(0.010)	(0.006)	(0.007)	(0.005)
PFIDummy*Income	-0.009	-0.008	-0.016	-0.014	-0.014
	(0.008)	(0.009)	(0.008)	(0.008)	(0.006)
Demographics	✓	✓	✓	✓	✓
Economic controls		✓	✓	✓	✓
Political controls			✓	✓	✓
Other				✓	✓
Regional fixed effects					✓
Observations	**105**	**103**	**103**	**103**	**103**

Notes. The table reports Average Partial Effects from GLM estimations of the vote share for the DP on BFI (panel A) and PFI (panel B) interacted with demographic structure, income and unemployment. BFIDummy, PFIDummy, income, employment and the five age classes are dummies which equals 1 if the province registers values higher than the mean of the distribution, and 0 otherwise. Control variables are the same as in table 1. Robust standard errors clustered by provinces in parenthesis. * p<0.10 ** p<0.05, *** p<0.01

Overall, these estimates suggest that the impact of false information may vary by age and unemployment rates. We find evidence that provinces with high incidence of young individuals and false information report higher vote shares for FSM and Lega and lower for the DP. Moreover, good performances of the Lega have been registered in provinces with high incidence of elderlies and political false information. Last, false information appears to be a strong predictor of vote shares for the FSM in presence of high unemployment rates.

6.2 False information drivers

The exposure to false information may be related to some local characteristics, such as share of female or unemployed. In this section, we explore the linkage between false information and a set of socio-demographic, economic, and topological features. Results are shown in table 12. Age appears to be the only characteristic predicting the likelihood to interact with misleading contents on Twitter. While this evidence is consistent with previous studies finding that the probability to share false information online is associated with age (Guess et al., 2019; Grinberg et al., 2019), the declination of this relation differs. In fact, the aforementioned studies find a positive association of the false information sharing behavior and being elderly, whereas our estimates suggest a negative association with this age class and a positive association with the one 55-64. These discrepancies may be explained in light of some considerations. In the first place, we consider the Italian case, whereas the aforementioned studies focus on the US. Secondly, it is possible that the share of elderlies using Twitter in Italy is very low. Twitter users are indeed on average younger than the overall population. Third, the kind of false information contemplated affects the results. Guess et al., (2019) focus on fake news presented as traditional news thus excluding a set of illustrative and meme fake news, whereas Grinberg et al. (2019) map such tweets linking to a political disinformation account.
Overall, this estimate suggests that for a 1% increase in the share of individuals aged 55-64, the average level of false information in the province increases by 0.39 points. It is difficult to discern the reason why this age class is more vulnerable to false information as we do not control, for instance, for the ideological slant or the news consumption behavior (also for the granularity level of this analysis). Possible explanations might rely in ideology, information sources, frequency of news consumption, type of information consumed, and time spent on social media.

Table 12. False information drivers

Dep. Var.:	False information
Male	-0.049 (0.246)
Migrants share	0.038 (0.032)
Age 25-34	-0.201 (0.201)
Age 35-44	-0.020 (0.166)
Age 45-54	-0.318 (0.235)
Age 55-64	0.390** (0.190)
Elderly	-0.100* (0.055)
Population	0.001 (0.001)
Education	-0.001 (0.010)
Unemployment	-0.023 (0.019)
Income	0.015 (0.015)
Broadband	0.006 (0.008)
Fixed effects	✓
Observations	**104**

7 Robustness checks

Here we discuss the results from some robustness checks, with particular attention to the FSM, since it is the party for which we find stronger evidence.

Accounting for endogenous users. In the first place, we hypothesize that users that have created a Twitter account during the 2018 may be endogenous to the elections. We thus exclude tweets generated from these users from the computation. As we can see from table 13, which reports estimates for the FSM, Lega, and DP results are confirmed for the former and the estimated coefficient of the full model (column 5) is stable within the various specifications. On the other hand, the exclusion of likely endogenous users results in the fall of statistical significance for the correlation between the index and the vote for the Lega.

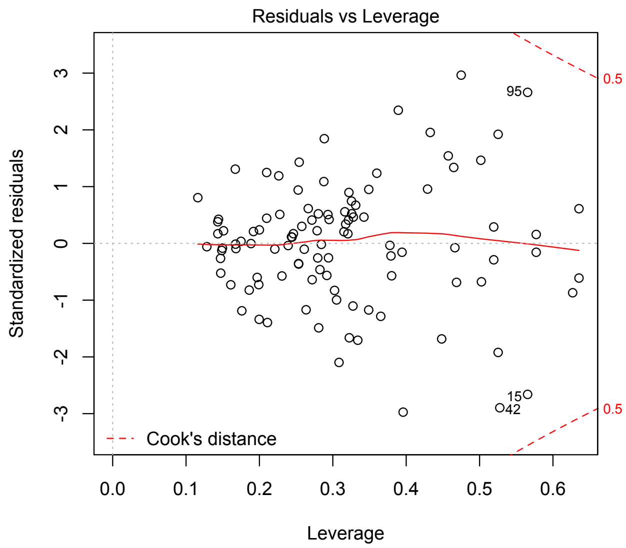
Table 13. BFI without 2018 users and performances of main parties

Dep. Var.:	(1)	(2)	(3)	(4)	(5)
FSM	0.016**	0.018***	0.019***	0.020***	0.016***
	(0.007)	(0.007)	(0.005)	(0.005)	(0.006)
The Lega	-0.004	-0.009	-0.004	-0.007	-0.003
	(0.006)	(0.005)	(0.005)	(0.005)	(0.003)
DP	-0.003	-0.002	-0.002	-0.007	-0.001
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Demographics	✓	✓	✓	✓	✓
Economic controls		✓	✓	✓	✓
Political controls			✓	✓	✓
Other				✓	✓
Fixed effects					✓
Observations	**105**	**103**	**103**	**103**	**103**

Notes: This table reports Average Partial Effects from GLM regressions of the vote share for main parties (rows) on the Broad False Information index with the exclusion of tweets posted by users which created an account in 2018. Model specifications are the same as in table 1. Reference category for incumbency: center-right; reference category for employment sectors: primary; reference category for gender: female; reference category for age: 18-24. Robust standard errors clustered by provinces in parenthesis. Controls include tweets per capita. * p<0.10 ** p<0.05, *** p<0.01

Robustness to outliers. In a further robustness check we control for the presence of outliers. We address this issue by means of the leverage-residuals plot and the calculation of the Cook's distance. Both the leverage-residual plot (figure 9) and the values of the Cook's distance indicate the absence of outliers in the regression for the complete specification of the model. Indeed, all the observations plotted in the graph fall within the 0.5 level curve, which represents the threshold above which an observation can be considered influential.

Figure 9. Leverage-residual plot of the FSM regression



Alternative measures. In this section we explore whether the change in the measurement of both the dependent variables and the index affects the results. First, we compute a different measure of the vote shares comparing the number of votes on the number of eligible voters. As we can see from table 14, results do not change: we observe no correlation with the choice to vote for DP or the Lega and a positive and statistically significant correlations in all the specifications of the model for the FSM. Considering our preferred specification (column 5 of table 14), the magnitude of coefficients is reduced by 0.006 points in the full model reasonably for the inclusion of abstained in the computation that affects the magnitude of the effect.

Table 14. GLM estimations with an alternative measure of the vote shares

Dep. Var.: Vote share of various parties	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
FSM	0.012**	0.016***	0.017***	0.019***	0.010**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Lega	-0.005	-0.005	-0.002	-0.003	0.002
	(0.005)	(0.004)	(0.004)	(0.004)	(0.002)
DP	-0.003	-0.003	-0.003	-0.002	-0.002
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Demographics	✓	✓	✓	✓	✓
Economic controls		✓	✓	✓	✓
Political controls			✓	✓	✓
Other				✓	✓

Fixed effects					✓
Observations	**105**	**103**	**103**	**103**	**103**

Notes: Table presents Average Partial Effects from GLM regressions for the vote share of main parties calculated as number of votes on the number of total eligible voters on the BFI. Model specifications are the same as in table 1. Reference category for incumbency: center-right; reference category for employment sectors: primary; reference category for gender: female; reference category for age: 18-24. Robust standard errors clustered by provinces in parenthesis. Controls include tweets per capita. * p<0.10 ** p<0.05, *** p<0.01

We then repeat the estimates using an alternative indicator for false information computed by comparing the number of accounts interacting with misleading contents with the total number of accounts in the area. Again, results are confirmed for the FSM in all specifications even with an increase of the significance of the coefficient in the complete model (column 5 of table 15), whereas the low correlation found for the Lega in the benchmark model disappears and no changes are reported for DP.

Table 15. GLM estimations with an alternative measure of the BFI

Dep. Var.: Vote share of various parties	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
FSM	0.009***	0.006***	0.005**	0.007***	0.007**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Lega	-0.002	-0.003	0.001	0.001	0.003
	(0.002)	(0.002)	(0.002)	(0.001)	(0.008)
DP	-0.002	-0.003*	-0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Demographics	✓	✓	✓	✓	✓
Economic controls		✓	✓	✓	✓
Political controls			✓	✓	✓
Other				✓	✓
Fixed effects					✓
Observations	**105**	**103**	**103**	**103**	**103**

Notes: Table presents Average Partial Effects from GLM regressions of vote share on the BFI computed as number of users interacting with disinformation by the number of total users in the area. Model specifications are the same as in table 1. Reference category for incumbency: center-right; reference category for employment sectors: primary; reference category for gender: female; reference category for age: 18-24. Robust standard errors clustered by provinces in parenthesis. Controls include tweets per capita. * p<0.10 ** p<0.05, *** p<0.01

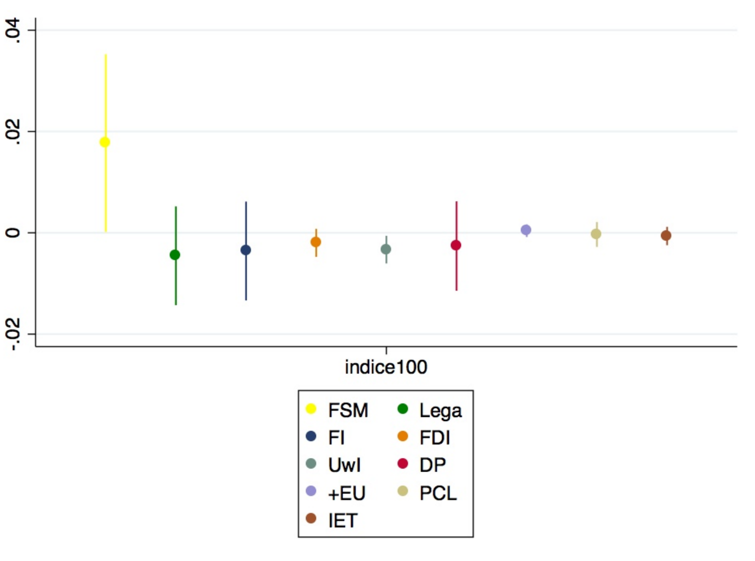
Alternative models. Here we want to test the robustness of our estimates by implementing alternative models to explore our research question and we do so through OLS, LPM and Multinomial Logit. For the LPM we have constructed alternative dependent variables for the FSM, Lega, and DP that equals 1 if the province registers vote share above the mean of the distribution and 0 otherwise. Table 16 presents results from the OLS (column 1 and 2) and LPM estimations (column 3 and 4). Again, estimates confirm a positive association between the vote for the FSM and the exposure to general false information that results in a 0.018 points increase in the vote share to an increase of one hundred units of BFI for the OLS estimate (column 2). The LPM estimation is not robust to the addition of regional fixed effects but indicates that an increase of 100 misleading tweets corresponds to an 0.117 points increase of the probability to vote for this party (column 3). Last, coefficients either for the Lega or DP are not significant in both specifications. Figure 10 plots coefficients from the OLS estimation.

Table 16. OLS and LPM regressions on the vote for FSM and the Lega.

Dep. Var.:	**(1)**	**(2)**	**(3)**	**(4)**
FSM	0.022***	0.018**	0.117**	0.032
	(0.006)	(0.008)	(0.049)	(0.036)
The Lega	-0.008	-0.002	0.010	-0.001
	(0.005)	(0.006)	(0.015)	(0.020)
DP	-0.001	0.000	0.011	-0.001
	(0.003)	(0.004)	(0.048)	(0.053)
Demographics	✓	✓	✓	✓
Economic controls	✓	✓	✓	✓
Political controls	✓	✓	✓	✓
Other		✓		✓
Fixed effects		✓		✓
Observations	**103**	**103**	**103**	**103**

Notes: This table shows the results from OLS (column 1 and 2) and LPM (column 3 and 4) regressions. Each row is a different regression having as dependent variable the specified party and cell reports the estimated coefficients and robust standard errors clustered by province. Demographic set: male; unemployment rate; migrants share; share of people aged 25-34, 35-44, 45-54, 55-64, 65 and higher (reference category=18-24 years old); log of resident population; people with high school or university diploma; share of employees in the secondary and tertiary sector (reference category=primary sector). Economic set: taxable income; firms per capita; log of local public expenditure. Political set: share of votes obtained to the previous election; incumbency (reference category=center-right). Supplementary set: average level of urbanization; mountainousness; broadband; tourism rate. Controls include tweets per capita. * p<0.10 ** p<0.05, *** p<0.01

Figure 10. Estimated coefficients from OLS regressions of vote shares on the BFI



Notes: The figure plots the estimated coefficients and confidence interval from OLS regressions for main parties. Vote shares on BFI. All regressions include the complete set of controls and regional fixed effects.

Our previous estimations derive from the implementation of independent linear equations for main parties' vote shares. Nevertheless, one may pinpoint that our estimations are not independent each other. Indeed, as Katz and King (1999) and Tomz et al. (2002) argue, voting data in multiparty elections have two fundamental features. First, the dependent variable is bounded in an interval between 0 and 1 as it represents a portion of the total number of votes, whereas OLS models assume a normally distributed and unbounded dependent variable. We already account for this limitation by implementing a generalized linear model which has been demonstrated to better fit estimations with fractional dependent variables (Papke and Wooldridge, 1996). Second, the vote portions of all parties sum to 1, implying that observations are not independent each other. To control for these issues, we also perform a Multinomial Logistic regression[22]. Considering that the probability for a party to win varies depending on whether it runs in coalition or alone, the model here is estimated accounting for the presence of two coalitions in the ballot. Results are presented in table 16. Estimates reveal the presence of statistically significant

[22] The specification is as follows: $\pi_{ij}=\exp(\eta_{ij})/\sum_{k=1}^{J-1}\exp(\eta ik)$ where $\eta_{ij}=\alpha_j+x'_i\beta_j+\varepsilon i_{ij}$ and $\eta_{ik}=\alpha_k+x'_i\beta_k+\varepsilon_{ij.}$

associations between the exposure to false information and the probability to observe positive performances either of the FSM and the center-left (reference category = center-right). While the sign of the coefficient for the FSM is stable across specifications, the coefficient for the center-left coalition (hereafter CL) varies from negative to positive as we move to the fully specified model. This variation may be due to the addition of political and supplementary controls, suggesting that one or more of these variables are associated both with the index and with the probability to win. Overall, results from the complete specification of the multinomial logit (column 4 of table 17) suggest that a one-unit increase in false information exposure increases the probability to win for the FSM by 1.3 percentage point and by 1.8 for center-left parties with respect to the center-right.

Table 17. Multinomial Logit estimation with the general index of disinformation

	(1)		(2)		(3)		(4)	
	FSM	CL	FSM	CL	FSM	CL	FSM	CL
BFI	0.211***	-0.290***	0.571***	-0.153***	0.011***	0.019***	0.013***	0.018***
	(0.001)	(0.008)	(0.081)	(0.472)	(0.865)	(0.043)	(0.569)	(0.202)
Demographics	✓	✓	✓	✓	✓	✓	✓	✓
Economic controls			✓	✓	✓	✓	✓	✓
Political controls					✓	✓	✓	✓
Other							✓	✓
Akaike	116.732	116.732	114.868	114.868	107.244	107.244	114.410	114.410
Observations	**105**	**105**	**103**	**103**	**103**	**103**	**103**	**103**

Notes: Table presents Average Partial Effects from multinomial logistic regression using the Broad False Information index. Reference category: center-right. Demographics: share of male, log population, unemployment rate, share of employees by sector, share of population 18-24 years old, share of elderly, share of people with higher education, share of migrants. Economics: log of taxable income, firms per capita. Politics: incumbency and vote share of the parties at the previous election. Other: average level of urbanization, broadband. Standard errors in parenthesis. * p<0.10 ** p<0.05, *** p<0.01

These results lead to interesting remarks. The positive correlation between the exposure to false information and the probability to win both for the FSM and the CL indeed may be a cue of two different underlying mechanisms. On the one hand, one may suppose the presence of a positive attitude toward false information by both parties' supporters. On the other hand, one may suspect the compresence of two opposite attitudes, one for and the other against the content. In other words, results from the MNL may reveal that in provinces with high shares of users spreading false information, corresponds a high concentration of users contrasting it. Therefore, identifying the nature of the engagement for supporters of different parties, may contribute to the interpretation of the results. To this purpose, we classify the malicious tweets sample as pro or against the false information by means of a simple textual search by keywords. Assuming that tweets having the words ‘fake news’ or ‘hoax’ denounce the presence of misleading contents, we labelled as ‘against’ all tweets containing at least one of these words[23]. Even if this method does not allow to thoroughly exclude the presence of other contrary tweets in the sample, at least it allows to identify such tweets that explicitly debunk a fake news. We thus compute a new index based on the reduced sample and repeat estimates for the FSM and the DP. Results are presented in table 18. In addition to the positive, significant and robust correlation observed for the FSM, it emerges a negative correlation between pro fake news exposure and the vote shares for the DP. This result adds little evidence that perhaps we are registering the compresence of two opposite attitudes toward false information.

Table 18. Pro false information sample and the performances of FSM and DP

Dep. Var.:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
FSM	0.015**	0.019***	0.021***	0.020***	0.015**
	(0.006)	(0.006)	(0.049)	(0.005)	(0.006)
DP	-0.005	-0.010	-0.003	-0.003	-0.006*
	(0.004)	(0.016)	(0.003)	(0.003)	(0.003)
Demographics	✓	✓	✓	✓	✓
Economic controls		✓	✓	✓	✓
Political controls			✓	✓	✓
Other				✓	✓
Fixed effects				✓	✓
Observations	**103**	**103**	**103**		**103**

Notes: Table presents Average Partial Effects from GLM regression using the reduced, pro-fake news sample. Regressions include the tweet-per-capita control. Controls include tweets per capita. * p<0.10 ** p<0.05, *** p<0.01

7.1 Placebo test

In order to test the robustness of our results we conduct two placebo tests focusing only on the vote share for the FSM. The purpose of these tests is to verify whether the correlation we are capturing is driven by other factors related to the broader use of online social networks. Indeed, one may pose that provinces where people use more SNSs vote more for the FSM. In order to test this hypothesis, we build a measure of the exposure to mainstream information and of the sport salience on Twitter. We thus go back to our

[23] Tweets corresponding to this criterion are approximatively 70 and a manual check has been implemented to verify the goodness of the classification method.

database of geotagged tweets and exploit it to extract all tweets linking to a news from daily newspapers, or to sports newspaper. The index is measured by dividing the number of tweets in the province *i* by the total number of geotagged tweets in the province. We consider the national daily newspaper that are active both exclusively and partially online. As shown in table 19, which reports results from GLM regressions of the vote share for the FSM on the Information Index and the sports index, the sign of the coefficient is negative (except for model 3 and 2 for information and sport respectively) but not statistically significant. These tests corroborate the robustness of our previous findings adding little confidence about the goodness of our index at least ruling out the possibility that we are capturing the general usage of Twitter or social media.

Table 19. Placebo test: The vote share for the FSM and exposure to mainstream or sport news

Dep. Var. : Vote share of the FSM	(1)	(2)	(3)	(4)	(5)
Information sources	-0.387 (0.025)	-0.017 (0.024)	0.302 (0.025)	-0.002 (0.023)	-0.029 (0.014)
Sports sources	-0.047 (1.200)	0.044 (1.003)	-0.328 (0.871)	-0.591 (0.692)	-0.088 (0.501)
Demographics	✓	✓	✓	✓	✓
Economic controls		✓	✓	✓	✓
Political controls			✓	✓	✓
Other				✓	✓
Regional fixed effects					✓
Observations	**105**	**103**	**103**	**103**	**103**

Notes: table presents results from the placebo test where we regress the vote for the FSM on a measure of information spreading on twitter in 2019. Model specifications are the same as in table 1. Reference category for incumbency: center-right; reference category for employment sectors: primary; reference category for gender: female; reference category for age: 18-24. Robust standard errors clustered by provinces in parenthesis. * p<0.05, ** p<0.01, *** p<0.001

8 Conclusive remarks

In this paper we analyzed how false information relates to electoral outcomes. We attempted to provide some answers to this question by investigating the outcomes of misleading contents in the last Italian general election. Combining Twitter geotagged data with electoral data and other aggregate-level information, we found a significant and positive correlation between false information and the vote for the FSM. This result was robust to different specifications, to the addition of control variables and to the introduction of regional fixed effects. This result may be linked to specific features of

FSM voters, who have been found to share a stronger propensity for believing in conspiracy theories (Mancosu, 2017) and a lower trust towards institutions and mainstream media (Biorcio, 2014). The distrust in mainstream media is certainly a characteristic that encourages the research of alternative media (e.g. social networking sites) and information sources that may be less accurate, as argued in the introduction. This, in addition to the lack of trust in traditional parties and institutions, may determine a higher vulnerability to alternative facts. To the extent that false information intentionally targets these beliefs, it is reasonable to assume that the electorate of the FSM may be more vulnerable to misleading contents.

We also observed negative correlations of the broad false information index with parties belonging to the center-right coalition. These correlations though, disappeared when we tested our estimation by implementing alternative models and indicators.

The interaction of the two indexes with the demographic structure and unemployment rate reveals interesting results. Age (25-34) and unemployment appear to be good predictors of the performance of the FSM regardless of the nature of the disinformation. The analysis of the heterogeneity of false information with respect to the vote shares for the Lega reveals remarkable results when accounting for political disinformation. Estimates suggest that to high levels of false information and individuals aged 25-34 or more than 65 correspond high vote shares for this party, whereas no association emerges with economic features. Looking at the DP, interaction coefficients are statistically significant when we consider political false information and show a negative relationship with the vote shares in provinces with higher incidence of the following cohorts: 25-34, 45-54, and elderlies. Overall the heterogeneity analysis reveals that the propensity to vote for anti-establishment parties - FSM and Lega - is higher for provinces with high incidence of young individuals and false information. This evidence is corroborated by the negative sign observed for the interaction term of the same cohort in the regression for the DP. One possible explanation for these results may be the functional illiteracy. In fact, this is one of the individual level characteristics that increases the likelihood to believe in false claims (Zollo et al., 2017). In Italy, the 22% of 25-34 years old individuals are functionally illiterate[24]. This cohort also registers the higher level of unemployment, if we exclude the age class 20-24, which is a strong predictor for the vote share of the FSM. Unfortunately, with our data we are not able to disentangle the relationship between false information and voting outcomes by demographic structure or unemployment. In fact, unemployed may be more sensitive to disinformation as they can devote more time to get information or because they feel unsatisfied about their social conditions. We could also suspect that being young and unemployed are two cofounding factors of the outcome for the FSM. Perhaps young people, which are likely to be unemployed, spend more time

[24] Data retrieved from ISFOL, 2016 on OCSE-PIAAC data (2012).

on social media and are more likely than other cohorts to encounter misleading contents online. Future work should account for the frequency and sources of information - especially about politics –to better discern the relationship between false information and electoral outcomes.

When we estimate a multinomial logit, we find a statistically significant relation between the exposure to false information and the probability to observe high incidence of votes both for the FSM and the center-left coalition. However, little can be said about the nature of the commitment (in favor or contrary). The analysis with the reduced pro-disinformation sample reveals a positive and significant correlation with the performance of the FSM and a negative and statistically different from zero relation with the vote shares for the DP. These findings suggest that the endorsement of the two parties' supporters may be opposite, one triggering and one contrasting the spread of false information.

Overall, we draw on the literature on echo chambers and polarization to interpret our results. We argue that supporters of different parties form different online echo chambers, i.e. polarized clusters of like-minded people (Del Vicario et al., 2016a). It has been showed that misinformation spreading online is strongly related to the presence of online polarization (Del Vicario et al., 2019). The polarization here is strictly related to the online environment and is not referred neither to elite nor masses polarization. The online polarization is fostered by the convergence to ideologically-aligned and internally coherent contents, due to the confirmation bias and motivated reasoning. In these polarized clusters may spread either true or false information that have high probability to be believed by ingroup users and rejected by outgroup users. As individuals are more likely to believe in ideologically-aligned information (Allcott and Gentzkow, 2017), we expect supporters of different parties to believe to ideologically congruent information. To this purpose, the verification of the relationship between polarization and false information through field experiments represents a withdrawing implication for future research.

These results should be interpreted with caution for several reasons. First, the cross-sectional design of our research prevents the possibility to discern the direction of the relationship (reverse causality) and it cannot be excluded the presence of some factors that correlate both with the vote and the exposure to alternative facts. Second, our sample is not fully representative: in fact, Twitter users are relatively younger, well-educated, and left-oriented (Vaccari et al., 2013) compared to the average population. Third, there is reason to believe that our analysis underestimates the incidence of false information, for several reasons: first, we perform the analysis only on Twitter data, whereas large amount of disinformation and misinformation spread also through other SNSs; second, we focus on geotagged tweets, which represent a limited percentage of the total tweets.

Last, the geolocation requirement automatically excludes retweets from our sample as they are never geotagged.

Finally, through this attempt to measure the influence of false information on the last Italian general election, this work poses several questions and important implications for future research about the existence of a causal effect on voting behavior and on its possible persistence. Moreover, it should be clarified whether the effect of false information is mediated by other factors such as political polarization.

References

Agcom (2018). News vs. fake nel Sistema dell'informazione. Interim report, indagine conoscitiva Del. 309/16/CONS.

Alesina, A., and Passarelli, F. (2015). Loss aversion in politics. *American Journal of Political Science.* 63: 936-947. doi:10.1111/ajps.12440

Allcott, H. and Gentzkow, M. (2017). Social media and fake news in the 2016 election. *Journal of Economic Perspectives*, 31(2), 211–236.

Aragones, E. (1997). Negativity Effect and the Emergence of Ideologies. *Journal of Theoretical Politics,* 9 (2): 189–210.

Benkler, Y., Faris, R., Roberts, H., and Zuckerman, E. (2017). Study: Breitbart-led right-wing media ecosystem altered broader media agenda. *Columbia Journalism Review*, 3, 2017.

Berelson, B. R., Lazarsfeld, P. F., McPhee, W. N., and McPhee, W. N. (1954). Voting: A study of opinion formation in a presidential campaign. *University of Chicago Press*.

Berry, W. D., Berkman, M. B., and Schneiderman, S. (2000). Legislative professionalism and incumbent reelection: The development of institutional boundaries. *American Political Science Review*, 94(4), 859-874.

Butcher, P. (2019), Disinformation and democracy: The home front in the information war, *European Policy Centre discussion paper*.

Biorcio, R. (2014). The reasons for the success and transformations of the 5 Star Movement. *Contemporary Italian Politics*, 6(1), 37-53.

Bollen, J., Mao, H., and Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of computational science*, 2(1), 1-8.

Boxell, L., Gentzkow, M., and Shapiro, J. M. (2017). Greater Internet use is not associated with faster growth in political polarization among US demographic groups. *Proceedings of the National Academy of Sciences*, 114(40), 10612-10617.

Cadena, J., Korkmaz, G., Kuhlman, C. J., Marathe, A., Ramakrishnan, N., and Vullikanti, A. (2015). Forecasting social unrest using activity cascades. *PloS one*, 10(6), e0128879, 1-27.

Caldarelli, G., Chessa, A., Pammolli, F., Pompa, G., Puliga, M., Riccaboni, M., and Riotta, G. (2014). A multi-level geographical study of Italian political elections from Twitter data. *PloS one*, 9(5), e95809, 1-10.

Campante, F., Durante, R., and Sobbrio, F. (2018). Politics 2.0: The multifaceted effect of broadband internet on political participation. *Journal of the European Economic Association*, 16(4), 1094-1136.

Campbell, A., Converse, P. E., Miller, W. E., and Stokes, D. E. (1980). The American voter. *University of Chicago Press*.

Cantarella, M., Fraccaroli, N., and Volpe, R. (2019). Does Fake News Affect Voting Behaviour? *DEMB working paper*, 146, 1-17.

Carey, J. M., Niemi, R. G., and Powell, L. W. (2000). Incumbency and the probability of reelection in state legislative elections. *Journal of Politics*, 62(3), 671-700.

Claassen, R. L., and Highton, B. (2009). Policy polarization among party elites and the significance of political awareness in the mass public. *Political Research Quarterly*, 62(3), 538-551.

Dalton, R. J., and Klingemann, H. D. (2007). Citizens and political behavior, *The Oxford handbook of political behavior*.

Del Vicario, M., Bessi, A., Zollo, F., Petroni, F., Scala, A., Caldarelli, G., Stanley, H.E., Quattrociocchi, W. (2016a). The spreading of misinformation online, *Proceedings of the National Academy of Sciences*, 113(3), 554-559.

Del Vicario, M., Vivaldo, G., Bessi, A., Zollo, F., Scala, A., Caldarelli, G., and Quattrociocchi, W. (2016b). Echo chambers: Emotional contagion and group polarization on facebook. *Scientific reports*, 6, 37825, 1-12.

Del Vicario, M., Quattrociocchi, W., Scala, A., and Zollo, F. (2019). Polarization and fake news: Early warning of Potential misinformation targets. *ACM Transactions on the Web* (TWEB), 13(2), 10.

DellaVigna, S., and Kaplan, E. (2007). The Fox News effect: Media bias and voting. *The Quarterly Journal of Economics*, 122(3), 1187-1234.

Delli Carpini, M.X. and Keeter, S. (1996). What Americans Know about Politics and why it Matters. *New Haven: Yale University Press*.

Dennis, T. (1970). The Democratic Citizen. *New York: Cambridge University Press*.

Durante, R., and Knight, B. (2012). Partisan control, media bias, and viewer responses: Evidence from Berlusconi's Italy. *Journal of the European Economic Association*, 10(3), 451-481.

Enikolopov, R., Petrova, M., and Zhuravskaya, E. (2011). Media and political persuasion: Evidence from Russia. *American Economic Review*, 101(7), 3253-85.

Erikson, R. S., and Wlezien, C. (1996). Of time and presidential election forecasts. *PS: Political Science and Politics*, 29(1), 37-39.

Falck, O., Gold, R. and Heblich, S. (2014). E-Lections: Voting Behavior and the Internet. *American Economic Review*, 7, 2238–2265.

Fletcher, R., and Nielsen, R. K. (2018). Are people incidentally exposed to news on social media? A comparative analysis. *New media & society*, 20(7), 2450-2468.

Flynn, D. J., Nyhan, B., and Reifler, J. (2017). The nature and origins of misperceptions: Understanding false and unsupported beliefs about politics. *Political Psychology*, 38, 127-150.

Garz, M. (2018). Retirement, consumption of political information, and political knowledge. *European Journal of Political Economy*, 53, 109-119.

Gentzkow, M. (2006). Television and Voter Turnout. *Quarterly Journal of Economics* 121 (3), 931–72.

Grinberg, N., Joseph, K., Friedland, L., Swire-Thompson, B., and Lazer, D. (2019). Fake news on Twitter during the 2016 US presidential election. *Science*, 363(6425), 374-378.

Groshek, J. and Koc-Michalska, K. (2017). Helping populism win? Social media use, filter bubbles, and support for populist presidential candidates in the 2016 US election campaign. *Information, Communication and Society*, 20(9), 1389-1407.

Grossman, G. M., and Helpman, E. (2019). Electoral Competition with Fake News (No. w26409). *National Bureau of Economic Research*.

Gruzd, A., and Roy, J. (2014). Investigating political polarization on Twitter: A Canadian perspective. *Policy and Internet*, 6(1), 28-45.

Gu, L., Kropotov, V., and Yarochkin, F. (2017). The fake news machine: how propagandists abuse the internet and manipulate the public. Trend Micro, 5.

Guess, A., Nagler, J., and Tucker, J. (2019). Less than you think: Prevalence and predictors of fake news dissemination on Facebook. *Science advances*, 5(1), eaau4586.

Hogan, R. E. (2004). Challenger emergence, incumbent success, and electoral accountability in state legislative elections. *The Journal of Politics*, 66(4), 1283-1303.

Howard, P. N., Kollanyi, B., Bradshaw, S., Neudert, L.M. (2017). Social Media, News and Political Information during the US Election: Was Polarizing Content Concentrated in Swing States? *COMPROP DATA MEMO* 2017.8.

Huang, H. (2017). A war of (mis) information: The political effects of rumors and rumor rebuttals in an authoritarian country. *British Journal of Political Science*, 47(2), 283-311.

Inglehart, R., and Norris, P. (2017). Trump and the populist authoritarian parties: the silent revolution in reverse. *Perspectives on Politics*, 15(2), 443-454.

Kahneman, D. and Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47(2), 263-292.

Katz, J. N., and King, G. (1999). A statistical model for multiparty electoral data. *American Political Science Review*, 93(1), 15-32.

Kuklinski, J., Paul Q., Jennifer J., David S., and Robert R. (2000). Misinformation and the Currency of Citizenship. *Journal of Politics*, 62, 791-816.

Kull, S., Ramsay, C., and Lewis, E. (Winter, 2003/2004). Misperceptions, the Media, and the Iraq War. *Political Science Quarterly,* 118(4), 569–598.

Lazer, D. M., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., Metzger, M. J., Nyhan, B., Pennycook, G., Rothschild, D., Schudson, M., Sloman, S. A., Sunstein C. R., Thorson, E. A., Watts, D. J., and Zittrain, J. L. (2018). The science of fake news. *Science*, 359(6380), 1094-1096.

Lewis-Beck, M. S., and Bellucci, P. (1982). Economic influences on legislative elections in multiparty systems: France and Italy. *Political Behavior*, 4(1), 93-107.

Lewis-Beck, M. S. (1986). Comparative Economic Voting: Britain, France, Germany, Italy. *American Journal of Political Science*, 315-346.

Lewis-Beck, M. S. (2006). Does economics still matter? Econometrics and the vote. *The Journal of Politics*, 68(1), 208-212.

Lijphart, A. (1979). Religious vs. linguistic vs. class voting: the “crucial experiment” of comparing Belgium, Canada, South Africa, and Switzerland. *American Political Science Review*, 73(2), 442-458.

Luskin, R. C., Fishkin, J. S., and Jowell, R. (2002). Considered opinions: Deliberative polling in Britain. *British Journal of Political Science*, 32(3), 455-487.

Mancosu, M., Vassallo, S., and Vezzoni, C. (2017). Believing in conspiracy theories: Evidence from an exploratory analysis of Italian survey data. *South European Society and Politics*, 22(3), 327-344.

Papke, L. E., and Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of applied econometrics*, 11(6), 619-632.

Permanyer, I., and D'AMBROSIO, C. O. N. C. H. I. T. A. (2015). Measuring social polarization with ordinal and categorical data. *Journal of Public Economic Theory*, 17(3), 311-327.

Petrova, M., Sen, A., and Yildirim, P. (forthcoming). Social media and political donations: New technology and incumbency advantage in the United States.

Rose, R., and Urwin, D. (1969). Social cohesion, political parties and strains in regimes. *Comparative Political Studies*, 2, 7-67.

Shao, C., Ciampaglia, G.L., Varol, O., Flammini, A., and Menczer, F. (2018). The spread of low-credibility content by social bots, *Nature communications*, 4787, 9(1), 1-9.

Silverman, C. This analysis shows how fake election news stories outperformed real news on facebook (BuzzFeed, 2016); www.buzzfeed.com/craigsilverman/viral-fake- election-news-outperformed-real-news-on-facebook.

Soroka, S. N. (2006). Goog news and bad news: Asimmetric responses to economic information. The ournal of Politics, Vol. 68, No. 2, May 2006, Pp. 372–385.

Steinert-Threlkeld, Z. C., Mocanu, D., Vespignani, A., and Fowler, J. (2015). Online social networks and offline protest. *EPJ Data Science*, 4(1), 1-9.

Strömberg, David. (2004). Mass Media Competition, Political Competition, and Public Policy. *Review of Economic Studies*, 71(1), 265–84.

Tomz, M., Tucker, J. A., and Wittenberg, J. (2002). An easy and accurate regression model for multiparty electoral data. *Political Analysis*, 10(1), 66-83.

Tumasjan, A., Sprenger, T. O., Sandner, P. G., and Welpe, I. M. (2011). Election forecasts with Twitter: How 140 characters reflect the political landscape. *Social science computer review*, 29(4), 402-418.

Vaccari, C., Valeriani, A., Barberá, P., Bonneau, R., Jost, J. T., Nagler, J., and Tucker, J. (2013). Social media and political communication. A survey of Twitter users during the 2013 Italian general election. *Rivista italiana di scienza politica*, 43(3), 381-410.

Van Kessel, S. (2015). Populist parties in Europe: Agents of discontent? *Springer*.

Vujić, S., and Zhang, X. (2018). Does Twitter chatter matter? Online reviews and box office revenues. *Applied Economics*, 50(34-35), 3702-3717.

Wang, Y., Callan, J., and Zheng, B. (2015). Should we use the sample? Analyzing datasets sampled from Twitter's stream API. *ACM Transactions on the Web* 9,3, Article 13.

Weeks, B. E., and Garrett, R. K. (2014). Electoral consequences of political rumors: Motivated reasoning, candidate rumors, and vote choice during the 2008 US presidential election. *International Journal of Public Opinion Research*, 26(4), 401-422.

Zhang, X., Fuehres, H., and Gloor, P. A. (2011). Predicting stock market indicators through twitter "I hope it is not as bad as I fear". *Procedia Social and Behavioral Sciences*, 26, 55-62.

Zollo, F., Bessi, A., Del Vicario, M., Scala, A., Caldarelli, G., Shekhtman, L., Havlin, S., Quattrociocchi, W. (2017). Debunking in a world of tribes. *PloS one*, 12(7), e0181821, 1-27.

Appendix tables

Table A1: Distributions of the social media population and the total Italian population (%) for gender and age classes.

Age/gender	Social		Population	
	Male	Female	Male	Female
13-17	2	2	2	2
18-24	7	8	4	3
25-34	11	12	6	5
35-44	10	10	7	7
45-54	10	10	8	8
55-64	6	6	7	7
65+	3	4	10	13

Source: Digital Report 2019 and Istat. Data available at January 2019.

Table A2: List of Twitter disinformation accounts

	Name	link
1	Rosario Marcianò	http://www.tankerenemy.com
2	Il FattoneQuotidiano	http://www.ilfattonequotidiano.it
3	Corriere del Mattino	http://www.agenziedistampa.altervista.org
4	Corriere del Corsaro	http://www.corrieredelcorsaro.it
5	Il Populista	http://www.ilpopulista.it
6	Vox	http:// www.voxnews.info
7	IlMerdoneQuotidiano	https://www.ilmerdone.wordpress.com
8	Irresponsabile	http:// www.irresponsabile.com/
9	RomaNews24	
10	Notixweb	https://www.notixweb.com
11	Sputtaniamotutti	http://www.sputtaniamotutti.reattivonews.org
12	StopEuro	http://www.stopeuro.news/
13	Web News24	http:// www.webnews24h.it
14	Open Your Eyes	http:// www.blogopenyoureyes.altervista.org
15	Italia_nel_Caos	http://www.tankerenemy.com
16	Piovegovernoladro	http://www.piovegovernoladro.info
17	La Chiave Orgonica	http://chiaveorgonica.altervista.org/
18	Dangerous news	http://www.notiziepericolose.blogspot.com
19	IlGiornale	http://www.ilgiornale.it/

20	ApriLaMente	http://aprilamente.myblog.it/
21	Dionidream	http://www.dionidream.com
22	NonSiamoSoli	http://nonsiamosoli.net
23	Pianetablunews	http://pianetablunews.wordpress.com/
24	Scienza e Conoscenza	http://www.scienzaeconoscenza.it
25	Segnidalcielo.it	http://www.segnidalcielo.it
26	Autismo & Vaccini	http://autismovaccini.org/
27	Informasalus	http://www.informasalus.it/
28	TzeTze	http://www.tzetze.it
29	Vacciniinforma	http://www.vacciniinforma.com/
31	Vivo in Salute	http://www.vivoinsalute.com
32	Break Notizie	http://www.breaknotizie.com
33	Catena Umana	http://www.catenaumana.it
34	CheSuccede	http://www.chesuccede.it
35	Diretta News	http://www.direttanews.it
36	Il Faro sul Mondo	http://www.ilfarosulmondo.it
37	Il Patriota	http://www.ilpatriota.blogspot.it
38	Imola Oggi	http://www.imolaoggi.it
39	InformarexResistere	https://www.informarexresistere.fr
40	iTaLiaPatriaMia	https://www.italiapatriamia.eu
41	LoSai	http://www.losai.eu
42	Riscatto Nazionale	http://www.riscattonazionale.net/
43	Rischio Calcolato	http://www.rischiocalcolato.it
44	Sapere è un Dovere	http://sapereeundovere.com
45	Silenzi e Falsità	http://www.silenziefalsita.it/
46	Ticinolive	http://www.ticinolive.ch
47	Video Virali Web	http://www.videoviraliweb.com
48	Rosario	http://www.lonesto.it
49	Hack the Matrix	http://www.hackthematrix.it
50	LiberaMenteServo	http://www.liberamenteservo.it
51	Nexus Edizioni	http://www.nexusedizioni.it
52	Nibiru2012.it	https://www.nibiru2012.it
53	Terrarealtime	http://terrarealtime.blogspot.com/

Table A3: Examples of false stories in our sample and keywords used for detection

Story	**Keywords**	**Type of false information**	**Source**
The advent of a weather disturbance named Burian that would have caused an ice-cold winter	Burian	Hoax	https://www.butac.it/ma-non-doveva-esser-un-inverno-da-era-glaciale/

in Italy.

Emma Bonino (the leader of +Europa) dishes out cannabis during the political meetings of her party.	+Europa/Bonino+cannabis; +Europa/Bonino+weed; +Europa/Bonino+drug;	Pseudo-politics	https://www.butac.it/la-cannabis-europa/
Emma Bonino and the Lega, are funded by Soros (this accusation is sometimes also directed to the FSM). She is also accomplice with Soros in the project of invasion of Italy.	Bonino+soros; Bonino+invasion; Bonino+fund();	Conspiracy Theory/hoax	https://www.butac.it/soros-paga-tutti/
Pamela Matropietro -the 18-years-old Italian girl murdered in Macerata the 30th of January 2018- has been murdered by three Nigerian with a Voodoo rite. Furthermore, the killers of the girl are supposed to be cannibals as they ate her organs.	pamela + voodoo; pamela + cannibal; cannibal + nigerian; nigerian+voodoo;	Pseudo-Journalism	https://www.butac.it/gli-organi-asportati-a-macerata-e-lindignazione/

Table A4: List of scientific hoaxes and related keywords used for detection

	Hoax	Keywords
1	Vaccine and autism	%vaccineandautism%; %vaccine%+%autism%; %autismandvaccine%
2	Chemtrails	%chemtrails%
3	Flat Earth	%Flat Earth%; %Flatearth%;
4	Anti-mucus diet	%Mucus% + %diet%
5	Reptilians	%Reptilians%
6	New Germanic Medicine	%germanic%+%medicine%
7	Stamina	%stamina%
8	OGM	%ogm%; %monsanto%
9	Glyphosate	%glyphosate%
10	Piltdown Man	%Piltdown Man%; %Piltdownman%

Chapter 3: False information and voting behaviour: Evidence from European elections in Italy*.

Concetta Danese[1], Andrea Fazio[2]

Abstract:

We explore the impact of online false information on voting behaviour. We scrape geotagged Twitter data for the 42 days before the 2019 European elections to build an index of the exposure to misleading contents across Italian provinces. We then match this information with electoral data to study how the spreading of false information relates to the performance of political parties. A First difference analysis is then performed exploiting data collected before the 2018 political election. Our results suggest that false information is not correlated with voter turnout, but it is associated to voting choices. The positive correlation found with the performances of the Movimento 5 Stelle and Partito Democratico suggests that different parties may benefit from the consumption of false information. We argue that supporters of these parties are clustered around false information.

Keywords: False Information, Electoral Outcomes, Social Networking Sites, Political Economy

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1 Introduction

The transformations of the digital ecosystem have undermined the information accuracy (Bakir and McStay, 2018), entailing the risk for citizens to inform their political opinions based on both true and false information. In addition, the impact of false information on public opinion may be considerable if one considers that it expresses a negative sentiment (Vosoughi et al., 2018) and citizens are asymmetrically influenced by negative news (Soroka, 2006). Yet, empirical evidence on the impact of false information on voting behaviour are «essentially nonexistent in literature» (Lazer et al., 2018:1095).

We explore the impact of false information on the electoral outcomes of the 2019 European election in Italy. In this work, we refer to false information as totally or partially misleading contents produced regardless of the intention to mislead. We carry out an aggregate-level analysis at province level. An index of false information is built based on Twitter data. Data have been collected for the forty-two days before 2019 elections and twenty days before 2018 elections by interrogation of the streaming Application Programming Interface (API) using the unique parameter of the geolocation. We then select misleading tweets according to the following identification criteria: interactions with disinformation accounts; links to fake articles; sharing of fake photos and videos; keywords of misleading information. For the identification of accounts and stories, we rely on third-party independent fact-checkers websites. The resulting dataset is composed of 2.618 misleading tweets for the 2019 and 4.118 misleading tweets for the 2018. The index of false information is built by dividing the number of false information tweets by the total number of geotagged tweets in the province. These data are then matched with electoral data from the Ministry of the Interior.

We investigate how the exposure to online false information relates to voter turnout and the performances of main Italian parties across Italian provinces, with particular attention to *Partito Democratico* (Democratic Party), *Movimento 5 Stelle* (Five Star Movement), and *Lega* (League). We then implement a First Difference model between the 2019 and 2018 elections in Italy, in order to: 1) test whether our results can be extended to Italian elections in general; 2) add robustness to the findings by eliminating bias due to unobserved time-invariant characteristics.

Results from the cross-sectional analysis show that false information affects voting behaviour in different ways. The exposure to false information on Twitter appears to be positively associated with the performance of *Movimento 5 Stelle* (hereafter M5S) and *Partito Democratico* (hereafter PD), and negatively associated with the vote share for the left-wing party +Europa. These results are robust to a battery of control variables and regional fixed-effects. First, we argue that false information may advantage some parties while damaging others. Second, we interpret the positive correlation of the exposure to misleading contents and vote shares for M5S and PD in the light of the literature on echo chambers and online polarization (Pariser, 2011; Del Vicario et al., 2016a, b). While the engagement of different parties' supporters is not identifiable through our data, this result may be suggestive of the presence of two online clusters that are polarized toward false information. However, this engagement may be either in favour or against false information.

Results from the First Difference analysis suggest a positive and significant correlation between false information and M5S vote share. Finally, we find no significant correlation between false information and voter turnout in both the specifications we use.

Studying the effect of false information on voting behaviour entails considerable endogeneity problems. Our specification allows us to control both for observable and unobservable characteristics in order to ensure the goodness of our results. Nevertheless, we cannot exclude the presence of reverse causality issues between party affiliation and exposure to misleading contents. However, this work adds preliminary evidence on the relationship between false information and voting, proposing a novel methodology for the detection of online disinformation that relies on geotagged data.

Our contribution bridges two strands of the literature. First, we add to the literature on the political outcomes of false information by showing that misleading contents may affect voting choices but not voter turnout. Early studies argued that misperceptions and misinformation could influence attitudes toward political and economic issues such as the US war in Iraq (Kull et al., 2003) or collective preferences (Kuklinski et al., 2000). In their seminal study Allcott and Gentzkow (2017) estimate that the average American voter read and remembered one or perhaps several fake news. Furthermore, authors estimate that if fake news were effective as a TV campaign ad, they would have changed voting choices in the measure of hundredths of percentage points. Evidence about the effect of false information on voting behaviour are uneven. If some studies find that the exposure to false political rumours may decrease the probability to vote for the interested candidate (Weeks and Garrett, 2014) or cause anti-government attitudes (Huang, 2017), other studies find no evidence of a causal effect between the exposure to fake news on Facebook and the change in vote shares for populist parties in Italy (Cantarella et al., 2019). We add to this literature by proposing a new methodology to measure false information online that exploits geotagged data and providing additional evidence of how false information relates to electoral outcomes in Italy. Our work also contributes to the recent debate about the relation between fake news and online polarization. Albeit there is a comprehensive literature on the effect of the Internet and social media on ideological polarization (e.g., Boxell et al., 2017; Bakshy et al., 2015, Pariser, 2011), less is known about the relation between polarization and fake news. According to Tucker et al. (2018) directionally motivated reasoning and partisanship increase the likelihood to believe in false claims. To this regard, Del Vicario et al. (2019) use group polarization on Facebook as proxy to detect fake news on the web. On the other hand, a recent study from Suhay et al. (2018) shows that the exposure to online negative and partisan messages increases affective polarization. To the extent that false claims mainly express negative sentiment (Vosoughi et al., 2018) we can suppose that also partisan false information increases partisan polarization.

The rest of the paper is organized as follows: section 2 describes data used and the applied methodology for the selection of misleading contents to include in the analysis; section 3 illustrates descriptive statistics; section 4 presents the empirical strategy; section 5 presents the results; section 6 discusses the results; section 7 concludes.

2 Data and methods

2.1 Measure of false information

Our measure of false information is obtained by scraping data from Twitter. We focus on social media data as most of the fake news are consumed via social media and a low percentage of people directly access malicious contents from disinformation sources (Allcott and Gentzkow, 2017; Fourney et al., 2017).

Twitter is the sixth most used social networking site in Italy, with a penetration rate of the 32% of the population aged between 16-64 years old[3]. Furthermore, the 26,3% of Italians use the Internet as main source of information, the 36,5% get informed on SNSs, of which the 5,8% on Twitter[4].

Our data collection follows two stages. Firstly, we collect tweets through interrogation of the streaming Application Programming Interface (API) for the twenty days before the National Election in the 2018 (February 13th, March 04th) and for the forty-two days before the 2019 European election (April 15th and May 26th). The streaming API filters real-time tweets and allows the selection of different parameters to scrape data. Within these parameters we selected the geolocation of the tweet in Italy as unique constraint to scrape data, that is, a sample of geotagged tweets about any topic has been returned. The geolocation of the tweet is the key element of our methodology, because it allows to assign each tweet to a specific province. This data extraction strategy returns at most the one percent of the total activity on the platform responding to the selected parameter. This may pose some issues about the goodness of these data. In this regard, Wang et al. (2015) compare streaming API data with the overall activity in the same time, finding that the former truthfully reflects the overall patterns. In addition, the suitability of Twitter data

[3] Data retrieved from the 2019 digital report from We Are Social.

[4] Data retrieved from AGCOM (2017), Rapporto sul consumo di informazione.

for social research is corroborated by the increasing number of studies exploiting these data to forecast, for instance, electoral results (e.g. Tumasjan, 2011; Caldarelli et al., 2014) or social unrests (Steinert-Threlkeld et al., 2015).

In a second stage, we detect tweets with disinformation contents using four specific identification criteria:

1. *Direct interaction of the user with disinformation accounts*, i.e. reply to a tweet or quoted tweets. We draw on the independent fact-checking website BUTAC[5] for the identification of malicious websites and blogs (appendix tables A1 and A2 list the websites for which we found a correspondent Twitter account for both years)[6].
2. *Links to misleading articles.* We consider the case where the user retrieves the false information directly from the disinformation website and shares it in Twittersphere. We identify these cases by looking at the links attached to tweets and searching the domains of websites as in the previous point.
3. *Keywords of misleading articles*. Even if users are not directly interacting with a disinformation account, it can happen that they are only discussing about a false content. We cover this possibility by detecting tweets based on keywords that identify a false information. Again, we draw on independent fact-checking websites[7] for the identification of the salient false stories spreading in the period of interest (table A3 and A4 of the appendix presents some examples of stories for both years).
4. *Keywords of well-known scientific hoaxes.* We apply the same strategy as in point (3) for the detection of well-known scientific hoaxes, e.g. chemtrails and vaccine and autism (table A5 of the appendix shows selected hoaxes and the related keywords used for their detection).
5. *Photos and videos.* We consider the case where the user shares a meme or a video containing inaccurate information without any cues in the text or in other information attached to the tweet. We detect these tweets through media links attached. Figure 1 summarizes the five identification criteria and the relative implemented strategy.

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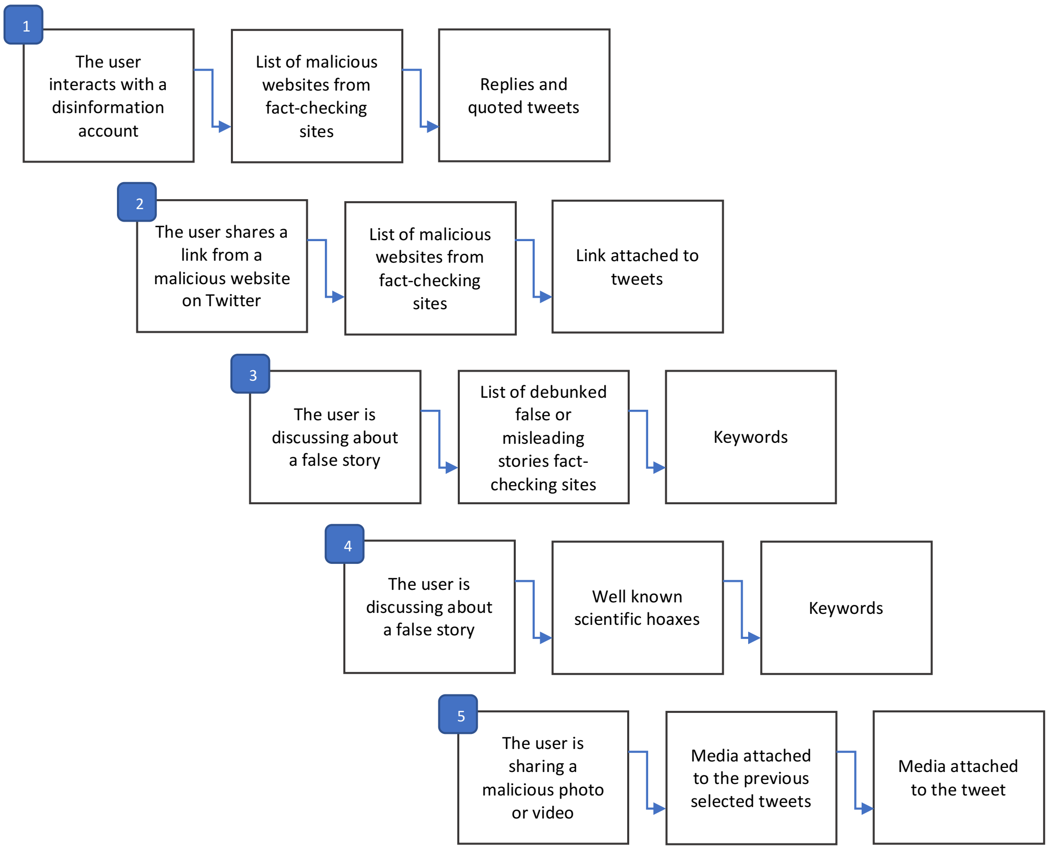
[5] Bufale Un Tanto Al Chilo (BUTAC): https://www.butac.it/. This independent fact-checking website posts corrections to false or misleading stories and provides a list of suspicious websites and blogs that are classified on the basis of their activity, e.g. pseudo-science, pseudo-politics, satire.

[6] This identification criteria follows the methods implemented by Fletcher and Nielsen (2018) for fact-checking websites) and Bessi et al. (2015) for Facebook groups active in debunking.

[7] We refer to BUTAC, Pagella Politica and the fact-checking section of the website *Open Online* for this point.

Figure 1. Identification criteria and implemented detection strategies.



We aggregate our tweets by province according to the place provided by the platform. We build our measure of local exposure to false information by dividing the number of false information tweets in the province *i* by the total number of tweets in the province. Between April 15th and May 26th (42 days), we have gathered 543.224 geotagged tweets out of which 2.618 have been identified as bearers of partially or totally false contents. Users interacting with misleading contents represent the 1.72% of the total.

2.2 Electoral data

We use data from the Ministry of the Interior for the 2018 general political election and 2019 European election. We aggregate data at province level (NUTS 3). Data contain information about the number of votes obtained by each political party and the number of total and eligible voters. We compute the dependent variable as the number of votes obtained by the party in the province *i* divided by the number of total votes in the same province. The analysis focuses on the vote shares of main Italian parties: Lega and M5S, the two populist and anti-establishment parties[8] that were at the leading of the country until September 2019, and four main parties in the national political supply: the left-wings PD and +Europa, and the right-wings Forza Italia and Fratelli d'Italia. For the 2018 election, we have not included the province of Aosta as it is a pure First-Past-the-Post (FPP) system, differently from the rest of Italy that is a Mixed-Member proportional system. Overall, our dataset comprises 213 provinces, 106 for the 2018 and 107 for the 2019.

2.2.1 Political context

The 2018 Italian political supply was composed of a center-right coalition (Forza Italia, Lega, Fratelli d'Italia, Noi con l'Italia), a center-left coalition (PD, +Europa, Civica Popolare, Italia Europa Insieme), the M5S and other minor parties. European elections have presented the voter with a similar supply. Apart from the presence of European parties (e.g. *Europa Verde*), European elections are differentiated by the political one for the absence of electoral coalitions.

The two elections show different trends. The 2018 election sees as winner the center-right coalition that conquests the North of the country. However, if one considers single parties' performances, the party gaining the highest vote percentage was the M5S with 32.68% of votes (data for the chamber of deputies). The Lega increased its vote share from the 4.09% in 2013 to 17.37% of votes in 2018. At the European election, the Lega alone has obtained the majority of the votes in three out of the five districts in which Italy was split (North-East, North-West, and the Center). If Lega's rising trend also follows at the European election, this is not true for the M5S that halves its votes (from 32.68 in 2018 to 17.07 in 2019). From a geographical perspective, parties' balance changed. In 2013 the M5S was the most geographically uniform party of Italy (Emanuele, 2015), and in the 2018 it already moved away from the North concentrating in the South and the Center. The European election sees an increasing expulsion of the M5S that now is strong only in the less economically advanced regions (Emanuele and Maggini, 2019). To the retreat of the M5S corresponds the progress of the Lega which conquests some regions of the South. Last, the PD has recovered part of the support, perhaps for the loss of consensus for the M5S and as alternative to the Lega. The PD passed from 25.43% of votes in 2013 to 18.76% in 2018 to finally rise again in 2019 with 22.69 percentage of votes.

[8] The Lega and the M5S are classified as populist by several authors. See for example Inglehart and Norris (2017); Van Kessel (2015); Guiso et al. (2017).

2.3 Control variables

We include some control variables in our model. Socio-demographic controls include: the share of females, share of individuals aged 25-34, 35-44 or with more than 65 years old, share of migrants, unemployment rate, share of employees in the secondary and tertiary sectors, share of individuals with higher education. Political controls encompass the vote share of the political party at the 2018 election as well as categorical variables that measures the political administration of the province. We further consider the aggregate level of taxable income, the average level of urbanization, and broadband coverage. Socio-demographic variables and urbanization are retrieved from the Italian National Bureau of Statistics (ISTAT). Most of these data are available for both years except for urbanization –which refers to the year 2018- and education –which refers to the year 2017. We gather data on the share of households with low, large and high-speed Internet access from the Italian Authority for Communications Guarantees (AGCOM). Last, data on the aggregate taxable income are available for the 2017 and are downloaded from the Italian Ministry of the Economy and Finance. Table 1 lists the control variables, and table 2 shows descriptive statistics.

Table 1. Control variables

Variables	Computation
Female	N. of female on the total population
Migrants share	N. of regularly resident migrants on the total population
Employment share per sector	Incidence of employees per sector: primary sector, secondary, buildings, services, hotel and catering
Unemployment rate	N. of unemployed people on the total of population 18-65 years
Age	Number of individuals aged 25-34; 35-44; 65 and more on the total population
Education	N. of people with high school or university diploma on the total of the population
Taxable income	Log of the aggregate taxable income
Votes share (2018)	Vote share of the party at the previous Italian general election (2018)
Urbanization	Mean of the urbanization level of the municipalities as measured by the Italian National Institute of Statistics. It varies from 1 (densely urbanized) to 3 (scarcely urbanized)

Broadband supply	Incidence of households served with speed in range 0-2 Mbps or more than 500 Mbps.

Table 2: Descriptive statistics

	2018			2019		
Variable	**Obs**	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
Panel A: Dependent variables and Broad False Information index						
Index	106	0.569	0.628	107	0.453	0.437
M5S	106	31.852	10.001	107	17.167	8.216
The Lega	106	16.626	8.998	107	33.47	9.456
Democratic Party	106	17.071	5.262	107	20.616	5.809
Turnout	106	73.027	5.535	107	56.291	10.899
Panel B: control variables						
Female	106	50.996	0.490	107	51.217	0.498
Migrants	106	7.955	3.386	107	8.159	3.449
Unemployment	106	11.923	6.031	107	10.977	5.906
Age: 25-34	105	10.908	1.108	107	10.743	1.040
Age: 35-44	105	13.959	0.663	107	13.209	0.660
Elderly	106	15.035	2.132	107	23.304	2.326
Employment: secondary	106	19.834	8.83	107	26.469	8.335
Employment: services	106	47.304	6.49	107	68.286	7.438
People with HS or univ. diploma	106	59.688	7.671	107	/	/
Taxable income	106	7562074558	9544482571	106	/	/
Urbanization	106	2.637	0.298	107	2.636	0.298
Broadband	106	67.676	10.986	106	28.032	14.923
Low speed broadband	/	/	/	107	9.073	4.949

Note: Boadband refers to 30-100 Mbps for 2018 and 101-1000 Mbps for 2019.

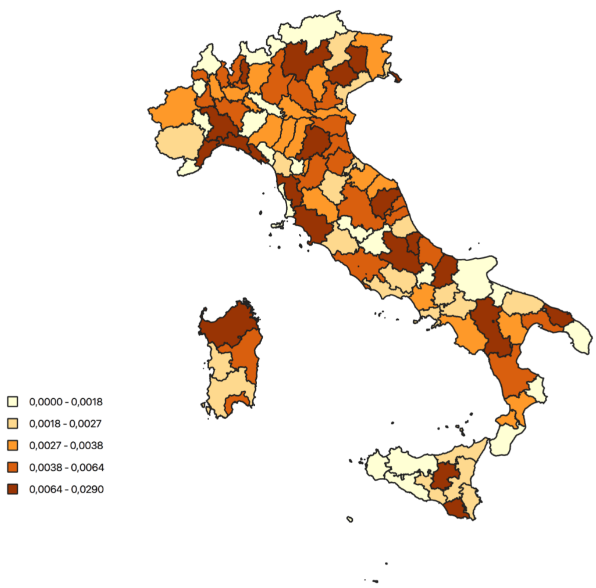
3 Descriptive Statistics

3.1 The 2019 false information data

On average, we register a very low incidence of misleading contents on the total geotagged activity of Italian twitter users (0.45 out of 100 tweets). Hereafter we discuss the geographical distribution of the index, time trends and users' activity features for the 2019 sample. Last, indexes for 2019 and 2018 are compared.

Geographical distribution. Looking at the geographical distribution of our index, we observe no systematic trend across the national territory (figure 2). In order to have a statistical measure of how index levels change across the Italian provinces, we compute the mean for each macro-region following the official classification of the Italian National Bureau of Statistics (North-West, North-East, Center, South, Islands).

Figure 2. Geographic distribution of the false information index (2019)



We find no statistically relevant difference between the levels of exposure to false information across these areas, which are in all cases close to the mean of the distribution[9]. This preliminary evidence suggests that the probability to engage with malicious contents is not explained by geographical features.

Time trend. Figure 3 and figure 4 illustrate the daily evolution of the false information and general geotagged tweets respectively. As can be noted, the false information curve follows the general one, presenting the same drops of the general geotagged sample. Apart from these drops, we observe a relatively constant evolution of the misleading contents in the observation period (mean=82 tweets per day for false information). At the same time, the curves equally increase in the view of the election (days 24th and 25th).

Figure 3. Evolution of the number of false information tweets (2019)

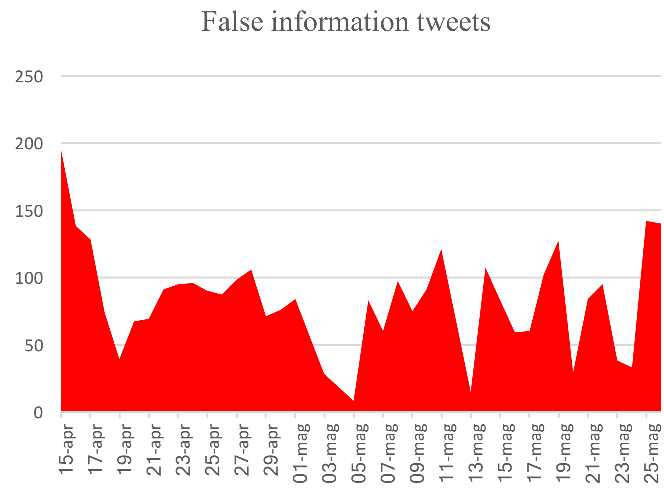
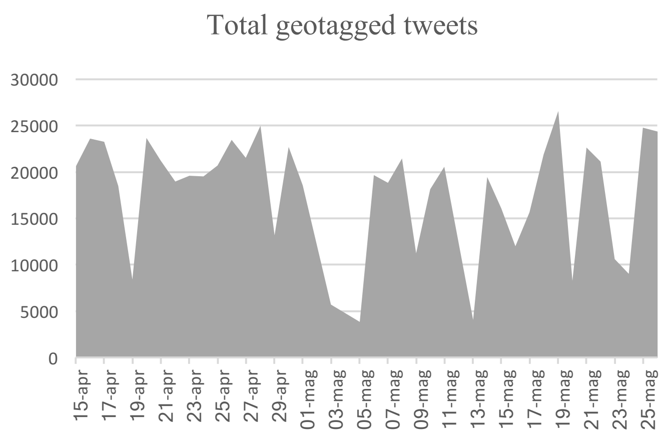


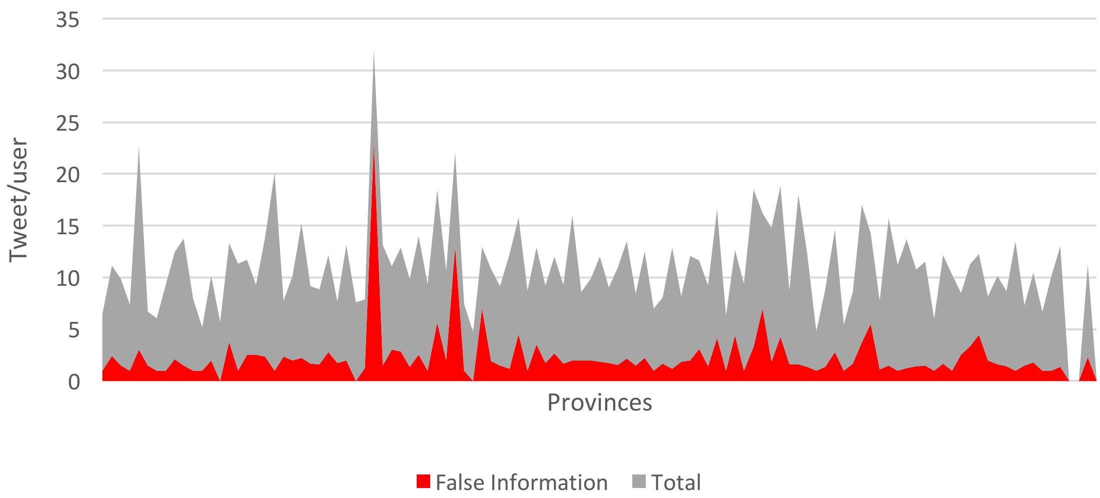
Figure 4. Evolution of the number of total geotagged tweets (2019)



[9] Total mean: 0.45; North-West: 0.42; North-East: 0.42; Center: 0.52; South: 0.47; Islands: 0.46.

Users. Overall, the 1.72% of users have been exposed to misleading contents in the month and a half before the 2019 election. The low number of users exposed to misleading contents is most likely due to the fact that we are underestimating the incidence of fake news tweets. Indeed, we focus only on geotagged posts on Twitter, whereas most of the people do not allow for the geolocation to be captured and much disinformation spreads also in other social media.
In order to have a measure of the intensity of users' activity, we consider the number of tweets per user by province. On average, one user has posted 2.3 tweets in the interested period, whit an intensity four times lower than the general activity (~9 tweet/user). Figure 5 shows the average number of false information tweets per user compared with the total activity. In general, the most active users appear to be located in few provinces if one considers that almost two out of three provinces present values below the mean of the distribution of disinformation tweets.

Figure 5. Number of tweets per user by province (2019)



Notes: The figure shows the number of tweet per user (general tweets=grey, misleading tweets=red) in each province. The number of tweet per user is computed as number of tweets in province *i* divides by the number of users in the province.

Previous works show that activities on the web (e.g. likes, shares, websites visits) follow a power-law distribution (Adamic et al., 2000; Zollo et al., 2017). In our case this means that, few users post most of the tweets. Figures 6 and 7 show the density distributions and relative complementary cumulative distribution functions for the tweet count and of the number of tweets per user. The long right tail of the histogram and the low concentration of observations having high-intensity activity suggest that both densities are well fitted by power law distribution. These findings are consistent with previous works analysing the features of false information spreading online, which state that most of these contents are spread by few 'super-spreaders' (Grinberg et al., 2019; Guess et al., 2019; Shao et al., 2018).

Figure 6. Density and complementary cumulative distribution function (CCDF) of the number of tweets per user

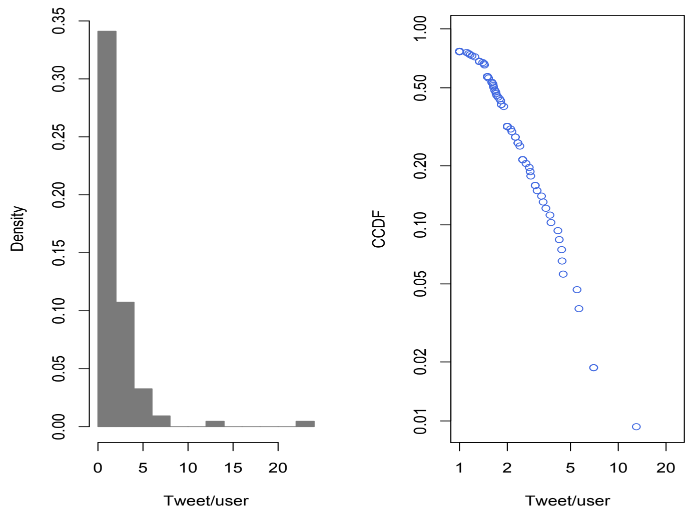
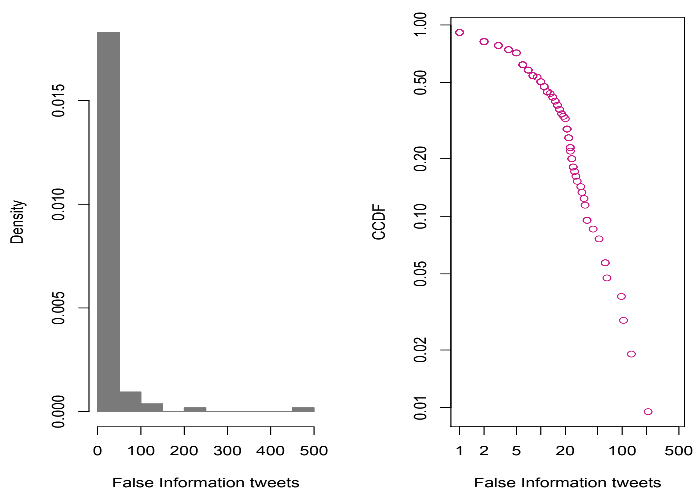


Figure 7. Density and complementary cumulative distribution function (CCDF) of the number of tweets

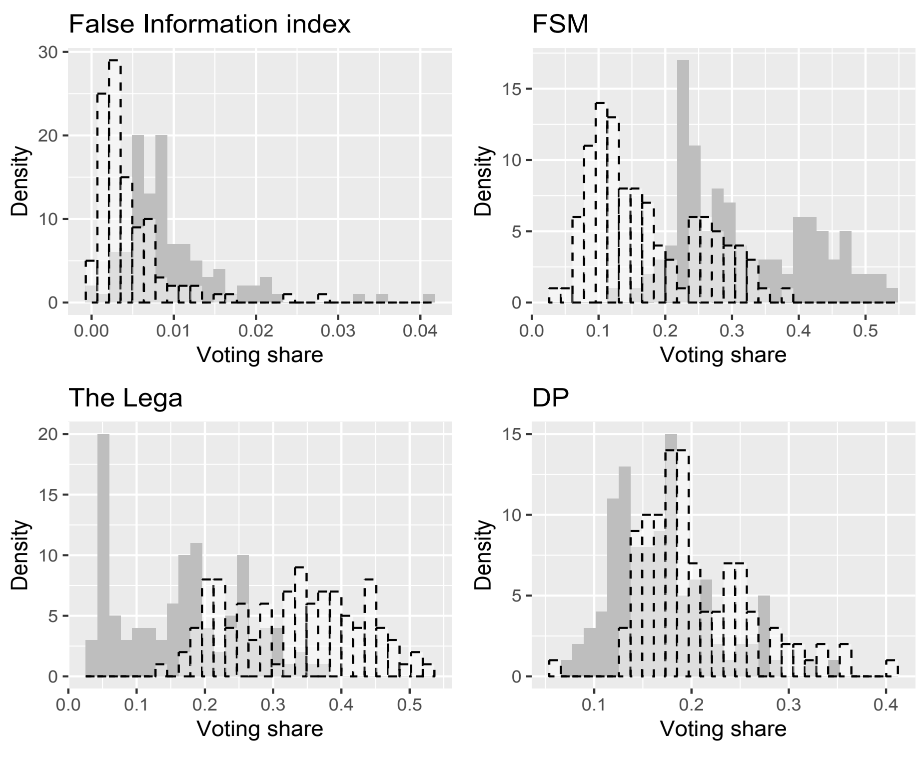


3.2 False information and vote trends between 2018 and 2019

In order to implement the first difference analysis, we exploit data collected on the 2018 Italian national election, following the same methodology of the 2019. The 2018 sample counts 4,118 unique tweets, almost the double of the 2019, produced by 1,874 distinct users and an average incidence level of the 1% on the total geotagged sample. The decrease in false information spreading between 2018 and 2019 here registered is in line with the analysis from AGCOM about disinformation spreading in Italy before the European election. The authority states that, compared with 2018, the amount of disinformation spreading online is lowered, with the politics category showing the highest decrease (10,1% points).

The index distribution in the top left panel of figure 8 shows a decrease in mean and variance from the 2018 (grey histogram) to the 2019 (white dashed histogram). The figure also illustrates the frequency distribution for the parties we are studying. The votes share for the M5S (top right) presents the same negative trend of the index, whereas the right sliding of the frequency distributions for the Lega (bottom left) and the PD (bottom right) indicate an improvement of their electoral performance.

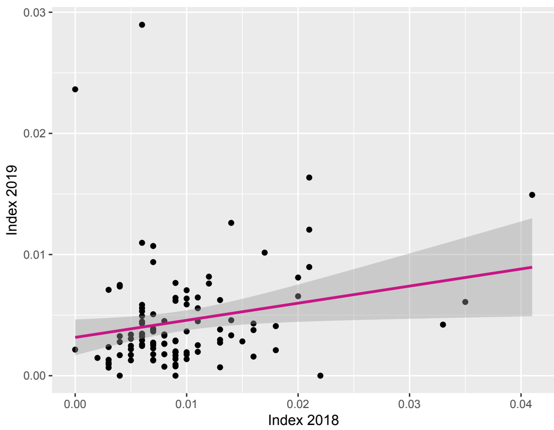
Figure 8. Density distribution of the 2019 and 2018 FI and parties vote share



Notes: Distribution of the 2018 (grey histogram) and 2019 (white-dashed histogram) of the False Information index (top left panel), and vote shares for the Five Star Movement (FSM, top right), The Lega (bottom left) and Democratic Party (DP, bottom right).

As illustrated by figure 9, there is a certain degree of correlation between the 2018 and 2019 indexes. We further explore this evidence by computing the Pearson linear correlation index and implementing an OLS regression having on the left-hand of the equation the 2019 index and on the right-hand the 2018 one. Results confirm preliminary graphical evidence of a slight correlation: we register a Pearson index of 0.212 and the p-value of the regression is 0.080 (coef=0.141).

Figure 9. Linear correlation of false information indexes 2018 and 2019.



Notes: Scatter plot and approximated linear regression line for the correlation between the false information index in 2018 (x-axes) and 2019 (y-axes).

4 Empirical strategy

In this section, we discuss the empirical strategy used to estimate the relationship between false information and electoral outcomes. The first step in our analysis is to investigate the existence of a correlation between the exposure to false information online and a vector of 2019 political outcomes. We implement a generalized linear model of the following form:

$$y_{ip} = \alpha_0 + \beta false\_inf_i + \gamma X_i + \eta_i + \varepsilon_{ip} \tag{1}$$

Where i indexes provinces and p the party. Y is the dependent variable of our model and it measures the vote share for the interested parties and the turnout. False_inf represents our index of false information spreading on Twitter, X is a vector of control variables, η are regional fixed effects, and ε is the error term. Following Papke and Wooldridge

(1996), we implement a generalized linear model. This model is more appropriate for our data as the dependent variable is fractional and varying in an interval between 0 and 1.
In the second part of our analysis, we try to understand the persistency of false information effects on voting by implementing a first difference model of the following form:

$$\Delta y_{ip(2019\text{-}2018)} = \alpha_0 + \beta \Delta false\_inf_{i(2019\text{-}2018)} + \gamma \Delta X_{i(2019\text{-}2018)} + \varepsilon_{ip} \qquad (2)$$

Δy is a vector of the changes in the election outcomes between 2019 and 2018. $\Delta false\_inf_i$ is the difference in the amounts of false claims, ΔX_i is a vector capturing the change in the control variables, ε_{ip} is the error term. The first-difference estimation removes the bias from the presence of time-invariant factors at the province level.

5 Results

5.1 False information and voter turnout

Before analysing the effect of false information on voting behaviour, it is worth to understand whether it is associated with voter turnout. Most of the literature has investigated the effects of fake news on voting while neglecting the possible effects on voter turnout. Nonetheless, in the light of recent studies about the potential political outcomes of political rumours (Weeks and Garrett, 2014; Allcott and Gentzkow, 2017), it is relevant to study whether false claims influence voter turnout or not.
The results from the cross-sectional analysis are presented in table 3. The estimated coefficient of the false information exposure is negative, though not significant. This result holds even when we include a large set of control variables in the GLM specification and when we use a different specification. This result is very interesting and in line with the literature on hate speech. A recent paper by Antoci et al. (2019), shows that if people are exposed to online civility they show higher trust, while the exposure to online incivility does not affect trust. According to the authors, online incivility has no influence on trust because people consider online incivility as the norm -i.e. online, people expect to find incivility. Similarly, it is plausible that people do not expect to find truthful information online, hence reading false contents online do not affect their willingness to vote. Indeed, most of the false information consumption occurs in echo chamber where political polarized people consume false information and strengthen their beliefs (see e.g. Del Vicario et al., 2016a, b). Furthermore, this interpretation would explain why false claims affect voting, but do not affect voter turnout.

Table 3: False Information and Voter Turnout (GLM)

Dep. Var.:	**Voter Turnout**
False information	-0.005
	(-0.75)
Income(log)	0.046*
	(2.30)
Low-speed Connection	-0.549
	(-1.84)
High-speed Connection	0.052
	(0.59)
Women	-0.062
	(-1.73)
Age 25-34	-0.037
	(-1.04)
Age 35-44	0.378
	(0.12)
Elderly	-0.442
	(-0.28)
Foreigners	0.634
	(0.93)
Secondary Sector	-0.025
	(-0.10)
Tertiary Sector	-0.070
	(-0.31)
Unemployment	-0.002
	(-1.06)
Education	-0.001
	(-0.13)
Urbanization	0.149**
	(3.16)
Regional dummies	Yes
N	**106**

Notes: The table shows the average partial effects of the generalized linear model. The dependent variable is voter turnout. The variable labeled false information measure the number of misleading tweets by province. Standard errors are clustered by province. t statistics in parenthesis * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.2 False information and European Elections.

As table 4 shows, we find a detectable correlation of false information on voting. Overall, results suggest the presence of a statistically significant association between the exposure to false claims and the electoral performances of the M5S and the left-wing PD. Indeed, increasing the false information index by 100 units increases the vote share for the M5S by 0.007 points[10]. The estimated coefficient for the PD is statistically different from zero and suggests that 100 units increase in false information corresponds to an increase of the PD vote share by 0.012 points. Last, we find no correlation between the false information index and the vote share for Lega.

We include in our analysis some controls. As expected, the 2018 vote share shows a strong correlation with our dependent variable. Income is positively correlated with PD voting share and negatively associated with the performance of the Lega. The vote share for the Lega also shows a low, but significant and negative correlation with the share of individuals with high education and a positive and significant correlation with the share of migrants living in the Italian provinces. Unemployment, urbanisation, age and gender do not show any particular effect on voting.

Finally, we control for broadband coverage. In our model, we included two variables: one measures the percentage of households with low Internet connection (0-2 Mbps) and the other measures the number of households with high-speed Internet connection (101-1000 Mbps). These two variables do not show any particular effect on voting behaviour[11].

Table 4: False Information and Voting outcomes (GLM)

	(1)	**(2)**	**(3)**
Dep. Var.:	**M5S**	**PD**	**Lega**
False information	0.007*	0.012**	0.000
	(2.49)	(3.19)	(0.06)
M5S 2018	0.025***		
	(0.017)		
PD 2018		0.034***	
		(0.013)	
Lega 2018			0.029***
			(0.146)
Incumbency	0.001	-0.001	-0.002
	(0.62)	(-0.85)	(-1.34)
Log(Income)	0.014	0.021**	-0.026**
	(1.41)	(2.65)	(-3.17)
Broadband low	-0.434*	-0.440	0.280
	(-2.46)	(-1.74)	(1.75)

[10] The size of the effect is computed as: $\hat{\beta}\hat{\phi}(\hat{\beta}'x)$.

[11] In order to further explore how the relation between false information and voting outcomes is declined, we tried to identify pro from against false information tweets by labelling as 'against' all the items including the words 'fake news' or hoax. However, the very low amount of such tweets (19) and their exclusion from the sample did cause no change in main results. Results are available on request.

Broadband	-0.017	0.095*	0.055
	(-0.62)	(2.14)	(1.45)
Women	0.547	-0.240	0.026
	(0.26)	(-0.13)	(1.65)
Age 25-34	0.021	0.010	0.029
	(1.31)	(0.48)	(1.57)
Age 35-44	-0.024	0.035*	0.019
	(-1.41)	(2.44)	(1.11)
Elderly	0.327	0.012	0.015
	(0.39)	(1.36)	(1.89)
Foreigners	-0.254	0.270	0.606*
	(-0.97)	(1.01)	(2.00)
Secondary Sector	-0.060	-0.240	-0.197
	(-0.47)	(-1.76)	(-1.65)
Tertiary sector	-0.002	-0.251	-0.119
	(-0.01)	(-1.83)	(-1.01)
Unemployment	0.001	-0.001	0.000
	(0.73)	(-0.67)	(0.39)
Education	-0.001	0.002	-0.003*
	(-1.00)	(1.90)	(-2.25)
Urbanization	0.022	-0.059**	0.002
	(0.96)	(-3.09)	(0.08)
Regional Dummies	Yes	Yes	Yes
N	**103**	**103**	**103**

Notes: The table shows average partial effects of the generalized linear model. The dependent variable is the vote share of the three main Italian parties. The variable labeled false information measures the number of misleading tweets by province. Standard errors are clustered by province. T statistics in parenthesis * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To account for the fact that our index may capture other aspects, such as the general usage of social media or other web features, we include an additional control that proxies the level of tweeting in the province. This indicator is computed as total number of geotagged tweets divided by the total population in the province. Results, which are presented in table 5, show an increase in the coefficients' magnitude whereas no difference can be found in the level of significance.

Table 5: False Information and Voting outcomes (tweets per capita included as control)

Dep. Var.:	**M5S**	**PD**	**Lega**
False Information	0.028*	0.041**	0.003
	(2.49)	(3.17)	(0.22)
Tweets per capita	0.162	0.423	-0.404
	(0.80)	(1.94)	(-1.90)
Regional dummies	Yes	Yes	Yes

N	103	103	103

Notes: The table shows average partial effects of the generalized linear model. Each row represents a different regression for the specified party. Tweets per capita= (total geotagged tweets/population)*1000. Each cell shows estimated coefficients for the indexes and relative t statistics in parenthesis. Standard errors are clustered by province. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Looking at the performance of other parties (table 6), the index shows no associations with the right-wing parties Forza Italia (FI) and Fratelli d'Italia (FDI), whereas it appears a negative and statistically significant correlation with the vote share for the left-wing party +Europa.

Table 6: False Information and Voting outcomes, other parties (GLM)

Dep. Var.:	**FI**	**FDI**	**+Europa**
False Information	-0.009	-0.002	-0.070**
	(-0.35)	(-0.12)	(-2.60)
Regional dummies	Yes	Yes	Yes
N	**103**	**103**	**103**

Notes: The table shows average partial effects of the generalized linear model. Each row represents a different regression for the specified party. Each cell shows estimated coefficients for the index measuring the number of misleading tweets by province. Controls include tweets per capita. Standard errors are clustered by province.
t statistics in parenthesis * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Placebo test. In our empirical framework, we wanted to be sure to capture the correlation between false information and voting behaviour. The problem with our index is that it might be correlated with other factors such as the Twitter usage or the usage of social media in general. Thus, one might think that our index is capturing other correlated effects instead of false information. To ensure the goodness of our estimates we run a placebo test by exploiting our geotagged database to build a measure of "information exposure". Like the false information index, the new index is measured as the total number of users' interaction with mainstream information accounts[12] on the total number of geotagged tweets in the province. We regress the vote share on the information index. If our measure of false information is capturing the effect of the overall activity on Twitter or social media usage, by running this test, we should get results similar to those presented in the previous paragraph. Results are displayed in table 7. We find no statistically significant relationship between the information index and voting behaviour. This result adds little

[12] We included Twitter accounts of mainstream, daily, national newspapers, either printed (traditional newspaper which moved to the online world) or digital (newspaper that are planned to be exclusively digital).

robustness to our main findings –at least for what concerns possible correlation with Twitter usage.

Table 7: Mainstream Information and Voting outcome (GLM)

Dep. Var.	**Vote shares**
M5S	-0.004
	(0.41)
Lega	-0.027
	(-0.12)
PD	0.033
	(0.36)
+Europa	-0.021
	(-0.26)
Controls	**Yes**
Regional dummies	**Yes**
N	**106**

Notes: The table shows the average partial effects of the generalized linear model. The dependent variable is the vote share of the three main Italian parties. The variable labelled information accounts measures the number of tweets of the mainstream information accounts by province.
t statistics in parenthesis * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To add robustness to our findings a second placebo test is implemented. One may in fact posit that the same individuals may consume both information and disinformation. Drawing on the geotagged database, we build a measure of the sport salience discourse on Twitter. Tweets matching at least one of the following conditions are considered:

- interactions (reply) with a sporting newspapers[13];
- mentioning at least one sporting newspapers account;
- linking to an article of the aforementioned newspapers.

The index is computed by dividing the number of sport related tweets on the total tweets in the province[14]. We then regress parties vote shares on this index. Results are displayed in table 8. No significant relationship emerges between the index and parties' performance, adding robustness to our findings.

Table 8: Sport tweets and performance of various parties

Dep. Var. Vote shares	**Sport tweets**

[13] The included newspaper are: *La Gazzetta dello Sport, il Corriere dello Sport, Tuttosport*.
[14] We thought advisable to avoid football related hashtags as they can be used in tweets covering any topics (i.e. hashjacking).

M5S	0.002
	(0.41)
Lega	-0.001
	(-0.12)
PD	0.002
	(0.36)
+Europa	-0.002
	(-0.99)
Controls	**Yes**
Regional dummies	**Yes**
N	**106**

Notes: The table shows the average partial effects of the generalized linear model. The dependent variable is parties' vote share. Each row represents a different regression for the specified parties. Cells report estimated coefficients for the football index.
t statistics in parenthesis * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3 First Difference Analysis

So far, we have shown that false information may be associated with voting and that this relation may not be determined by the usage of social media in general. However, we might suppose that other factors may intervene. Indeed, it is reasonable to assume that false claims correlate with a wide range of unobservable territorial characteristic, such as social capital and social norms. Furthermore, since people consuming such contents are more likely to be politically polarized, it is possible that false information correlates also with political ideology or with some cultural backgrounds. We might also suppose that false information captures some general trends effect, since it usually focuses on well-known people or facts.

To disentangle the false information effect from the possible additional effects mentioned above, we perform a first difference analysis with province fixed effects. The advantage of a first difference analysis relies on the fact that we are able to control for all the time invariant characteristics at province level. As explained in the previous section, Italians have voted both in 2018 for the national elections and in 2019 for the European and municipal elections. Although the two elections are not comparable in many aspects, they should not differentiate very much about the effect (if any) that false information has on voting outcomes. Albeit we have documented a decrease in the level of false claims, we assume that their effect on the electorate should not diverge from an election to another.

Differently from the GLM specification, now we are trying to study whether false information has a persistent correlation with voting by favouring a party rather than another. Furthermore, we are able to get rid of all the time invariant characteristics - between 2018 and 2019- at province level.

We expect to find different results with respect to the GLM specification since in this case the research question is slightly different. While with the previous specification we were studying the correlation between misleading contents and voting in the specific case of the European elections, now, we are studying whether false information plays a specific role in Italian elections in general.

We control for changes in the following socio-demographic features: population, share of female, individuals aged 25-34, 35-44 and more than 65, share of migrants, unemployment rate and share of employees in the secondary and tertiary sector and the change in broadband coverage. We also include a dummy variable to control for the year effects so to capture common trends. The results shown in tables 9 and 10 indicate a very interesting evidence. The signs of the coefficients are the same as those in the previous specification; nonetheless, the correlation is significant only for the M5S. Indeed, an increase of 100 units in false information consumption is associated to an increase of M5S vote share of 0.007 points. Notwithstanding, we are not able to claim any causal effect between fake news and voting since there might be reverse causality issues. However, these results seem to suggest significant correlation between the vote for the M5S and false information consumption.

Table 9: False Information and Vote shares (First Difference)

	(1) **M5S**	(2) **PD**	(3) **Lega**
False information	0.006*	0.001	-0.002
	(0.003)	(0.002)	(0.003)
Controls	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
N	**208**	**208**	**208**
adj. R^2	**0.978**	**0.782**	**0.977**

Notes: The table shows the coefficients of the first difference estimator. The dependent variable is the vote share of the three main Italian parties. The variable labeled false information measures the number of misleading tweets by province. Controls include tweets per capita. Robust standard errors clustered by province in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: False Information and Vote shares – other parties (First Difference)

	(1) **FI**	(2) **FDI**	(3) **+Europa**
False information	-0.001	-0.003	-0.001
	(0.002)	(0.002)	(0.001)

Controls	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
N	**208**	**208**	**208**
adj. R^2	**0.658**	**0.378**	**0.342**

Notes: The table shows the coefficients of the first difference estimator. The dependent variable is the vote share of the specified party. The variable labeled false information measures the number of misleading tweets by province. Controls include tweets per capita. Robust standard errors clustered by province in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We repeat the analysis also for the voter turnout. Again, the coefficient remains negative and not significant as in the GLM specification (table 11). Consequently, we cannot claim any significant correlation between fake news consumption and voter turnout.

Table 11: False Information and Voter Turnout (First Difference)

Dep. Var.:	**Voter turnout**
False information	-0.007
	(0.008)
Controls	Yes
Year dummies	Yes
N	**208**
adj. R^2	**0.926**

Notes: The table shows the coefficients of the first difference estimator. The dependent variable is the voter turnout. The variable labeled false information measures the number of misleading tweets by province. Controls include tweets per capita. Robust standard errors clustered by province in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The above reported results however do not account for the differences in the collection periods of the two samples[15]. Indeed, the probability for a province to be included in the sample changes over the observation period and, in general, a measure computed from data collected over a longer period should be considered more precise. Hence, we repeat our analysis using two sample weights. Given that in the 2019 we collected data for 40 days and in the 2018 for 20 days, the first weight equals 2 for the 2018 and 1 for the 2019. The second weight normalizes the two periods over the month selected as a standard time reference. The resultant weight equals 1.5 for 2018 and 0.75 for 2019. Results are shown in table 12. The introduction of weights caused no change in estimates and coefficients are comparable in size and significance to the previous regression.

[15] Data have been retrieved over a period of 20 days in 2018 and 42 days in 2019.

Table 12: weighted FD regression

	(1) **M5S**	(2) **PD**	(3) **Lega**
Weight 1	0.007**	0.002	-0.002
	(0.003)	(0.002)	(0.003)
Weight 2	0.007**	0.002	-0.002
	(0.003)	(0.002)	(0.003)
Controls	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
N	**212**	**212**	**212**
adj. R^2	**0.978**	**0.779**	**0.976**

Notes: The table shows the coefficients of the weighted first difference analysis. The dependent variable is the vote shares of main parties. Weight 1= 2 for 2018 and 1 for 2019; weight 2=1.5 for 2018 and 0.75 for 2019. Robust standard errors clustered by province in parenthesis * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6 Discussion

Our empirical evidence about the relationship between false information and electoral outcomes might find several explanations. Overall, we argue that false information correlates with the performances of the parties that are more sensitive to these misleading narratives, either with positive or negative attitude.

Results from the cross-sectional analysis reveal a positive correlation of our index with the performances of both the M5S and the PD. This finding may be indicative of positive stances of both parties' supporters toward false information. However, this interpretation would involve the presence of different misleading contents that are supportive of the ideologies of the two parties. Indeed, the literature on selective exposure to information finds that individuals tend to prefer ideologically aligned contents (e.g. Freedman and Sears, 1965; Jonas et al., 2001). In other words, it is very unlikely that M5S and PD supporters share the same views about a specific topic targeted by false information. Nevertheless, we are unable to accurately discern the user's stance on false information and the support for this thesis is limited. On the other hand, these results may be suggestive of the coexistence of two different attitudes toward false information, one in favour and one against. We argue that our results are suggestive of the presence of two polarized clusters around false information, one in favour and one against. This hypothesis is consistent with the literature on echo chambers and online polarization. Even if a strand of the literature finds that social networking sites increase cross-cutting contents exposure (e.g. Bakshy et al., 2015), other studies register the presence of segregated communities in online interactions (e.g. Del Vicario et al., 2016b).

Furthermore, notwithstanding the prevalence for individuals to access news contents directly visiting outlets pages, when it comes to social networking sites, information habits appear more polarized and the ideological distance between individuals increases (Flaxman et al., 2016). Overall, these findings suggest that the likelihood to encounter cross-cutting contents on SNSs is followed by the formation of echo chambers determined by the online debate on shared topic by users having different beliefs. This is specifically true for a social media like Twitter, where users' connections are asymmetric and not reflect the friendship network. This hypothesis is corroborated by the study of Gruzd and Roy (2014) finding that, in election periods, interactions between supporters of different parties on Twitter tend to be conflictual and more partisan voters are less willing to moderate their allegiances. In light of this evidence, we can assume that the interactions between M5S and PD voters are clustered around false information. The results by Mancosu et al. (2017) let us suppose the direction of users' stances. The authors show that the electorate of the M5S is more inclined to believe to conspiracy theories and the intention to vote for M5S correlates with well-known conspiracy, e.g. believing that the moon landing has never happened. As voters of different parties are supposed to have different views on a shared dialogue and that the M5S electorate has been found to be more sensitive to conspiracy theories, we suppose that M5S supporters share a positive attitude toward false information whereas DP supporters show a negative attitude. However, this result should be interpreted with caution and future works should pay attention to the linkage between false information and online polarization.

Results from the first difference analysis suggest that only the M5S benefits from the spreading of false information. Again, we rely on results from Mancosu et al. (2017). Indeed, if the voters of the M5S are more likely to believe in conspiracy theories, than it is not so surprising to find that false information consumption correlates with M5S voting. These results are in line with a literature suggesting that the conspiracism is a phenomenon ascribable to populist parties (see e.g. Sunstein and Vermeule 2009; Barreto et al. 2011). Furthermore, we have to stress that the M5S gives an extreme importance to the web. The aim of the party is that of implementing direct democracy via web participation (see e.g. Sæbø et al., 2015). Given the importance of social media in the M5S propaganda, it is plausible that its voters are very active online.

On the contrary, the Lega party has focused its strategy around its leader -Matteo Salvini. Although the Lega's leader is one of the most active politicians in the web, the political strategy of the Lega is mainly ideological. The Lega main political theme regards the anti-immigration policy, the anti-European sentiment and it emphasises the Italian religious roots. In this case, the main success of the party is likely to be other than the consumption of false information. Indeed, the Lega was born with a strong regional dimension, but when Matteo Salvini became the leader, he started to broaden the political dimension of the Lega focusing on Italian sovereignty (see e.g. Albertazzi and Giovannini, 2018).

7 Conclusion

In the present work, we studied the effect of false information on voting outcomes in the case of the European elections held in Italy in May 2019. By scraping geotagged data from Twitter, we built a measure of false information at province level. We then regressed political outcomes on our variable measuring misleading contents plus a set of political and socio-demographic controls. We used two different specifications. First, we implemented a GLM specification in the spirit of Papke and Wooldridge (1996) to assess the effect of false information on the choice of whether and how to vote. The results showed that the spread of false information does not affect voter turnout, but it positively correlates with M5S and PD voting and negatively correlates with the performance of +Europa. We suggest that false claims are unrelated to voter turnout because they do not affect people's trust in the political system. Indeed, we expect that a mechanism similar to that of online hate speech apply to fake news (Antoci et al., 2019). On the other hand, we argue that false information has multiple effects on the electorate. In particular, we find that misleading contents positively correlate with the two parties that are more sensitive both to the spreading of false information and online activity. The literature on false information suggests that misleading contents are likely to be consumed in echo chambers, i.e. online environments where similar users form clusters (Del Vicario et al., 2016a, b). We then argue that our results are suggestive of the presence of two different echo chambers and consistent with the literature on online polarization.

Second, we run a first difference analysis to understand whether false claims play a role in the Italian elections in general. We exploit the fact that one year before the European elections, Italians have been called to go at the ballot box for the national elections. This specification helps us to control for all the time invariant characteristics at province level. The results of our first difference analysis show a positive correlation between M5S voting and false information consumption. Again, this correlation is in line with the literature suggesting that M5S electorate is more likely to believe in conspiracy theories (Mancosu et al., 2017).

Our results contribute to the ongoing debate on false claims and voting behaviour in many aspects. To the best of our knowledge, no one has previously investigated the relation between voter turnout and false information. Furthermore, we show that false claims do not advantage a single party. Since the consumption of false contents mainly occurs in the so-called echo chambers, among politically polarized individuals, it is plausible to observe counter echo chambers who consume a false claim not because they believe it, rather because they fight it. Some studies have tried to detect causal effect between fake new and voting (see e.g. Cantarella et al., 2019). The idea behind these studies is that if people believe in false information, they will vote accordingly. This extremely recent field of research was born after the controversial US election of the 2016, where the majority of the false claims were supporting a candidate rather than another (Allcott and Gentzkow, 2017). Nevertheless, at least for the Italian case, our results suggest that the spreading of false information is only contributing to further polarize voter opinions. This work concludes with one main implication for future research. Indeed, it is still unclear which are the influences between polarization and false information, as well as whether and how it affects electoral outcomes.

References

Adamic, L. A., and Huberman, B. A. (2000). Power-law distribution of the world wide web. *Science*, *287*(5461), 2115-2115.

Albertazzi, D., Giovannini, A., and Seddone, A. (2018). 'No regionalism please, we are Leghisti!'The transformation of the Italian Lega Nord under the leadership of Matteo Salvini. *Regional & Federal Studies*, *28*(5), 645-671.

Allcott, H. and Gentzkow M., (2017). Social media and fake news in 2016 election. *Journal of Economic Perspecti*ves, 31(2), 211-236.

Antoci, A., Bonelli, L., Paglieri, F., Reggiani, T., and Sabatini, F. (2019). Civility and trust in social media. *Journal of Economic Behavior & Organization*, *160*, 83-99.

Antoci, A., Delfino, A., Paglieri, F., Panebianco, F., and Sabatini, F. (2016). Civility vs. incivility in online social interactions: An evolutionary approach. *PloS one*, *11*(11), e0164286.

Bakir, V., and McStay, A. (2018). Fake News and The Economy of Emotions. *Digital Journalism*, 6:2, 154-175.

Bakshy, E., Messing, S., and Adamic, L. A. (2015). Exposure to ideologically diverse news and opinion on Facebook. *Science*, *348*(6239), 1130-1132.

Barreto, M. A., Cooper, B. L., Gonzalez, B., Parker, C. S., and Towler, C. (2011). The Tea Party in the age of Obama: mainstream conservatism or out-group anxiety? *In Rethinking Obama*,105-137. *Emerald Group Publishing Limited.*

Bentivegna, S. (2006). Rethinking politics in the world of ICTs. *European journal of communication*, *21*(3), 331-343.

Bessi, A., Coletto, M., Davidescu, G. A., Scala, A., Caldarelli, G., and Quattrociocchi, W. (2015). Science vs conspiracy: Collective narratives in the age of misinformation. *PloS one*, *10*(2), e0118093.

Bessi, A. (2016). Personality traits and echo chambers on facebook. *Computers in human behavior,* 65, 319-324.

Boxell, L., Gentzkow, M., and Shapiro, J. M. (2017). Greater Internet use is not associated with faster growth in political polarization among US demographic groups. *Proceedings of the National Academy of Sciences*, *114*(40), 10612-10617.

Caldarelli, G., Chessa, A., Pammolli, F., Pompa, G., Puliga, M., Riccaboni, M., and Riotta, G. (2014). A multi-level geographical study of Italian political elections from Twitter data. *PloS one,* 9(5), e95809, 1-10.

Cantarella, M., Fraccaroli, N., and Volpe, R. (2019). Does Fake News Affect Voting Behaviour? *DEMB working paper*, 146, 1-17.

Del Vicario, M., Bessi, A., Zollo, F., Petroni, F., Scala, A., Caldarelli, G., Stanley, H.E., Quattrociocchi, W. (2016a). The spreading of misinformation online. *Proceedings of the National Academy of Sciences*, vol. 113 no. 3, 554-559.

Del Vicario, M., Vivaldo, G., Bessi, A., Zollo, F., Scala, A., Caldarelli, G., and Quattrociocchi, W. (2016b). Echo chambers: Emotional contagion and group polarization on Facebook. *Scientific reports,* 6, 37825, 1-12.

Del Vicario, M., Quattrociocchi, W., Scala, A., and Zollo, F. (2019). Polarization and fake news: Early warning of Potential misinformation targets. *ACM Transactions on the Web (TWEB)*, *13*(2), 10.

Emanuele, V. (2015). Vote (de-) nationalisation and party system change in Italy (1948–2013).

Contemporary Italian Politics, 7(3), 251-272.

Emanuele, V., and Maggini, N. (2019). Il M5S "resiste" solo nelle province a maggior richiesta di assistenzialismo. Available at: https://cise.luiss.it/cise/2019/05/27/il- M5S-resiste-solo-nelle-province-a-maggior-richiesta-di-assistenzialismo/.

Enke, B. (2018). Moral values and voting. *National Bureau of Economic Research*.

Flaxman, S., Goel, S., and Rao, J. M. (2016). Filter bubbles, echo chambers, and online news consumption. *Public Opinion Quarterly*, Vol. 80, Special Issue, 298–320.

Fletcher, R., and Nielsen, R. K. (2018). Are people incidentally exposed to news on social media? A comparative analysis. *New media and society*, 20(7), 2450-2468.

Fourney, A., Racz, M. Z., Ranade, G., Mobius, M., Horvitz, E. (2017). Geographic and Temporal Trends in Fake News Consumption During the 2016 US Presidential Election. *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management,* 2071-2074.

Freedman, J. L., and Sears, D. O. (1965). Selective exposure. *Advances in experimental social psychology* 2, 57-97. Academic Press.

Grinberg, N., Joseph, K., Friedland, L., Swire-Thompson, B., and Lazer, D. (2019). Fake news on Twitter during the 2016 US presidential election. *Science*, 363(6425), 374-378.

Gruzd, A., and Roy, J. (2014). Investigating political polarization on Twitter: A Canadian perspective. *Policy and Internet*, 6(1), 28-45.

Guess, A., Nagler, J., and Tucker, J. (2019). Less than you think: Prevalence and predictors of fake news dissemination on Facebook. *Science advances*, 5(1), eaau4586

Guiso, L., Herrera, H., Morelli, M., and Sonno, T. (2017). Demand and supply of populism. *London, UK: Centre for Economic Policy Research*.

Huang, H. (2017). A war of (mis) information: The political effects of rumors and rumor rebuttals in an authoritarian country. *British Journal of Political Science*, 47(2), 283-311.

Inglehart, R., and Norris, P. (2017). Trump and the populist authoritarian parties: the silent revolution in reverse. *Perspectives on Politics*, 15(2), 443-454.

Jonas, E., Schulz-Hardt, S., Frey, D., and Thelen, N. (2001). Confirmation bias in sequential information search after preliminary decisions: an expansion of dissonance theoretical research on selective exposure to information. *Journal of personality and social psychology*, 80(4), 557.

Kuklinski, J. H., Quirk, P. J., Jerit, J., Schwieder, D., and Rich, R. F. (2000). Misinformation and the currency of democratic citizenship. *The Journal of Politics,* 62(3), 790-816.

Kull, S., Ramsay, C., and Lewis, E. (Winter, 2003/2004). Misperceptions, the Media, and the Iraq War. *Political Science Quarterly* 118(4), 569–598.

Lazer, D. M., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., Metzger, M. J., Nyhan, B., Pennycook, G., Rothschild, D., Schudson, M., Sloman, S. A., Sunstein C. R., Thorson, E. A., Watts, D. J., and Zittrain, J. L. (2018). The science of fake news. *Science*, *359*(6380), 1094-1096.

Mancosu, M., Vassallo, S., and Vezzoni, C. (2017). Believing in Conspiracy Theories: Evidence from an Exploratory Analysis of Italian Survey Data. *South European Society and Politics*, 22(3), 327-344.

Papke, L. E., and Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of applied econometrics*, *11*(6), 619-632.

Pariser, E. (2011). The filter bubble: What the Internet is hiding from you. *Penguin UK.*

Sæbø, Ø., Braccini, A. M., and Federici, T. (2015). From the blogosphere into real politics: The use of ICT by the Five Star Movement. *From Information to Smart Society*, Springer, Cham 241-250.

Shao, C., Ciampaglia, G.L., Varol, O., Flammini, A., and Menczer, F. (2018). The spread of low-credibility content by social bots, *Nature communications*, 4787, 9(1), 1-9.

Steinert-Threlkeld, Z. C., Mocanu, D., Vespignani, A., and Fowler, J. (2015). Online social networks and offline protest. *EPJ Data Science*, *4*(1), 1-9.

Suhay, E., Bello-Pardo, E., and Maurer, B. (2018). The Polarizing Effects of Online Partisan Criticism: Evidence from Two Experiments. *The International Journal of Press/Politics* 23 (1): 95-115.

Sunstein, C. R., and Vermeule, A. (2009). Conspiracy theories: Causes and cures. *Journal of Political Philosophy*, *17*(2), 202-227.

Tucker, J. A., Guess, A., Barberá, P., Vaccari, C., Siegel, A., Sanovich, S., Stukal, D., and Nyhan, B. (2018). Social media, political polarization, and political disinformation: A review of the scientific literature. Political Polarization, and Political Disinformation: A Review of the Scientific Literature (March 19, 2018).

Tumasjan, A., Sprenger, T. O., Sandner, P. G., and Welpe, I. M. (2011). Election forecasts with Twitter: How 140 characters reflect the political landscape. *Social science computer review*, *29*(4), 402-418.

Vaccari, C., Valeriani, A., Barberá, P., Bonneau, R., Jost, J. T., Nagler, J., and Tucker, J. (2013). Social media and political communication. A survey of Twitter users during the 2013 Italian general election. *Rivista italiana di scienza politica*, *43*(3), 381-410.

Van Kessel, S. (2015). Populist parties in Europe: Agents of discontent? *Springer*.

Vosoughi, S., Roy, D., and Aral, S. (2018). The spread of true and false news online. *Science*, 359(6380), 1146-1151.

Wang, Y., Callan, J., and Zheng, B. (2015). Should we use the sample? Analyzing datasets sampled from Twitter's stream API. *ACM Transactions on the Web* 9(3), Article 13.

Weeks, B. E., and Garrett, R. K. (2014). Electoral consequences of political rumors: Motivated reasoning, candidate rumors, and vote choice during the 2008 US presidential election. *International Journal of Public Opinion Research, 26*(4), 401-422.

Zollo F, Bessi A, Del Vicario M, Scala A, Caldarelli G, Shekhtman L, et al. (2017) Debunking in a world of tribes. *PLoS ONE* 12(7): e0181821

Appendix

Table A1: List of Twitter disinformation accounts (2019)

	Name	Domain
1	Terrarealtime	http://terrarealtime.blogspot.com/
2	Nexus Edizioni	http://www.nexusedizioni.it
3	Non siamo soli	http://www.nonsiamosoli.com/
4	Pianeta blu news	https://www.pianetablunews.it/
5	Salto quantico	http://saltoquantico.org/
6	Segni dal cielo	https://www.segnidalcielo.it/
7	Eurosalus	https://www.eurosalus.com/
8	Informasalus	http://www.informasalus.it/
9	Medicenon	https://www.medicinenon.it/
10	Vivo in salute	https://www.vivoinsalute.com/
11	24orenotizie	http://www.24orenews.it/
12	Break notizie	https://www.breaknotizie.com/
13	Diretta news	https://www.direttanews.it/
14	Giornale news	http://ilgiornalenews.it/
15	Il faro sul mondo	https://www.ilfarosulmondo.it/
16	Il fattaccio	http://www.ilfattaccio.org/
17	Il primato nazionale	https://www.ilprimatonazionale.it/
18	Informa Italia	
19	Italianotizie24	https://www.italianotizie24.it/
20	Italiano sveglia	http://italianosveglia.com/
21	Libero giornale	http://liberogiornale.it/
22	Mafia capitale	
23	Movimento base Italia	
24	News24roma	
25	Nocensura	http://www.nocensura.com/
26	Notixweb	
27	Notizie24h	https://www.notizie24h.it/
28	Senza censura	https://www.senzacensura.org/
29	The tonic express	https://www.thetonicexpress.com/
30	Tg24ore	https://www.tg24-ore.com/
31	Ticinolive	http://www.ticinolive.ch/
32	Tutti i crimini degli Immigratl	http://tuttiicriminidegliimmigrati.com/
33	Tuttoinweb	http://www.tuttoinweb.com/
34	Ultimora24	https://t.me/ULTIMORA24
35	Conoscenze al confine	http://www.conoscenzealconfine.it/

36	Disinfonet	
37	Dinformazione	https://disinformazione.it/
38	ECPlanet	https://ecplanet.org/
39	Il navigatore curioso	https://ilnavigatorecurioso.myblog.it/
40	Libreidee	https://www.libreidee.org/
41	Misteri d'Italia	http://www.misteriditalia.it/
42	PandoraTV	https://www.pandoratv.it/
43	Attivotv	https://www.attivo.tv/
44	Kontrokultura	https://www.kontrokultura.it/
45	Dangerous news	http://notiziepericolose.blogspot.com/
46	Corriere del corsaro	http://www.corrieredelcorsaro.it/
47	Informare x resistere	https://informarexresistere.fr/
48	Rosario Marcianò	http://www.tankerenemy.com
49	Corriere del Mattino	http://www.agenziedistampa.altervista.org
50	Il Populista	http://www.ilpopulista.it
51	Vox	http:// www.voxnews.info
52	Il Merdone Quotidiano	https://www.ilmerdone.wordpress.com
53	Stop Euro	http://www.stopeuro.news/
54	Web News24	http:// www.webnews24h.it
55	Il Giornale	http://www.ilgiornale.it/
56	Apri La Mente	http://aprilamente.myblog.it/
57	Dionidream	http://www.dionidream.com
58	Scienza e Conoscenza	http://www.scienzaeconoscenza.it
59	Segni dal cielo	http://www.segnidalcielo.it
60	Autismo & Vaccini	http://www.autismovaccini.org/
63	Vaccini informa	http://www.vacciniinforma.com/
64	Vivo in Salute	http://www.vivoinsalute.com
65	Break Notizie	http://www.breaknotizie.com
66	Catena Umana	http://www.catenaumana.it
67	Che Succede	http://www.chesuccede.it
68	Diretta News	http://www.direttanews.it
69	Il Faro sul Mondo	http://www.ilfarosulmondo.it
70	Imola Oggi	http://www.imolaoggi.it
71	Sapere è un Dovere	http://www.sapereeundovere.com
72	Silenzi e Falsità	http://www.silenziefalsita.it/
73	LiberaMenteServo	http://www.liberamenteservo.it

Table A2: List of Twitter disinformation accounts (2018)

	Name	**link**
1	Rosario Marcianò	http://www.tankerenemy.com
2	Il FattoneQuotidiano	http://www.ilfattonequotidiano.it

3	Corriere del Mattino	http://www.agenziedistampa.altervista.org
4	Corriere del Corsaro	http://www.corrieredelcorsaro.it
5	Il Populista	http://www.ilpopulista.it
6	Vox	http:// www.voxnews.info
7	IlMerdoneQuotidiano	https://www.ilmerdone.wordpress.com
8	Irresponsabile	http:// www.irresponsabile.com/
9	RomaNews24	
10	Notixweb	https://www.notixweb.com
11	Sputtaniamotutti	http://www.sputtaniamotutti.reattivonews.org
12	StopEuro	http://www.stopeuro.news/
13	Web News24	http:// www.webnews24h.it
14	Open Your Eyes	http:// www.blogopenyoureyes.altervista.org
15	Italia_nel_Caos	http://www.tankerenemy.com
16	Piovegovernoladro	http://www.piovegovernoladro.info
17	La Chiave Orgonica	http://www.chiaveorgonica.altervista.org/
18	Dangerous news	http://www.notiziepericolose.blogspot.com
19	IlGiornale	http://www.ilgiornale.it/
20	ApriLaMente	http://www.aprilamente.myblog.it/
21	Dionidream	http://www.dionidream.com
22	NonSiamoSoli	http://www.nonsiamosoli.net
23	Pianetablunews	http://pianetablunews.wordpress.com/
24	Scienza e Conoscenza	http://www.scienzaeconoscenza.it
25	Segnidalcielo.it	http://www.segnidalcielo.it
26	Autismo & Vaccini	http://www.autismovaccini.org/
27	Informasalus	http://www.informasalus.it/
28	TzeTze	http://www.tzetze.it
29	Vacciniinforma	http://www.vacciniinforma.com/
31	Vivo in Salute	http://www.vivoinsalute.com
32	Break Notizie	http://www.breaknotizie.com
33	Catena Umana	http://www.catenaumana.it
34	CheSuccede	http://www.chesuccede.it
35	Diretta News	http://www.direttanews.it
36	Il Faro sul Mondo	http://www.ilfarosulmondo.it
37	Il Patriota	http://www.ilpatriota.blogspot.it
38	Imola Oggi	http://www.imolaoggi.it
39	InformarexResistere	https://www.informarexresistere.fr
40	iTaLiaPatriaMia	https://www.italiapatriamia.eu
41	LoSai	http://www.losai.eu
42	Riscatto Nazionale	http://www.riscattonazionale.net/
43	Rischio Calcolato	http://www.rischiocalcolato.it
44	Sapere è un Dovere	http://www.sapereeundovere.com
45	Silenzi e Falsità	http://www.silenziefalsita.it/

46	Ticinolive	http://www.ticinolive.ch
47	Video Virali Web	http://www.videoviraliweb.com
48	Rosario	http://www.lonesto.it
49	Hack the Matrix	http://www.hackthematrix.it
50	LiberaMenteServo	http://www.liberamenteservo.it
51	Nexus Edizioni	http://www.nexusedizioni.it
52	Nibiru2012.it	https://www.nibiru2012.it
53	Terrarealtime	http://www.terrarealtime.blogspot.com/

Table A3: Examples of false stories in our sample and keywords used for detection (2019)

Story	**Keywords**	**Type of false information**	**Source**
Avaaz (an international NGO whom mission is to foster the public decision to be taken based on public opinion) is funded by Soros	Soros + Avaaz	Fake news	https://www.butac.it/soros-avaaz-e-le-pagine-facebook-chiuse/
In France, lots of churches are burning in the silence of media, to make place for mosques.	Church/churches + fire; Church/churches + burns/burn; Church/churches+ muslims; Church/churches + mosques	Disinformation	https://www.butac.it/la-cannabis-europa/
A muslim manifestation against the police in Denmark.	Muslim/s+Denmark; Muslim/s + Copenaghen; Islam+ Copenaghen+police	Fake news	https://pagellapolitica.it/bufale/show/461/no-questo-video-non-mostra-scontri-tra-islamici-e-la-polizia-a-copenaghen
Conspiracy theories on the Notre Dame fire	e.g. dame+terrorist; dame+muslim; dame+statues+decapitate ;	Conspiracy thories	https://www.open.online/2019/04/15/le-bufale-e-le-teorie-di-complotto-sullincendio-di-notre-dame/

Table A4: Examples of false stories in our sample and keywords used for detection (2018)

Story	Keywords	Type of false information	Source
The advent of a weather disturbance named Burian that would have caused an ice-cold winter in Italy.	Burian	Hoax	https://www.butac.it/ma-non-doveva-esser-un-inverno-da-era-glaciale/
Emma Bonino (the leader of +Europa) dishes out cannabis during the political meetings of her party.	+Europa/Bonino+cannabis; +Europa/Bonino+weed; +Europa/Bonino+drug;	Pseudo-politics	https://www.butac.it/la-cannabis-europa/
Emma Bonino and the Lega, are funded by Soros (this accusation is sometimes also directed to the M5S). She is also accomplice with Soros in the project of invasion of Italy.	Bonino+soros; Bonino+invasion; Bonino+fund();	Conspiracy Theory/hoax	https://www.butac.it/soros-paga-tutti/
Pamela Matropietro -the 18-years-old Italian girl murdered in Macerata the 30th of January 2018- has been murdered by three Nigerian with a Voodoo rite. Furthermore, the killers of the girl are supposed to be cannibals as they ate her organs.	pamela + voodoo; pamela + cannibal; cannibal + nigerian; nigerian+voodoo;	Pseudo-Journalism	https://www.butac.it/gli-organi-asportati-a-macerata-e-lindignazione/

Table A5: List of scientific hoaxes and related keywords used for detection

	Hoax	Keywords
1	Vaccine and autism	%vaccineandautism%; %vaccine%+%autism%; %autismandvaccine%
2	Chemtrails	%chemtrails%
3	Flat Earth	%Flat Earth%; %Flatearth%;
4	Anti-mucus diet	%Mucus% + %diet%
5	Reptilians	%Reptilians%
6	New Germanic Medicine	%germanic%+%medicine%
7	Stamina	%stamina%
8	OGM	%ogm%; %monsanto%
9	Glyphosate	%glyphosate%
10	Piltdown Man	%Piltdown Man%; %Piltdownman%