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Does fake news impact stock returns? Evidence from US and EU stock markets

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ABSTRACT

This study investigates the effects of fake news on stock returns of targeted firms. Fake news is information which is presented as true but which is in fact fabricated and meant to mislead readers. On the basis of disagreement models, we argue that the fact that some investors might not be able to discern whether a piece of news is true or fabricated can cause disagreement among investors on the true value of the firm. This will cause the stock prices of targeted firms to respond to the fake news, even if its informational content is non-existent. Using event study methodology and OLS regressions, we analyse a sample of fake news initiated by outsiders and announced in the US and Europe during the period 2007–2019. We find that negative false news items have negative and significant short-term effects on returns, while positive and neutral news items do not have a clear impact on stock returns. Moreover, we find no significant difference between traditional media outlets and social media. Our results thus provide new evidence on the information-based manipulations of financial markets.

1. Introduction

Information plays an increasingly central role in today's society (Wessel et al., 2016). Digital transformation,[1] defined as "the integration of digital technology into all areas of society, and the changes that result from this integration" by Kaplan & Haenlein (2019), helps to increase the diffusion and speed of sharing of information. However, digital transformation can also contribute to the production and dissemination of *misleading information*, in terms of "disinformation",[2] "misinformation"[3] and "fake news". Misleading information is an emerging cyber risk (Petratos, 2021) and can cause enormous damage especially to the financial sector and financial markets. The Covid-19 "infodemic" was particularly dangerous. The World Health Organization (WHO) defines "infodemic" as the over-abundance of information which makes it hard for people to find trustworthy sources and reliable guidance when they need it (WHO, 2020).

Internet has seen recent mushrooming of organizations and individuals deliberately spreading false information to seek financial

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[1] Digital transformation includes big data (Lee, 2019), the Internet of Things (Saarikko et al., 2017), and social media (Kaplan & Haenlein, 2010; Kaplan, 2012).

[2] Disinformation is when false or erroneous information is deliberately spread in order to damage a government, an organization, or a public figure.

[3] Misinformation is false information that is spread, regardless of whether there is intent to mislead.

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gain (Siering et al., 2017; Subramanian, 2017). This type of misleading information is the topic of this paper, and is commonly referred to as "fake news". Fake news proved harmful on a large scale in the US presidential elections and the Brexit referendum of 2016, and throughout the Covid-19 crisis. Information in fact plays a key role in every aspect of daily life, from politics to economics (Allcott & Gentzkow, 2017; Guo & Vargo, 2020; Tandoc Jr. et al., 2019). There has been much discussion about the effects of misleading information on the political process (Guo & Yu, 2020; Silverman, 2016), and the German government, for example, has introduced a law which fines social networks up to 50 million euros for failing to remove defamatory fake news and other illegal content (Faiola & Kirchner, 2017). The consequences of fake news on the financial sector have, however, been little examined and, although governments are starting to tackle the problem, financial markets, with their reliance on information, are particularly vulnerable. For example, as described by Karppi & Crawford (2016), in 2013, fake news of two explosions at the White House caused the S&P500 index to lose more than $130 billion in market capitalisation. Furthermore, fake news usually spreads through different media, including social media, which can cause huge losses very rapidly. For example, on 22 May 2023, a false but plausible account tweeted a photo of a fake story about an explosion at the Pentagon, the US Department of Defense.[4] The account used the graphics of the American financial news and media company Bloomberg, and the blue tick verification badge used until recently on Twitter profiles. The tweet deceived the American stock market, which fell slightly immediately after publication of the photo. The Dow Jones Industrial Index fell 85 points for a few minutes before bouncing higher again. Another example is the fake tweet from Eli Lilly which promised free insulin on 10 November 2022. The pharmaceutical multinational denied the news, but by the next day shares had plunged by about $22 billion.

Given the importance of the topic for the financial sector and the gap in the existing literature (see Section 2), especially with reference to the effects of fake news on financial markets, we examine the impact of fake news events on the stock market. Like other researchers (Chen et al., 2014; Kothari et al., 2009; Sun et al., 2016; Tetlock, 2007), we adopt a content analysis approach. Because there is debate in the literature on the relationship between traditional and social media, which can be considered either competitive or complementary (e.g., Ren et al., 2022), we also investigate whether fake news announced first by official or traditional media outlets[5] has a different impact from fake news announced first on social media.

Using the framework of a *disagreement model* (Hong & Stein, 2007), a particular class of heterogeneous-agent model, which expands on the classical Efficient Market Hypothesis (EMH), we argue that, although by definition fake news does not convey any informational content, the fact that some investors in the market cannot discern its non-informative nature will cause disagreement among investors about the true value of the targeted firm. This, in turn, will cause stock returns to react to the false news event.

Using a sample of 149 fake news events which took place in the period 2007–2019, we extend the recent literature that investigates the impact of fake news on stock returns (Clarke et al., 2020; Kogan et al., 2021). Previous studies focused on fake news perpetrated by the targeted firms themselves: false news articles about financial matters were solicited by insiders to artificially inflate expectations about the firms. Our study differs from this literature in that it focuses on a sample of items produced by outsiders, who could have other motives, including political, to spread fake news (Allcott & Gentzkow, 2017). We therefore study the impact of false news items which are not primarily financial in content, and our definition of false news is broader than that used in previous literature.

We assess the impact of fake news on stock markets using two different empirical methods, as is usual in financial markets literature (Ahern, 2009; Cappa et al., 2022; MacKinlay, 1997). First, we run an event study to assess the impact of a false news item on stock returns. Second, we run a multivariate OLS regression on cumulative abnormal returns (CARs) in order to control for other determinants of the same returns. We find that, in general, equity markets react to false information in the very short term, and that negative false information elicits a negative response, while positive false information elicits a positive response. Our results also show that there seems to be no significant difference between traditional media outlets and social media: both media seem to be equally credible when fake news starts to spread. This is consistent with literature (e.g., Bar-Gill et al., 2020; Sismeiro & Mahmood, 2018) recognizing that the relationship between traditional and social media is complementary. We thus extend the literature on the association between social media and traditional media, highlighting the need for policy makers to pay equal attention to the two sources of information. The study thus offers new insights on the economic costs of reputational risk and on the impact of media communication on the economic and financial world. It follows that our results are of practical relevance for market authorities in developing detection mechanisms for information-based manipulation.

The remainder of the paper is organized as follows. Section 2 presents the related literature. Section 3 provides an overview of the empirical research design, including the event study, the OLS regression and the description of our sample. In Section 4, we present our results. Section 5 discusses the implications and concludes.

2. Literature review

In the last few years, there has been a proliferation of “fake news”, i.e., information which is clearly not true and which is made up with the purpose of financial or political gain (Subramanian, 2017;Bradshaw & Howard, 2018). Today, of course, social media contribute to the dissemination of information (Hu et al., 2015), and important recent research (Bae et al., 2021; Schuetz et al., 2021) investigated how to combat the infodemic on social media during the Covid-19 pandemic. Historically, traditional news media played a dominant role (Tetlock, 2007) but studies have shown the increasing strength of social media in influencing stock prices and volatility (Ranco et al., 2015; Sprenger et al., 2014) and their importance is recognized by both regulators and market participants

[4] https://edition.cnn.com/2023/05/22/tech/twitter-fake-image-pentagon-explosion/index.html

[5] Like Ren et al. (2022), we define “traditional media” as the digitalised print media, including newspaper articles.

(Gan et al., 2020). This is also because when the fake news phenomenon moves from social media to the business and financial world, things become even more serious (Hajli, 2014; Knight & Tsoukas, 2019; Susarla et al., 2016), partly because fake news spreads faster than real news (Clarke et al., 2020; Vosoughi et al., 2018). Just one item of fake news can burn billions of dollars in a matter of seconds (Karppi & Crawford, 2016).

Much of the literature is about the social impact of fake news (e.g., Wardle & Derakhshan, 2017), its evolution patterns (Jang et al., 2018; Vosoughi et al., 2018), and its identification through machine learning techniques (Clarke et al., 2020; Dong et al., 2018; Kogan et al., 2021), but few studies so far have been made of its impact on financial markets. This is mainly because, although many approaches have been tried, it is difficult to define and identify precisely what fake news is (Lazer et al., 2018;Tambini, 2017; Verstraete et al., 2017; Wardle & Derakhshan, 2017). Many authors (Kimmel, 2004; Pound & Zeckhauser, 1990; Van Bommel, 2003) opt for the definition of fake news as a "rumour", or financial gossip travelling around financial markets before a big event takes place. The problem with this approach is that fake news, by definition, is not true, while rumours can be related to genuine events (Ullah et al., 2014). Since 'rumour' cannot be used as a synonym for fake news, other authors focus on real episodes. For example, Huberman & Regev (2001) study market reaction to a 1988 article published in the *New York Times* about a pharmaceuticals company, *EntreMed*, (now EMND) which had apparently discovered a cure for cancer. As described by Abelson (1998), the stock price of the company skyrocketed from 12$ to 80$, which had a spillover effect on the entire biotech sector. The curious aspect of this event is that the same news had been published months earlier in the scientific journal *Nature,* so the information brought to the market by the NYT article was not new. Nevertheless, the financial world reacted enthusiastically. A similar event is observed by Carvalho et al. (2011) and by Marshall et al. (2014). In 2008, an article first published in 2002 about United Airlines' parent company bankruptcy resurfaced and was mistakenly believed to report a new bankruptcy filing by the same company. On the same day, the stock price of the company plummeted by more than 70% before Nasdaq Stock Exchange halted trading. When the "news" was declared to be false, the price rebounded, but it remained more than 10% below the initial price of that day. Moreover, after three trading sessions, the stock was still trading below the two standard deviation bands implied by the model of Carvalho et al. (2011). The authors also find a persistent contagion effect on the airline industry. In these two cases, the news was not entirely new, but neither was it false; the papers by Huberman & Regev (2001), Carvalho et al. (2011) and Marshall et al. (2014) in fact discuss stale rather than fake news. Fake news however is false information which can be reliably denied (Ullah et al., 2014).

Given this definition of fake news, we could postulate that financial markets should not react to the dissemination of false information, as stated by the EMH. However, the representative agent model developed by Fong (2021) suggests that fake news can lead to a decrease in market efficiency as investors may take decisions based on this misleading information. In fact, the recent studies by Clarke et al. (2020) and Kogan et al. (2021), that focus on a sample of false stock promotion articles published on a financial crowd-sourced platform, demonstrate that fake news temporarily impacts stock price returns of small cap firms. The EMH does not allow for this type of irrational behaviour, but it can be interpreted by behavioural models. For example, Barberis et al. (1998) build an agent model of over- and underreaction based on conservatism and representativeness: agents react to random shocks and interpret them as phenomena of mean-reversion or continuation of a trend. These models, however, assume that the information shock is caused by true information, and are thus not applicable to fake news. To overcome this limitation, Fong (2021) postulates a model in which false information can also impact investor behaviour. This is closely related to the fact that false news can distort the perception of reality (Flynn et al., 2017) and that readers are generally attracted to sensationalism and scandal (Gibson & Zillmann, 1994; Lee et al., 2015; Shoemaker & Reese, 1996), which are typical traits of fake news stories (Vosoughi et al., 2018). Furthermore, psychological literature finds that people tend to focus on negative rather than positive information (Cianci & Falsetta, 2008; Ito et al., 1998; Kahneman & Tversky, 1979; Smith et al., 2006). Regarding the source of information, some researchers (e.g. Deng et al., 2018) show that investor sentiment expressed in social media impacts on stock returns; and other researchers (e.g., Antweiler & Frank, 2004; Dong & Gil-Bazo, 2020; Siganos et al., 2014; Sprenger et al., 2014) also use social media sentiment as a proxy for investor sentiment. In other words, it is implicitly assumed that sentiment is a type of information and is disseminated through social media.

False news can generate a misperception of the value of a firm, and thus mislead investors in their decision-making. In this regard, Dong et al. (2022) also find that, when information is disseminated, social media predicts absolute stock returns for a longer interval (from $t + 2$ to $t + 10$) while traditional media is predictive only for the next day. The misperception may be more serious for small firms, which are more vulnerable to problems of liquidity and media attention (Gutierrez & Stretcher, 2015), and in fact Kogan et al. (2021) find that the effect of the false news shock is stronger for the smaller firms in their sample. However, the implications for larger firms remain unexplored. Previous studies focused on a sample of fake news items announced by the target itself (Clarke et al., 2020; Kogan et al., 2021), but importantly our sample of items were produced by outsiders, possibly for other intents besides stock price manipulation. A firm may be targeted by an outsider because of divergent social and political opinions for example (Allcott & Gentzkow, 2017). But even if the reasons for dissemination are not economic it can still have financial implications for the targeted firm.

On the basis of these considerations, we postulate our research question as: *Do stock price returns of firms react to fake news produced by outsiders?*

3. Data and methodological framework

3.1. Data and sample description

In order to answer to our research question, we analyse a sample of fake news items. Collecting a sample of fake news items is complex, and previous studies adopt individual methods (see, e.g., Clarke et al., 2020; Kogan et al., 2021). In this study, we follow an approach similar to that of Ullah et al. (2014) and Li et al. (2018), but since we are investigating externally produced fake news items, we focus on fact-checking websites. Fact-checking has recently attracted attention in the journalistic ecosystem (Lowrey, 2017), and although its impact on popular opinion is as yet not determined, fact-checkers are an important source for combating the spread of fake news (Tandoc Jr., 2019). Three fact-checking websites are used to construct our dataset: "Snopes", "Politifact" and "Pagella Politica". They were selected for three important reasons. First, at the time of data collection, each fact-check was tagged by content which allowed us to collect all news items related to businesses. Second, they are recognised in the US and Europe (Graves & Cherubini, 2016; Jiang & Wilson, 2018; Walter et al., 2020) and in the communication literature (Nieminen & Rapeli, 2019). Third, they are assessed by the International Fact-Checking Network as fair and transparent fact-checking agencies (Jiang & Wilson, 2018).

All news items deemed false and tagged as related to firms were hand-collected from these three sources, yielding an initial sample of 233 fake news items. We also searched the LexisNexis database for all the fact-checked news, and for each item identified: date, name of the targeted firm, its economic sector,[6] the stock exchange where it is listed, the country where the fake news spread, and whether any other business or macroeconomic event occurred on the same day. Any other items of fake news found through the process of using LexisNexis were added to the dataset. All items had to meet all the following criteria: i) the news concerns at least one specific target firm; ii) the target firm is listed on an official stock exchange at the time of publication of the news; iii) the date of publication can be clearly identified; iv) there were no major and noticeable confounding events,[7] including earnings announcements and macroeconomic ones. These criteria were also used by Carlini et al. (2020).

In order to identify the type of information conveyed by the fake news items, i.e. positive, negative or neutral, each piece of news underwent manual content analysis. Bearing in mind the limitations of a methodology based on manual content analysis, we followed an approach common in the literature (Hussain et al., 2018; Xie et al., 2019), and calculated the "Krippendorff Alpha" (Hayes & Krippendorff, 2007) as a reliability measure. In particular, each fake news item is coded by two coders as "1" if it is considered to convey negative information, as "2" if it is considered to convey neutral information, and as "3" if it is considered to convey positive information. These data were used to calculate the alpha as a measure of inter-coder reliability. We obtain a bootstrapped mean with 1000 repetitions of 0.722, which is higher than the threshold value of 0.67 for useful conclusions (Hussain et al., 2018).

The final sample consisted of 149 fake news items appearing between 2007 and 2019 regarding 77 publicly listed companies.[8] Panel A of Table 1 shows the distribution of the fake news items classified according to the economic sector and geographic area of firms over the period 2007–2019.

Most of the sample (about 77%) is clustered in the period 2014–2019. This is probably because post-hoc fact checking as a discipline has developed only in recent years (Mantzarlis, 2018), particularly, after the 2016 US presidential elections and the Brexit referendum. Regarding the kind of information conveyed by the news, 111 (75%) news items are negative, 25 (16%) are positive, and 13 (9%) are neutral.[9] With reference to economic sectors,[10] "Services" has the highest number of observations, at 72, followed by "Manufacturing", with 65 observations, and "Financials", with 12 observations. One reason may be that "Services" includes tech companies, which were the favourite targets of fake news writers in our sample.[11] Our sample includes 21 fake news items (14%) published in Europe, and 128 (86%) published in the US. Panel B reports the classification according to the stock exchange where the targeted firm is listed. It shows that of the 128 US fake news items, 69 targeted NYSE listed firms and 59 targeted Nasdaq listed companies.

After collecting the sample of fake news items, we obtained from the Thomson Reuters Datastream database all the variables used in the analysis by means of the Mnemonic. Table 2 reports the market capitalization and the descriptive statistics of the variables related to the targeted firms. Panel A shows that average market capitalization grew from $63bn to $101bn in the period 2007–2019, although it slowed at the beginning of the 2008 financial crisis. We note that the mean market size of the firms in our sample is much bigger than those in previous literature. The average size in Clarke et al. (2020) is $41.3 ml, while for Kogan et al. (2021) it is $7.3 ml. It can, therefore, be presumed that our results should not be affected by bias in media attention, and it should thus be possible to generalise them, at least for negative items. Appendix A shows an example of each type of information conveyed by fake news.

Panel B reports descriptive statistics[12] of the variables used in the analysis, which are described in Appendix B. Our sample consists of firms showing good profitability, with an average ROA of 8.310. In addition, the firms in our sample tend to be overvalued, with an

[6] The 11 sectors and 24 industry-groups of the Global Industry Classification Standard (GICS) were used.

[7] While we control for any major confounding event as suggested by Ullah et al. (2021), eliminating every possible source of bias is deemed impossible without losing statistical power of the analysis (Eden et al., 2022). Moreover, as demonstrated by Sorescu et al. (2017), in short-term event studies it may be unnecessary to eliminate confounded observations and it may also introduce a larger bias if the initial sample size is already small, as is our case.

[8] The list is available on request.

[9] Consistently with main literature (See Li (2018) for a recent example) the neutral items subsample is restricted to news items with no clear indication of the type of information conveyed, and is therefore small (Zhang, 2018).

[10] Since we classify firms by sector using the 24 GICS Industry Groups, "Services" include Commercial & Professional Services, Transportation, Consumer Services, Retailing, Food & Staples Retailing, Healthcare Equipment & Services, Software & Services, Communication Services, Media & Entertainment; "Manufacturing" includes Energy, Materials, Capital Goods, Automobiles & Components, Consumer Durables & Apparel, Food Beverage & Tobacco, Household & Personal Products, Pharmaceuticals Biotechnology & Life Sciences, Technology Hardware & Equipment, Semiconductors & Semiconductor Equipment, Utilities; and "Financials" include Banks, Diversified Financials, Insurance, Real Estate.

[11] For example, Facebook, Apple and Alphabet together accounted for 21 fake news items, but many more tech companies are included in the sample.

[12] The number of observations is lower than 149 because two firms in the sample were in financial distress when the fake news was published and were thus excluded from the cross-section analysis.

Table 1
Descriptive Statistics of the fake news sample.

Panel A) Composition of fake news by year, economic sector and geographic area.

Year	Services	Financials	Manufacturing	US	Europe	Total
2007	2	0	0	2	0	2
2008	0	0	1	1	0	1
2009	0	0	1	1	0	1
2010	0	0	5	5	0	5
2011	0	1	5	4	2	6
2012	3	3	5	6	5	11
2013	3	1	3	5	2	7
2014	8	1	11	17	3	20
2015	11	1	7	19	0	19
2016	11	0	13	21	3	24
2017	14	3	5	18	4	22
2018	10	1	8	19	0	19
2019	10	1	1	9	3	12
Total	72	12	65	128	21	149

Note: The table shows the distribution of fake news items by economic sector and geographic area over the period 2007-2019.

Panel B) Composition of fake news by stock exchange.

Stock Exchange	Number of Fake News Items	% of the sample
NYSE	69	46.00%
Nasdaq	59	40.00%
BIT	13	8.67%
LSE	3	2.00%
Euronext	2	1.33%
MCX	2	1.33%
Nasdaq OMX	1	0.67%
Total	149	100%

Note: Panel A shows the distribution of fake news items by economic sector and geographic area over the period 2007-2019. Panel B shows the distribution of fake news by the stock exchange where the targeted firm is listed. NYSE is the New York Stock Exchange. Nasdaq is the National Association of Securities Dealers Automated Quotation. BIT is Borsa Italiana, the main Italian stock Exchange. LSE is the London Stock Exchange. Euronext is the European New Exchange Technology, the largest stock exchange in Europe. MCX is the Moscow Exchange, the largest exchange group in Russia. Nasdaq OMX is the Nasdaq Nordic, the common name of the Nasdaq subsidiaries that operate marketplaces for securities in the Nordic, Baltic and Caucasian regions of Europe.

average P/B ratio of 6.043, and highly leveraged, with a debt-to-equity ratio equal to 122.22 on average.

Appendix C reports the results of the correlation analysis in Table 1C this shows correlation values ranging from -0.419 to 0.542. This means that the variables are suitable for further analyses. These findings are confirmed by the Variance Inflation Factors (VIF) analysis shown in Table 2C: there are no variables showing VIF values above 10, so multicollinearity is not an issue in our sample (Allison, 1999).

3.2. Event study

Consistently with previous studies (Clarke et al., 2020; Kogan et al., 2021), we use event study methodology to evaluate the effect of fake news on stock prices, and whether this reaction varies according to type of information conveyed, i.e. positive, negative or neutral. This methodology is widely used in finance literature (Arcuri et al., 2018; Cappa et al., 2022; Pessarossi & Weill, 2013; Unsal et al., 2017), and is appropriate for investigating whether an informational event has a systematic effect on the value of a company, which could allow an investor to gain excess profits. This technique estimates abnormal returns following fake news made available to the market on day *t*. The publication of the fake news, thus, explains the changes in stock prices.

In order to estimate the impact of a fake news announcement, we need a measure of daily Abnormal Returns (AR). In essence, ARs are calculated as the stock return on a given day *t* minus the predicted "normal" return over the event window (EW). Following a standard approach, we use several EWs with different lengths. The EW is defined as the time period from $-\tau_1$ days before and $+\tau_2$ days after announcement of the fake news. The date of announcement is day 0. We assume that daily stock returns are consistent with Sharpe (1963) and estimate the market model for each security over a 250-day period, using an OLS regression as follows[13]:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \quad (1)$$

[13] Since our sample is heterogeneous in terms of both geography and sector, we implement three different regressions: the first using MSCI geographical indices (i.e. MSCI US, MSCI Europe and MSCI EM); the second using MSCI GICS sector indices and the third using MSCI GICS industry group indices. However, we present only the results from the first analysis, since the results of the other two regressions do not change substantially. All calculations are available from the authors on request.

Table 2
Market capitalization of targeted firms and descriptive statistics.

Panel A) Market capitalization.

Year	N	Average	St. Dev.	Median	Min	Max
2007	65	63,134.82	96,300.09	21,598.38	47.45	474,433.80
2008	65	59,557.35	90,200.89	18,053.67	21.61	463,960.90
2009	66	42,338.72	64,744.40	11,862.66	10.09	350,167.80
2010	66	47,182.85	66,240.85	15,171.38	33.63	278,359.40
2011	68	54,910.53	79,065.57	17,679.79	42.88	404,086.50
2012	71	53,842.87	89,913.44	15,224.54	34.99	524,560.30
2013	71	64,504.75	94,041.90	18,703.12	70.34	423,067.80
2014	73	70,940.96	102,258.20	25,301.48	52.51	541,507.00
2015	72	77,961.07	118,512.60	31,069.65	78.33	752,015.80
2016	75	74,235.87	110,482.42	21,964.42	58.18	539,307.30
2017	75	86,514.32	140,109.08	26,008.07	70.37	798,655.80
2018	74	100,085.32	178,962.07	27,420.87	66.61	935,055.80
2019	73	101,111.37	181,264.20	25,357.50	56.74	918,311.40

Panel B) Descriptive statistics of the firm characteristics.

	N	Mean	St. Dev.	Median	Min	Max
ROA	147	8.310	7.360	6.741	0.000	20.110
PBV	147	6.043	4.040	4.738	1.092	14.860
EPS	147	3.101	2.415	2.850	0.000	8.375
PE	147	32.703	19.420	36.702	0.000	123.550
LEV	147	122.222	74.720	132.789	0.000	402.430
BETA	147	0.963	0.967	0.459	0.325	1.747
SIZE	147	17.083	17.430	1.877	13.969	19.324
SIGMA	147	0.021	0.016	0.014	0.007	0.105
OWNERSHIP	102	0.223	0.172	0.160	0.05	0.520

Note: Panel A shows the descriptive statistics of the market capitalization (source: Thomson Reuters Datastream) of targeted firms over the period 2007-2019. The number of firms changes because some firms were delisted, and others were listed for the first time. Reported are: the number of targeted firms (N.), the mean (*Average*), the standard deviation (*St.Dev.*), the *Median*, the minimum (*Min*) and the maximum (*Max*), market capitalization value observed in each year. Data are in US$ million. Panel B shows the descriptive statistics of the control variables which are used in the econometric analysis. Reported are: the number of targeted firms (*N.*) the average (*Mean*), the standard deviation (*St.Dev.*), the *Median*, the minimum (*Min*) and the maximum (*Max*). Data in US$ million. N. is equal to 147 because two observations are not included in the OLS regression since they were in financial distress during the spread of the fake news.

where $R_{i,t}$ is the stock return of the targeted company *i* on day *t*, $R_{m,t}$ is the rate of return of the market portfolio on day *t*, α_i is the idiosyncratic risk component of stock *i*, β_i is the beta coefficient of stock *i* and $\varepsilon_{i,t}$ is the disturbance term. Using firm-specific parameters estimated with the market model,[14] the abnormal return is given by:

$$AR_{i,t} = R_{i,t} - (\widehat{\alpha}_i + \widehat{\beta}_i R_{m,t}) \tag{2}$$

To consider multiple-day periods, we compute Cumulative Abnormal Returns (CARs) for each stock *i* as the sum of the daily abnormal returns for all days *t* in the event window:

$$CAR_i(\tau_1, \tau_2) = \sum_{t=\tau_1}^{\tau_2} AR_{i,t} \tag{4}$$

where (τ_1, τ_2) is the EW. The average CAR for the event period (τ_1, τ_2) is given by:

$$\overline{CAR}(\tau_1, \tau_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(\tau_1, \tau_2) \tag{5}$$

where *N* is the number of events.

We test the statistical significance of the CARs. The first parametric test (T_1), described by Campbell et al. (1997), tests the hypothesis that the information newly available to the market has no impact on the CARs:

[14] As stated by Binder (1998), cross-sectional dependence is a minor problem when event dates are not "clustered" and securities are randomly chosen (i.e. come from different industries), as is in our case. To overcome the problem, we also use market model abnormal return estimates (Chandra et al., 1990).

$$T_1 = \frac{\overline{\mathrm{CAR}}(\tau1,\tau2)}{\sqrt{\widehat{\sigma}^2(\tau1,\tau2)}} \approx \mathcal{N}(0,1) \tag{6}$$

Harrington & Shrider (2007) demonstrate that T_1 can be biased in evaluating the statistical significance of CARs in the short term. To validate the results obtained through T_1, we thus perform a nonparametric sign test T_2 (Campbell et al., 1997; MacKinlay, 1997):

$$T_2 = \left[\frac{N^{(+/-)}}{N} - 0.5\right] \frac{\sqrt{N}}{0.5} \approx \mathcal{N}(0,1) \tag{7}$$

where N is the number of events and $N^{(+/-)}$ is the number of events with a positive or negative CAR. The null hypothesis states that fake news is not followed by statistically significant CARs. Therefore, the null hypothesis is rejected when a significant number of negative/ positive CARs are recorded. We define a statistically significant CAR as one that passes both T_1 and T_2.

3.3. Econometric model

To analyse the relationship between CARs following fake news and fake news and firms' characteristics we run block stepwise ordinary least square (OLS) regression. Our equation takes the following form:

$$CAR_i = \alpha + \beta_1 X_i + \beta_2 CONTROL_j + \beta_3 GEO_k + \beta_4 YEAR\_FE_{i,t} + \varepsilon_i \tag{10}$$

where i denotes the cross section of the fake news, t represents the time, and j and k indicate the firm and country, respectively. The dependent variable is the CAR that is derived from the event study results. We test two different models. In Model 1, the term X is the vector related to the information conveyed and the source of the fake news. We expect a negative (positive) item to have a negative (positive) impact on abnormal returns and neutral news items to have no impact. In Model 2, we add the term CONTROL for firm-specific variables. Specifically, we measure profitability using the return on assets (ROA) (Haugen & Baker, 1996). Market ratios considered are the Price-Book value (PBV), earnings per share (EPS) and Price-Earnings ratio (P/E) (Basu, 1977; Fama & French, 1992; Haugen & Baker, 1996). We assess riskiness through leverage and beta (Bhandari, 1988; Fama & French, 1992; Haugen & Baker, 1996). Among the firm characteristics, we add size (SIZE) and the standard deviation of the daily returns (SIGMA). These variables are measured at the fiscal year end of the year prior to the fake news being published. Moreover, all continuous variables are winsorized at 10% and 90% in order to deal with outliers. We include the business sector (i.e., manufacturing, services and financials) by using dummy variables. Model 2 also contains a geographical dummy variable to check whether there are differences between Europe and US, and a stock exchange dummy variable to verify whether the reaction changes according to the stock exchange (i.e. NYSE or Nasdaq). Table 1B in the Appendix summarizes all variables used in the econometric model. All the variables related to firms and market characteristics are obtained from Thomson Reuters Datastream.

4. Results

4.1. Event study results

To verify stock price reactions to fake news, we perform different analyses on the overall sample and on some subsamples. For the whole sample consisting of 149 fake news items on 77 publicly listed firms between 2007 and 2019, Table 3 shows that average CARs are negative in all EWs. This means that the fake news is negative information which leads to negative CARs. However, the most interesting result comes from the observation of the EW(0,1), one day after the publication of the news: this shows statistically significant CAR (at 90%) which is also economically significant at − 1.094%. Overall, we find that fake news has a negative impact on market returns, at least in the very short term.

Similarly to Li (2018), in order to discover whether different kinds of information conveyed triggers different reactions, we focus on three sub-samples: negative, positive and neutral news, as reported in Table 4. Focusing on negative news (Table 4, Panel A), our results show that CARs are all negative. Moreover, looking at the EWs after publication of negative fake news, three windows, (0,5), (0, 3) and (0,1), out of four are statistically and economically significant, showing returns of − 1.123%, − 1.667% and − 1.765% respectively. We therefore interpret significant results after the event date as evidence that negative fake news items can influence negatively stock returns in the short term, consistently with the literature (Clarke et al., 2020; Kogan et al., 2021). Looking at the other two subsamples (Table 4, Panels B and C), only half of the CARs are positive for positive news items, which conflicts with our predictions. The evidence seems to suggest that markets anticipate positive fake news, although in a negative manner: EW(−10,−1) and EW(−5,−1) are statistically and economically significant, showing mean CARs of − 4.144% and − 4.003%, respectively. While this may appear surprising, we note that the sample of positive items is very small and, thus, results might not be generalizable. As we show in Fig. 2, this effect might be related to a high volatility of the returns on the days prior to the publication of the fake news. Looking at EWs (0,5) and (0,1), however, there is a statistically significant reaction after the publication, which is positive, showing mean CARs of 1.374% and 1.252%, respectively. For the subsample of neutral news items, all CARs are positive, which is somewhat surprising, and, as in the case of negative news items, there appears to be a reaction on the market. So, these two subsamples partially confirm our previous finding that stock markets react to the publication of fake news. Note, however, that the two subsamples are too small to permit generalization of results.

Table 3
The impact of fake news on stock returns: the overall sample.

Event Window	Mean CAR	N. of news	T_1	T_2
(−10; 10)	-1.658%	149	-1.799 * *	1.229
(−5; 5)	-1.405%	149	-2.031 * *	0.901
(−3; 3)	-1.213%	149	-1.715 * *	0.573
(−1; 1)	-1.215%	149	-2.241 * *	-0.737
(−10; −1)	-1.146%	149	-1.755 * *	0.573
(−5; −1)	-0.874%	149	-1.628 *	1.229
(−3; −1)	-0.118%	149	-0.284	0.901
(0; 10)	-0.513%	149	-0.689	0.082
(0; 5)	-0.531%	149	-0.941	-0.410
(0; 3)	-1.095%	149	-1.974 * *	0.573
(0; 1)	-1.094%	149	-2.206 * *	1.557 *

Note: Table 3 reports the event study carried out on 149 fake news items about listed firms between 2007 and 2019. We measure the predicted normal firm returns using the market model. The CAR statistical significance is verified using two tests (T_1 and T_2) reported in Eqs. (6) and (7). * ** , * *, * denote statistical significance at 1%, 5% and 10% respectively (one tailed test).

Table 4
The impact of fake news on stock returns: the role of the information conveyed.

	Panel A: 111 negative news			Panel B: 25 positive news			Panel C: 13 neutral news		
Event Window	Mean CAR	T_1	T_2	Mean CAR	T_1	T_2	Mean CAR	T_1	T_2
(-10, 10)	-1.883%	-1.805**	1.424*	-3.306%	-1.255	-0.600	3.422%	1.653**	-0.832
(-5, 5)	-1.534%	-2.018**	1.424*	-2.628%	-1.202	-0.200	2.051%	1.508*	-1.387*
(-3, 3)	-1.747%	-2.247**	0.854	-0.098%	-0.042	-0.200	1.198%	1.483*	-0.832
(-1, 1)	-1.757%	-2.683***	0.285	0.517%	0.396	2.200**	0.086%	0.170	-0.277
(-10, -1)	-0.852%	-1.311*	-0.285	-4.144%	-1.804**	-2.200**	2.113%	1.133	-0.277
(-5, -1)	-0.411%	-0.828	1.044	-4.003%	-1.922**	-1.400*	1.195%	0.871	-0.832
(-3, -1)	-0.079%	-0.203	0.664	-0.766%	-0.451	-0.600	0.797%	0.901	0.277
(0, 10)	-1.031%	-1.089	0.854	0.839%	0.668	1.400*	1.309%	1.387*	-0.277
(0, 5)	-1.123%	-1.560*	1.424*	1.374%	1.527*	2.200**	0.856%	1.958**	-2.496***
(0, 3)	-1.667%	-2.459***	1.424*	0.668%	0.530	1.400*	0.401%	0.942	-0.277
(0, 1)	-1.765%	-2.804***	2.373***	1.252%	1.672**	1.400*	0.116%	0.284	0.277

Note: Table 4 reports event studies carried out on 149 fake news items about listed firms between 2007 and 2019. We define the type of information conveyed by each item by analysing the content of the fake news. We measure the predicted normal firm returns using the market model. The CAR statistical significance is verified using two tests (T_1 and T_2) reported in Equations (6) and (7). ***, **, * denote statistical significance at 1%, 5% and 10% respectively (one tailed test).

The results presented in Table 4 are also shown in Figs. 1–3. Fig. 1 shows the average abnormal returns for negative fake news items: they show that, on the day the fake news is given (i.e. day 0), abnormal returns are consistently negative, at almost − 2%. This confirms our initial insight that negative fake news items have a negative short-term impact on stock returns. Fig. 2 shows the average

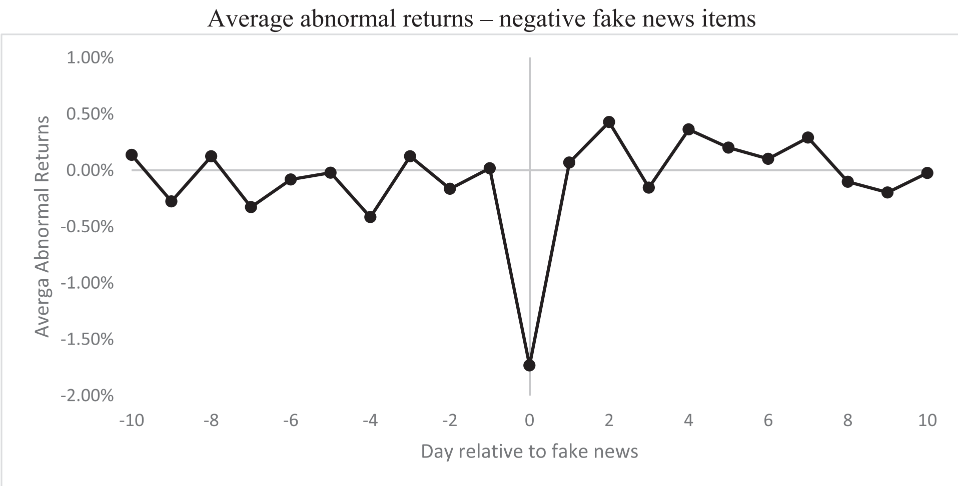

Fig. 1. The figure shows the day-by-day average abnormal returns for negative fake news items from 10 days before to 10 days after the publication of the fake news, obtained from the event study analysis.

daily abnormal returns for positive fake news items. In this case (as shown in Table 4), results are weaker: the effect of fake news items seems less pronounced and no clear trend can be observed. However, we can observe a positive average abnormal return, about 1%, on day 0. Lastly, Fig. 3 shows the average abnormal returns for neutral fake news items: this confirms the results of Table 4, which show no clear reaction to neutral items. Moreover, the returns themselves are also very small and range from a minimum of roughly − 0.3% to a maximum of 0.7%. These additional results seem to confirm our previous findings from the CARs analysis: the negative items have a clear negative impact on the returns, while the effect of positive and neutral items is bland and almost non-existent. However, in this case too, note that the small size of the samples of positive and neutral items may affect the results. These results, thus, seem to be in line with the psychological literature that finds that people tend to focus on negative rather than positive information (Smith et al., 2006).

Next, we group our news items by region, i.e. Europe and US, as shown in Table 5. In the European subsample (Table 5, Panel A), most of the CARs are negative and show low statistical significance. The only statistically and economically significant window is EW (0,5) showing a return equal to 2.029%. As above, however, the sample is very small, and the findings are thus not generalizable. For the US sample (Table 5, Panel B), significant CARs can be seen in the (−10,10) and (−5,5) EWs. It may be the case that in dynamic markets like the US, other factors impact stocks in such a long period. We thus perform an additional analysis on the US sample, using only the negative news items (Table 5, Panel C), since the majority of the sample is made up of items which convey negative information. This confirms our initial insight: symmetrical windows (−10, 10) and (−5,5) are still significant. US markets also react to fake news items. Asymmetrical EWs also match our expectations: EWs (0,5) and (0,1) have statistically and economically significant CARs, at − 1.463% and − 1.657% respectively. So overall, these findings suggest that both European and US markets react to fake news items.

The US subsample is then broken down into two further groups: stocks listed on New York Stock Exchange (NYSE) and stocks listed on Nasdaq. The aim is to investigate whether different market microstructures lead to different stock price reactions.[15] Table 6 shows the impact of negative fake news on NYSE and Nasdaq stocks. The analysis was also made on the whole sample of fake news, but since most of the sample is composed of negative fake news, results do not change substantially.

Table 6 Panel A shows that, like the complete US sample, NYSE stocks appear to react to false news: the event windows (−5,5), (−3,3), (0,5) and (0,1) are all statistically significant and show mean CARs equal to − 1.910%. − 1.962%. − 2.094% and − 2.041%, respectively.

Looking at the Nasdaq sample (Table 6 Panel B), we find that no symmetrical EWs show economically and statistically significant abnormal returns. Moreover, Nasdaq also shows no significant EWs after the publication of the fake news, unlike NYSE, which has two significant EWs out of four.

Finally, we investigate whether there are differences between different types of news sources. To do this, we focus on two different sub-samples: items published by social media (e.g. social networks and blogs) and items published by official sources (e.g. newspapers and business wires), because similarly to what happens with official news items (Soroka et al., 2018), markets may react in different ways to the two kinds of medium.[16] Table 7 shows that items from both sources generate negative abnormal returns in the short term, even though, consistently with Li (2018), the impact of official sources appear a little stronger. We note, however, that in the case of official media items, the sample is very small, and results might not be generalizable.

4.1.1. Econometric results

To analyse the link between stock market returns and fake news, we use the CARs obtained from the event study analysis as dependent variables in regression models. In particular, we regress on the CARs from the Event Windows (0, 1) and (−1, 1). We focus on the shortest windows because, as we noted in the event study analysis, fake news items tend to impact stock returns in the short term. Table 10 reports the results of Models 1 and 2 for Event Windows (−1,1) and (0,1).

As far as the type of information conveyed is concerned, Model 1 shows that a fake news item conveying neutral information seems to have no impact on stock returns while a negative (positive) fake news item affects negatively (positively) abnormal returns, although these effects seem to appear in the very short term, only until the day after announcement of the fake news. In particular, for negative news items related to firms traded on the NYSE, we observe abnormal returns which range between − 0.08 to − 0.24. This effect seems to be counterbalanced in the shortest event window by the effect of the positive news items, which decrease this impact by 0.032. We observe no significant difference between sources.

Adding firm and market characteristics, as in Model 2, yields three interesting insights. First, only negative items seem to have an impact, while positive and neutral items do not show a significant coefficient. Second, size affects abnormal returns positively, and larger size appears to help firms to counteract the negative effects of fake news. This confirms the findings by Kogan et al. (2021) that false information has more impact on small firms than on big ones. Third, the effects of fake news seem to be stronger for manufacturing and financial firms.

Model 2 also includes regional and market dummy variables to capture any differences between Europe and the US, and between NYSE and Nasdaq. None of the variables are statistically significant: the country of origin and stock exchange on which the security is listed appear to have no effect. This is consistent with the findings of the event study in Section 4.1, that European and US markets react in similar ways to fake news.Table 8.

[15] As noted by Greene & Watts (1996), different microstructures may account for different price discovery processes once news is announced.

[16] Appendix D lists all the official and social media sources.

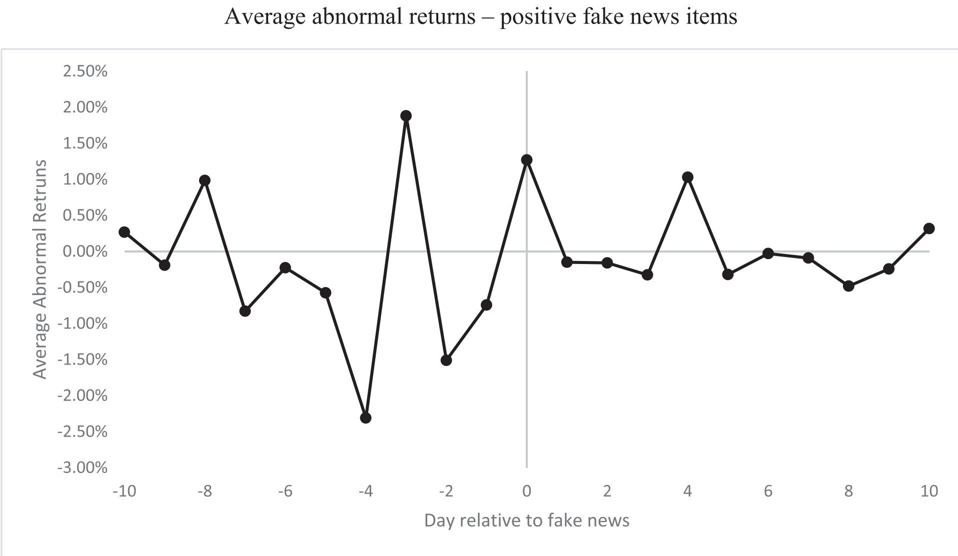

Fig. 2. The figure shows the day-by-day average abnormal returns for positive fake news items from 10 days before to 10 days after the publication of the fake news, obtained from the event study analysis.

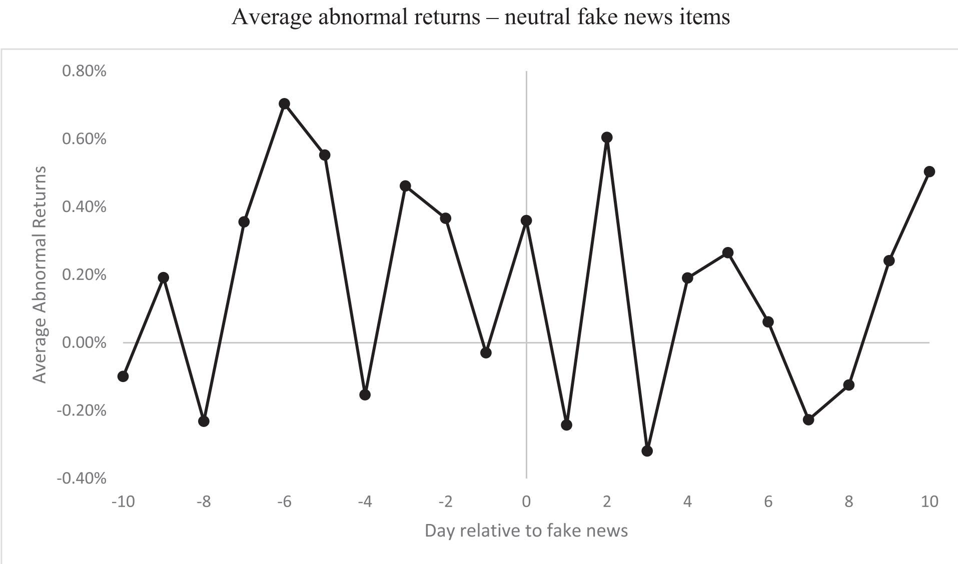

Fig. 3. The figure shows the day-by-day average abnormal returns for neutral fake news items from 10 days before to 10 days after the publication of the fake news, obtained from the event study analysis.

4.1.2. Additional tests

We repeat the same analysis on the Event Windows (−3, −1), (−3,3), (0,3), (−5, −1), (−5, 5) and (0, 5) to check whether the fake news items have a more lasting effect on abnormal returns (Table 9). The results confirm our previous findings that in general, fake news items tend to show their effects in the very short term. Overall, consistently with the previous literature (Clarke et al., 2020; Kogan et al., 2021; Ullah et al., 2014), we find evidence that markets do react to the publication of fake news in the short term. We also observe that there are no significant differences in the reactions between Nasdaq and NYSE.

We further test the robustness of our main model by running Models 1 and 2 on a sample in which the fake news items related to Alphabet, Apple and Facebook are excluded. These three firms in fact account for 21 items out of 147, and our results may be skewed by their presence. The results in Table 10 mostly confirm our results; items which convey negative (positive) information have a negative (positive) impact on CARs. The observations made above on size and the financial sector are confirmed.

As a final additional test, we also control for the percentage of total shares held by institutional investors (OWNERSHIP). Institutional investors are said to behave more rationally than retail investors, as they tend to be better informed (Park et al., 2014) and,

Table 5
The impact of fake news on stock returns: the effect on European and US firms.

	European firms			US firms					
	Panel A: 21 news items			Panel B: All 128 news items			Panel C: 102 negative news items		
Event Window	Mean CAR	T_1	T_2	Mean CAR	T_1	T_2	Mean CAR	T_1	T_2
(−10, 10)	0.334%	0.136	-0.655	-1.985%	-2.003 * *	1.591 *	-2.003%	-1.854 * *	1.584 *
(−5, 5)	0.322%	0.154	-1.091	-1.688%	-2.329 * **	1.414 *	-1.850%	-2.317 * *	1.782 * *
(−3, 3)	-2.651%	-1.176	0.655	-0.977%	-1.332 *	0.354	-1.641%	-1.977 * *	0.792
(−1, 1)	-1.647%	-0.952	-0.218	-1.144%	-2.031 * *	-0.707	-1.619%	-2.340 * **	0.000
(−10, −1)	-2.285%	-0.989	0.655	-0.959%	-1.459 * *	0.354	-0.624%	-1.044	-0.198
(−5, −1)	-1.708%	-0.895	0.218	-0.737%	-1.365 *	1.237	-0.387%	-0.782	1.188
(−3, −1)	-1.475%	-0.886	0.655	0.104%	0.264	0.707	-0.073%	-0.200	0.594
(0, 10)	2.619%	1.123	-1.964 * *	-1.027%	-1.337 *	0.884	-1.379%	-1.487 *	0.990
(0, 5)	2.029%	1.528 *	-1.964 * *	-0.951%	-1.554 *	0.354	-1.463%	-1.987 * *	1.584 *
(0, 3)	-1.176%	-0.774	0.218	-1.082%	-1.816 * *	0.530	-1.568%	-2.173 * *	1.188
(0, 1)	-0.663%	-0.601	1.091	-1.165%	-2.126 * *	1.237	-1.657%	-2.471 * **	1.980 * *

Note: Table 5 reports event studies carried out on 149 fake news items about listed firms between 2007 and 2019. We measure the predicted normal firm returns using the market model. The CAR statistical significance is verified using two tests (T1 and T2) reported in Eqs. (6) and (7). * ** , * *, * denote statistical significance at 1%, 5% and 10% respectively (one-tailed test).

Table 6
The impact of fake news on stock returns: the effect on NYSE and Nasdaq firms.

	Panel A: 56 NYSE news items			Panel B: 46 Nasdaq news items		
Event Window	Mean CAR	T_1	T_2	Mean CAR	T_1	T_2
(-10, 10)	-1.019%	-0.628	1.336*	-3.201%	-2.405***	0.885
(-5, 5)	-1.910%	-2.220**	1.871**	-1.777%	-1.245	0.590
(-3, 3)	-1.962%	-1.925**	1.336*	-1.250%	-0.922	-0.295
(-1, 1)	-2.068%	-2.507***	0.802	-1.073%	-0.929	-0.885
(-10, -1)	0.327%	0.407	-0.535	-1.781%	-2.056**	0.295
(-5, -1)	0.184%	0.301	0.802	-1.081%	-1.364*	0.885
(-3, -1)	0.009%	0.020	0.535	-0.172%	-0.288	0.295
(0, 10)	-1.345%	-0.925	0.802	-1.419%	-1.359*	0.590
(0, 5)	-2.094%	-2.359***	1.604*	-0.696%	-0.572	0.590
(0, 3)	-1.971%	-2.099**	0.802	-1.078%	-0.967	0.885
(0, 1)	-2.041%	-2.476***	1.336*	-1.190%	-1.089	1.474*

Note: Table 6 reports event studies carried out on 102 negative fake news items about firms listed on NYSE and Nasdaq between 2007 and 2019. We measure the predicted normal firm returns using the market model. The CAR statistical significance is verified using two tests (T_1 and T_2) reported in Equations (6) and (7). ***, **, * denote statistical significance at 1%, 5% and 10% respectively (one-tailed test).

Table 7
The impact of fake news on stock returns: the role of source.

	Panel A: 85 social media items			Panel B: 26 official media items		
Event Window	Mean CAR	T_1	T_2	Mean CAR	T_1	T_2
(−10, 10)	-1.816%	-2.011 * *	1.410 *	-2.102%	-0.631	0.392
(−5, 5)	-1.345%	-1.504 *	0.976	-2.152%	-1.533 *	1.177
(−3, 3)	-1.174%	-1.287 *	0.108	-3.620%	-2.596 * **	1.569 *
(−1, 1)	-1.486%	-1.916 * *	-0.325	-2.641%	-2.279 * *	1.177
(−10, −1)	-0.588%	-0.826	-0.108	-1.715%	-1.145	-0.392
(−5, −1)	-0.210%	-0.383	1.410 *	-1.071%	-0.945	-0.392
(−3, −1)	0.141%	0.342	0.759	-0.799%	-0.830	0.000
(0, 10)	-1.228%	-1.359 *	0.542	-0.387%	-0.140	0.784
(0, 5)	-1.135%	-1.365 *	0.759	-1.082%	-0.756	1.569 *
(0, 3)	-1.315%	-1.631 *	0.759	-2.820%	-2.408 * **	1.569 *
(0, 1)	-1.689%	-2.209 * *	1.627 *	-2.010%	-2.051 * *	1.961 * *

Note: Table 7 reports event studies carried out on 111 negative fake news items divided according to source. We measure the predicted normal firm returns using the market model. The CAR statistical significance is verified using two tests (T_1 and T_2) reported in Eqs. (6) and (7). * ** , * *, * denote statistical significance at 1%, 5% and 10% respectively (one-tailed test).

thus, less influenced by attention-grabbing events (Li et al., 2017). As a consequence, we should observe that a higher percentage of institutional ownership counterbalances the effect of fake news events on the cumulative returns.

Table 11 shows the effect of institutional ownership on CARs. Although most previous findings are confirmed, when institutional

Table 8
The impact of fake news on CARs.

	Model 1		Model 2	
	CAR(0,1)	CAR(-1,1)	CAR(0,1)	CAR(-1,1)
Constant	-0.096**	-0.088*	-0.190**	-0.242***
	(0.047)	(0.049)	(0.079)	(0.080)
POS	0.032*	0.029	0.031	0.025
	(0.019)	(0.020)	(0.020)	(0.021)
NEU	0.016	0.010	0.011	0.005
	(0.020)	(0.021)	(0.021)	(0.021)
OFF	0.002	-0.009	0.012	0.009
	(0.015)	(0.016)	(0.016)	(0.017)
ROA			0.001	0.001
			(0.001)	(0.001)
PBV			-0.001	-0.002
			(0.002)	(0.002)
EPS			-0.000	-0.001
			(0.003)	(0.003)
PE			0.000	0.000
			(0.000)	(0.000)
LEV			0.000**	0.000***
			(0.000)	(0.000)
BETA			-0.002	0.000
			(0.015)	(0.015)
SIZE			0.005	0.008**
			(0.004)	(0.004)
SIGMA			0.461	0.750
			(0.456)	(0.465)
FIN			-0.094***	-0.109***
			(0.027)	(0.028)
SECT			-0.024*	-0.028**
			(0.013)	(0.013)
Country			-0.010	-0.021
			(0.021)	(0.021)
Nasdaq			-0.001	0.006
			(0.013)	(0.013)
Year_FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.059	0.020	0.102	0.121
N	147	147	147	147

Note: This table shows results of Models 1 and 2. Our dependent variables are estimated CARs in the event windows (-1,1) and (0,1). In Model 1 independent variables are related to information conveyed and the type of the medium: POS are positive items; NEU are neutral items; OFF are items published by an official source. Model 2 adds to Model 1 some firm-specific and market-specific characteristics: ROA is the ratio between net income and total assets; ROE is the ratio between net income and total equity; PBV is the ratio between the stock market price and the book value of firm equity; EPS is calculated dividing firm profits by the number of common stocks outstanding; P/E is the ratio between firm's stock price and the firm's earnings per share; LEV is the debt to equity ratio; BETA is measured as the covariance of firm stock returns to stock market return; SIZE is the natural logarithm of the firm's total assets; FIN is a dummy variable equal to 1 if the firm belongs to the financial sector, 0 otherwise; SECT is a dummy variable equal to 1 if the firm is in the manufacturing sector, 0 otherwise; Country is a dummy variable equal to 1 if the firm is located in Europe, 0 if it is located in the US; Nasdaq is a dummy variable equal to 1 if the firm is listed on Nasdaq, 0 if it is listed on NYSE. Finally, ***, **, * denote the statistical significance at 1%, 5% and 10%, respectively. Standard errors are reported in parentheses.

ownership is added to the model, the short-term impact of positive items becomes non-significant. However, there is still a significant and negative impact of negative fake news items on cumulative abnormal returns.

The fact that the relationship observed with the amount of institutional ownership is non-significant can probably be explained by the fact that institutional investors are not immune to the typical psychological biases that plague retail investors, as found by a recent stream of literature (Jaiyeoba et al., 2018). In fact, as demonstrated in the behavioural finance literature (e.g., Ahmed, 2014; Jaiyeoba et al., 2020), institutional investors are prone to herding behaviour and can be affected by sensational events. This might explain the insignificant relationship found here between institutional ownership and abnormal returns.

5. Discussion and conclusions

Information is crucial in today's world, and social media platforms have changed the way it is created and shared. Matsa & Shearer (2018) note that almost 68% of Americans keep up with the news through social networks. This is alarming from two points of view. On the one hand, it shows that people are losing faith in traditional media outlets (Allcott & Gentzkow, 2017). On the other hand, even more worryingly, we are faced with the rise of organizations and individuals who deliberately disseminate false information in order to impact on politics or the financial world. It is widely acknowledged that "fake news" spreads easily and quickly, particularly on social media platforms. When fake news moves from the world of social media to the world of business and finance, the consequences can be

Table 9
Additional tests on longer CARs.

	Model 1			Model 2			Model 1			Model 2		
	CAR(-3,-1)	CAR(-3,3)	CAR(0,3)	CAR(-3,1)	CAR(-3,3)	CAR(0,3)	CAR(-5,-1)	CAR(-5,5)	CAR(0,5)	CAR(-5,-1)	CAR(-5,5)	CAR(0,5)
Constant	0.003	-0.109*	-0.112**	0.022	-0.248**	-0.271***	0.032	-0.079	-0.112**	0.033	-0.159	-0.192**
	(0.038)	(0.066)	(0.049)	(0.064)	(0.109)	(0.082)	(0.044)	(0.063)	(0.047)	(0.077)	(0.108)	(0.081)
POS	0.006	0.037	0.030	0.006	0.027	0.021	-0.039**	-0.013	0.027	-0.040**	-0.017	0.023
	(0.015)	(0.026)	(0.020)	(0.016)	(0.028)	(0.021)	(0.018)	(0.025)	(0.019)	(0.020)	(0.028)	(0.021)
NEU	0.008	0.024	0.015	0.021	0.029	0.008	0.014	0.021	0.008	0.013	0.017	0.004
	(0.016)	(0.028)	(0.021)	(0.017)	(0.029)	(0.022)	(0.019)	(0.027)	(0.020)	(0.020)	(0.028)	(0.021)
OFF	-0.008	-0.012	-0.005	-0.001	0.014	0.016	-0.016	-0.013	0.004	-0.015	-0.007	0.008
	(0.012)	(0.021)	(0.016)	(0.013)	(0.022)	(0.017)	(0.014)	(0.020)	(0.015)	(0.016)	(0.022)	(0.017)
ROA				-0.001	0.001	0.002				-0.002	-0.001	0.001
				(0.001)	(0.002)	(0.001)				(0.001)	(0.002)	(0.001)
PBV				-0.000	-0.002	-0.001				0.000	-0.002	-0.002
				(0.001)	(0.002)	(0.002)				(0.002)	(0.002)	(0.002)
EPS				0.001	-0.002	-0.003				0.002	-0.000	-0.002
				(0.002)	(0.004)	(0.003)				(0.003)	(0.004)	(0.003)
PE				-0.000	-0.000	-0.000				0.000	-0.000	-0.000
				(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
LEV				0.000	0.000**	0.000**				0.000	0.000*	0.000*
				(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
BETA				-0.009	0.007	0.016				-0.008	-0.010	-0.002
				(0.012)	(0.020)	(0.015)				(0.014)	(0.020)	(0.015)
SIZE				-0.001	0.007	0.008*				0.001	0.006	0.005
				(0.003)	(0.005)	(0.004)				(0.004)	(0.005)	(0.004)
SIGMA				0.580	1.017	0.437				0.315	0.996	0.681
				(0.369)	(0.632)	(0.477)				(0.448)	(0.626)	(0.472)
FIN				0.008	-0.080**	-0.087***				-0.049*	-0.094**	-0.045
				(0.022)	(0.038)	(0.028)				(0.027)	(0.037)	(0.028)
SECT				-0.018*	-0.048***	-0.030**				-0.016	-0.028	-0.013
				(0.010)	(0.018)	(0.014)				(0.013)	(0.018)	(0.013)
Country				-0.037**	-0.061**	-0.023				-0.002	-0.001	0.001
				(0.017)	(0.029)	(0.022)				(0.020)	(0.028)	(0.021)
Nasdaq				0.014	0.015	0.001				0.008	0.013	0.005
				(0.011)	(0.018)	(0.014)				(0.013)	(0.018)	(0.013)
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.028	0.000	0.057	0.057	0.047	0.117	0.189	0.003	0.167	0.167	0.010	0.159
N	147	147	147	147	147	147	147	147	147	147	147	147

Note: This table shows results of Models 1 and 2. Our dependent variables are estimated CARs in the Event Windows (-3,3), (-3,-1), (0,3), (-5,5), (-5,-1) and (0,5). In Model 1 independent variables are related to information conveyed and the type of medium: POS are positive items; NEU are neutral items; OFF are items published by an official source. Model 2 adds to Model 1 some firm-specific and market-specific characteristics: ROA is the ratio between net income and total assets; ROE is the ratio between net income and total equity; PBV is the ratio between the stock market price and the book value of firm equity; EPS is calculated dividing firm profits by the number of common stocks outstanding; P/E is the ratio between firm's stock price and the firm's earnings per share; LEV is the debt to equity ratio; BETA is measured as the covariance of firm stock returns to stock market return; SIZE is the natural logarithm of the firm's total assets; FIN is a dummy variable equal to 1 if the firm in the financial sector, 0 otherwise; SECT is a dummy variable equal to 1 if the firm is in the manufacturing sector, 0 otherwise; Country is a dummy variable equal to 1 if the firm is located in Europe, 0 if it is located in the US; Nasdaq is a dummy variable equal to 1 if the firm is listed on Nasdaq, 0 if it is listed on NYSE. Finally, ***, **, * denote the statistical significance at 1%, 5% and 10%, respectively. Standard errors are reported in parentheses.

Table 10
Additional test by excluding the most targeted firms.

	Model 1		Model 2	
	CAR(0,1)	CAR(-1,1)	CAR(0,1)	CAR(-1,1)
Constant	-0.086*	-0.086	-0.232***	-0.245***
	(0.048)	(0.054)	(0.081)	(0.090)
POS	0.038*	0.029	0.038*	0.028
	(0.021)	(0.023)	(0.022)	(0.024)
NEU	0.013	0.008	0.004	0.002
	(0.022)	(0.025)	(0.022)	(0.025)
OFF	-0.008	-0.010	0.007	0.009
	(0.017)	(0.019)	(0.018)	(0.020)
ROA			0.002	0.001
			(0.001)	(0.001)
PBV			-0.002	-0.002
			(0.002)	(0.002)
EPS			-0.001	-0.001
			(0.003)	(0.004)
PE			0.000	0.000
			(0.000)	(0.000)
LEV			0.000**	0.000**
			(0.000)	(0.000)
BETA			0.002	-0.001
			(0.015)	(0.017)
SIZE			0.008**	0.009**
			(0.004)	(0.004)
SIGMA			0.383	0.744
			(0.461)	(0.511)
FIN			-0.092***	-0.113***
			(0.027)	(0.030)
SECT			-0.019	-0.029*
			(0.014)	(0.016)
Country			-0.007	-0.023
			(0.021)	(0.024)
Nasdaq			0.010	0.011
			(0.016)	(0.017)
Year_FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.066	0.014	0.130	0.106
N	126	126	126	126

Note: This table replicates the analysis in Table 8 by excluding from the sample the fake news items related to Alphabet, Apple and Facebook. Our dependent variables are estimated CARs in the Event Windows (-1,1) and (0,1). In Model 1 independent variables are related to information conveyed and the type of the medium: POS are positive items; NEU are neutral items; OFF are items published by an official source. Model 2 adds to Model 1 some firm-specific and market-specific characteristics: ROA is the ratio between net income and total assets; ROE is the ratio between net income and total equity; PBV is the ratio between the stock market price and the book value of firm equity; EPS is calculated dividing firm profits by the number of common stocks outstanding; P/E is the ratio between firm's stock price and the firm's earnings per share; LEV is the debt to equity ratio; BETA is measured as the covariance of firm stock returns to stock market return; SIZE is the natural logarithm of the firm's total assets; FIN is a dummy variable equal to 1 if the firm belongs to the financial sector, 0 otherwise; SECT is a dummy variable equal to 1 if the firm is in the manufacturing sector, 0 otherwise; Country is a dummy variable equal to 1 if the firm is located in Europe, 0 if it is located in the US; Nasdaq is a dummy variable equal to 1 if the firm is listed on Nasdaq, 0 if it is listed on NYSE. Finally, ***, **, * denote the statistical significance at 1%, 5% and 10%, respectively. Standard errors are reported in parentheses.

serious: it can, in fact, burn billions of dollars in seconds. Starting from this consideration, this study investigates whether fake news systematically impacts on financial markets. On the basis of a sample of fake news items announced between 2007 and 2019, in both Europe and the US, we assess the impact of false information on stock markets, using two different empirical methods: an event study and a multivariate OLS regression on abnormal returns.

We find that, in general, stock markets react to false information, at least in the very short term, and that false negative information causes a negative response, while false positive information causes a positive response. However, our results show that there is a reaction to false information, but the reaction tends to evaporate quite quickly: in less than a week for negative items, and just a day for positive ones. This finding is consistent with psychology literature that demonstrates that people tend to pay more attention to negative than positive information (Smith et al., 2006). We also find that, at least in our sample, there is no discernible difference between items from official sources of news and items from social media. This could reflect the fact that social media attracts attention to a topic and this same attention makes people likely to find out more about the topic in traditional media (Ren et al., 2022). Our results also show that financial companies are more heavily penalized by investors when fake news appears. For the financial industry this implies that the scars from the 2008 crisis are not completely healed and there is still a great deal to do in restoring trust in financial institutions.

Given that fake news is by definition not true, it could be argued that in reality it does not have any informational value. But especially in the case of non-professional investors, the absence of informational content may be difficult to discern. Holthausen &

Table 11
Additional test including institutional ownership.

	Model 2	
	CAR(0,1)	CAR(-1,1)
Constant	-0.210**	-0.224**
	(0.100)	(0.112)
POS	0.014	0.014
	(0.029)	(0.033)
NEU	-0.004	-0.000
	(0.026)	(0.029)
OFF	0.020	0.011
	(0.021)	(0.023)
ROA	0.001	0.001
	(0.001)	(0.002)
PBV	-0.003	-0.004
	(0.002)	(0.002)
EPS	0.000	0.001
	(0.004)	(0.004)
PE	-0.000	0.000
	(0.000)	(0.000)
LEV	0.000***	0.000***
	(0.000)	(0.000)
BETA	-0.008	-0.011
	(0.019)	(0.021)
SIZE	0.007	0.007
	(0.005)	(0.006)
SIGMA	0.870	1.494*
	(0.714)	(0.797)
FIN	-0.161***	-0.185***
	(0.036)	(0.041)
SECT	-0.024	-0.029
	(0.017)	(0.019)
Country	-0.024	-0.034
	(0.025)	(0.028)
Nasdaq	0.003	0.010
	(0.019)	(0.021)
OWNERSHIP	-0.048	-0.003
	(0.051)	(0.057)
Year_FE	Yes	Yes
Adjusted R^2	0.210	0.158
N	102	102

Note: This table replicates the analysis in Table 8 by including among the control variables the percentage of institutional ownership. Our dependent variables are estimated CARs in the Event Windows (-1,1) and (0,1). In Model 1 independent variables are related to information conveyed and the type of the medium: POS includes positive items; NEU includes neutral items; OFF includes items published by an official source. Model 2 adds to Model 1 some firm-specific and market-specific characteristics: ROA is the ratio between net income and total assets; ROE is the ratio between net income and total equity; PBV is the ratio between the stock market price and the book value of firm equity; EPS is calculated dividing firm profits by the number of common stocks outstanding; P/E is the ratio between firm's stock price and the firm's earnings per share; LEV is the debt to equity ratio; BETA is measured as the covariance of firm stock returns to stock market return; SIZE is the natural logarithm of the firm's total assets; FIN is a dummy variable equal to 1 if the firm belongs to the financial sector, 0 otherwise; SECT is a dummy variable equal to 1 if the firm is in the manufacturing sector, 0 otherwise; Country is a dummy variable equal to 1 if the firm is located in Europe, 0 if it is located in the US; Nasdaq is a dummy variable equal to 1 if the firm is listed on Nasdaq, 0 if it is listed on NYSE; OWNERSHIP is the percentage of total shares held by institutional investors. Finally, ***, **, * denote the statistical significance at 1%, 5% and 10%, respectively. Standard errors are reported in parentheses.

Verrecchia (1990) find that information affects both the knowledge about a security's value and the degree of agreement of investors on the true value of the same security. Given the ambiguity of the information conveyed by fake news, we argue that the observed impact on the stock returns is related to the increase in the disagreement between investors on this informational content. Some investors might, in fact, value the information, while others might be able to distinguish between genuine and fake information.

Using a novel sample of fake news produced by outsiders, our study contributes to the literature on the effects of misinformation on financial markets through the lens of behavioural finance. An impact of fake news on stock returns is observed, but it appears to be short-termed and mostly observable for negative fake news items. This reflects the implications of the disagreement models (Hong & Stein, 2007) in which each investor has different priors about different securities. Since the “informational” content of fake news items is not inferred by all market participants, there is disagreement among investors, and as a consequence the fake news impacts on stock returns.

Our paper also provides important insights for practitioners. In a context where a better understanding of financial market behaviour is required (Clare et al., 2016), and knowing that fake news can impact on stock returns, authorities would be well-advised to promote monitoring of the web and social media in order to intercept ahead of time information-based manipulations. This implies that there is need for regulatory countermeasures to restore trust in financial markets, in order to mitigate the effects of this side of reputational risk.

The study, however, is not without shortcomings. Many subsamples were too small for results to be generalized. Comparison with a sample of genuine news items would make clearer the effects of information which is fake. Taking into account these limitations, further analyses should consider larger samples of European fake news items as well as larger samples of positive and neutral fake news. Banks and insurance companies are, in fact, more vulnerable to operational and reputational risks, and given that our sample contains a small number of financial firms, it would also be interesting to focus on the financial industry in future research. The virality of exposure to fake news meant it was not possible to measure its magnitude, but a further extension of this research would be to investigate what type of investor, i.e. retail or institutional, is more vulnerable to fake news items. Previous studies identifying retail trading activities are often based on proprietary datasets (e.g., Kaniel et al., 2008; Kaniel et al., 2012), which were not available to us. Further research could elaborate on these points.

In conclusion, we provide insight on the financial impact of fake news and take an additional step towards understanding the implications of fake news for society and for financial markets especially. Fake news is becoming increasingly common and impacting on firms as part of a broader definition of operational risk. Investors need to be aware of this in making business and investment decisions, and effective countermeasures need to be put in place.

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Declaration of Competing Interest

None.

Appendix A

Below, we report a sample of fake news for each kind of information conveyed, i.e. negative, positive and neutral.

Negative fake news.

Source: Snopes. Date: 22/07/2017.

Walmart has been adding a "phantom charge" of $10 to shoppers’ bills for 10 years.

> *“On 22 July 2017, a Facebook user claimed (in a since-deleted post) that Walmart had added a “phantom charge” of $10 to her bill for an item she hadn’t purchased, which was listed as a “JAJKET” on her receipt”.*

We classify this news as negative - the Facebook post claims that Walmart has been charging customers for years for extras they did not ask for.

Positive fake news.

Source: Politifact. Date: 02/05/2010.

BP recommends improvements around safety regulations.

> *“A letter from BP to the Minerals Management Service < <actually recommends improvements and specific recommendations around safety regulations should they choose to change them.> >"*

We classify this news as positive since BP is appears to be requesting stronger safety regulations. However, as Politifact notes, the letter actually suggests ways to make regulation less of a burden for BP.

Neutral fake news.

Source: Snopes. Date: 18/01/2018.

Facebook CEO Mark Zuckerberg bought a "super-yacht" for $150 million.

> *“An English-language Turkish newspaper published — then quickly scrubbed — a 18 January 2018 story reporting that Facebook CEO Mark Zuckerberg had made an extravagant purchase in Monaco.”*

We classify this news as neutral since the purchase of a yacht by the CEO of a company does not convey any specific positive or negative information.

Appendix B

Table 1B
Description of Variables.

Variables	Symbol	Description
CAR (−1,1)	*CAR (−1,1)*	Cumulative abnormal return in the period from 1 day before to 1 day after news publication.
CAR (0,1)	*CAR (0,1)*	Cumulative abnormal return in the period from publication day to 1 day after news publication.
Negative	*NEG*	Dummy variable, i.e. NEG = 1 if the fake news conveys negative information; NEG = 0 otherwise.
Positive	*POS*	Dummy variable, i.e. POS = 1 if the fake news conveys positive information; POS = 0 otherwise.
Neutral	*NEU*	Dummy variable, i.e. NEU = 1 if the fake news conveys neutral information; NEU = 0 otherwise.
Official	*OFF*	Dummy variable, i.e. OFF = 1 if the fake news was initially published by an official source; OFF = 0 otherwise.
ROA	*ROA*	Calculated as the ratio between net income and total assets.
Price-Book value	*PBV*	Measured as the ratio between the stock market price and the book value of firm equity.
Earnings per share	*EPS*	Calculated by dividing firm profits by the number of common stocks outstanding.
Price-earnings ratio	*P/E*	Measured as the ratio between firm's stock price and the firm's earnings per share.
Leverage	*LEV*	Calculated as the ratio between total debt and total equity.
Beta	*BETA*	Expresses firm systematic risk, measured by the covariance of firm stock returns to stock market return.
Firm size	*SIZE*	Calculated as the natural logarithm of the firm's total assets.
Sigma	*SIGMA*	This is the standard deviation of the daily returns.
Financials	*FIN*	Dummy variable, i.e. FIN = 1 if the firm belongs to the financial sector; FIN = 0 otherwise.
Sector	*SECT*	Dummy variable, i.e. SECT = 1 if the firm is in the manufacturing sector; SECT = 0 if the firm is in the services sector.
Country	*Country*	Dummy variable, i.e. Country = 1 if the firm is located in Europe; Country = 0 if the firm is located in the US.
Nasdaq	*Nasdaq*	Dummy variable, i.e. Nasdaq = 1 if the firm is listed on Nasdaq; Nasdaq = 0 if the firm is listed on NYSE.
Institutional ownership	*OWNERSHIP*	This is a variable representing the percentage of total shares held by institutional investors, such as pension funds or investment banks.

Note: The table describes the variables used in the econometric model reported in Equation (10). All variables pertaining to the CONTROL vector are measured at fiscal year-end of the year prior to the publication of the fake news, except for SECT and FIN, which are dummy variables pertaining to sectors. CARs are the dependent variables.

Appendix C

Table 1 C
Correlation analysis of the control variables.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
(1) ROA														
(2) PBV	0.164 *													
(3) EPS	0.542 *	-0.083												
(4) PE	-0.038	0.397 *	-0.100											
(5) LEV	-0.419 *	0.072	-0.331 *	-0.059										
(6) BETA	-0.334 *	-0.056	-0.075	-0.075	0.154 *									
(7) SIZE	-0.027	-0.287 *	0.449 *	-0.092	0.130	0.085								
(8) SIGMA	-0.117	0.173 *	-0.321 *	0.008	0.090	0.185 *	-0.202 *							
(9) FIN	-0.329 *	-0.247 *	-0.244 *	0.093	0.447 *	0.078	0.102	0.222 *						
(10) SECT	0.076	0.027	-0.013	-0.206 *	0.005	0.223 *	-0.017	-0.032	-0.250 *					
(11) Country	-0.309 *	-0.265 *	-0.251 *	-0.093	0.365 *	0.061	0.062	0.161 *	0.415 *	-0.108				
(12) Nasdaq	0.266 *	0.396 *	0.121	0.289 *	-0.206 *	0.047	-0.010	0.007	-0.177 *	0.021	-0.320 *			
(13) Official	-0.182 *	-0.092	-0.199 *	0.006	0.024	0.041	-0.092	0.135	0.159 *	0.128	0.397 *	-0.124		
(14) OWNERSHIP	-0.335 *	-0.202 *	-0.194 *	-0.166 *	0.237 *	0.000	0.099	-0.142	0.116	0.000	0.234 *	-0.352 *	0.232 *	

Note: this table shows the Pearson correlations between the variables used in the regression model. * denotes statistical significance at 10% or better.

Table 2 C
VIF analysis.

	VIF	SQRT_VIF	TOLERANCE
POS	1.967422	1.402648	0.5082792
NEU	1.331491	1.153903	0.7510376
OFF	1.993186	1.411802	0.5017094
ROA	2.194482	1.481379	0.4556883
PBV	2.191225	1.480279	0.4563658

(*continued on next page*)

Table 2 C (*continued*)

	VIF	SQRT_VIF	TOLERANCE
EPS	2.646882	1.626924	0.377803
PE	1.685456	1.298251	0.5933112
LEV	2.688254	1.63959	0.3719887
BETA	1.504768	1.22669	0.6645542
SIZE	1.941221	1.393277	0.5151398
SIGMA	1.477861	1.215673	0.6766537
FIN	2.210748	1.486858	0.4523356
SECT	1.342946	1.158855	0.7446317
Country	2.077254	1.441268	0.4814049
Nasdaq	1.674020	1.293839	0.5973645
OWNERSHIP	1.428759	1.195307	0.6999080

Note: This table shows the VIF test results. This is the set of variables: POS are positive items; NEU are neutral items; OFF are items published by an official source; ROA is the ratio between net income and total assets; PBV is the ratio between the stock market price and the book value of firm equity; EPS is calculated dividing firm profits by the number of common stocks outstanding; P/E is the ratio between firm's stock price and the firm's earnings per share; LEV is the debt to equity ratio; BETA is measured as the covariance of firm stock returns to stock market return; SIZE is the natural logarithm of the firm's total assets; SIGMA is the standard deviation of the daily returns; FIN is a dummy variable equal to 1 if the firm in the financial sector, 0 otherwise; SECT is a dummy variable equal to 1 if the firm is in the manufacturing sector, 0 otherwise; Country is a dummy variable equal to 1 if the firm is located in Europe, 0 if it is located in the US; Nasdaq is a dummy variable equal to 1 if the firm is listed on Nasdaq, 0 if it is listed on NYSE; OWNERSHIP is the percentage of total shares held by institutional investors.

Collinearity is a term used when two or more independent variables in a regression model are strongly correlated: this can cause serious issues in the estimation of size, sign and standard errors of the regression coefficients (Johnston et al., 2018). The degree of collinearity can be assessed by means of two classical statistical instruments. The first is the correlation analysis. In Table 1C we show the Pearson correlation values measured for all the pair of regressors used in our analysis: the values range from a minimum of − 0.419 to a maximum of 0.542. The second technique is called Variance Inflation Factor statistic (Allison, 1999): the VIF value for each independent variable can be obtained by regressing it against all others, and then calculating (1/[1-R]), where R is the r_squared value from the regression. As highlighted by Allison (1999), a VIF value above 10 is an indicator of strong multicollinearity. Since our values are well below this threshold, multicollinearity is not an issue in our analysis.

Appendix D

Table 1D
Categorization of the news source.

Type of source	
Official Media	Social Media
ABC News	4-chan
AGI (Agenzia Giornalistica Italiana)	Amplifying Glass (satire blog)
Bloomberg	Angry Patriot (nationalistic blog)
Business Wire	Bare Naked Islam (fake news website)
Dimartedì (Talk show aired by broadcasting channel LA7)	Daily Buzz Live (satire blog)
Dow Jones Newswire	David Wolfe (blog spreading pseudoscientific articles)
Face the Nation (political talk show aired by broadcasting channel CBS news)	DepartedMedia (fake news website)
Firm press releases	Empire News (satire blog)
Floor speeches	Facebook
Fox News	Florida News Flash (pseudojournalistic blog)
Hurriyet Daily News (Turkish newspaper)	Huzlers (fake news website)
La Repubblica (Italian newspaper)	Instagram
La Stampa (Italian newspaper)	Nahadaily (fake news website)
Mezz'ora in più (political talk show aired by broadcasting channel Rai3)	News Buzz Daily (satire blog)
MSNBC	Newswatch33 (fake news website)
On Point (radio show produced by WBUR-FM)	Onlysimchas (fake news website)
PR Newswire	People of Lancaster (satire blog)
Presidential Debate	Racket Report (satire blog)
Reuters	Red State (nationalistic blog)
SEC EDGAR system	Reddit
Sole 24 ore	Seeking Alpha
State of the State speech	smag31 (junk news blog)
State of the Union Address	Sun Gazing (fake news website)

(*continued on next page*)

Table 1D (*continued*)

Type of source	
Official Media	Social Media
The Washington Post	The Verge
The Wall Street Journal	theconservativetreehouse (nationalistic blog)
USA Today	True Activist (nationalistic blog)
WAPT (television station affiliated with ABC)	Trumpbetrayedus (junk news blog)
	Twitter
	Vellum Atlanta (junk news blog)
	Whatsapp
	World News Daily Report (junk news blog)
	Youtube

Note: This table shows the list of the fake news items sources categorized into two different types: official news sources and social media sources.

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