Twitter versus traditional news media: evidence for the sovereign bond markets

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Twitter versus Traditional News Media: Evidence for the Sovereign Bond Markets

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Abstract
This paper compares news in Twitter with traditional news outlets and then emphasizes their differential impact on Eurozone’s sovereign bond market for a homogeneous news topic. We find a two-way information flow between Twitter’s “Grexit” tweets and the respective mentions in traditional news outlets. The influence of Twitter on the traditional news is consistently more prolonged, especially in high-activity periods. We also assess the differential impact of the two news sources on sovereign spreads over and above the impact of economic/financial fundamentals, namely measures of default risk, liquidity risk and global financial risk. Our focus is on the borrowing costs of Eurozone’s periphery; for comparison reasons, we also consider France as a core Eurozone country. The effect of Twitter on the Greek sovereign spread is positive and of higher magnitude than that of traditional news outlets. Weak contagion effects are recorded primarily for the case of Portugal and Ireland.

Keywords: Grexit, Twitter, Traditional news outlets, Sovereign spreads.

JEL Classification: C10, G01, G12

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1. Introduction

Can the information content of a single tweet result in a country’s currency depreciation by 16%? Apparently, it can. On August the 10th 2018, President Trump announced, via Twitter, the doubling of tariffs on Steel and Aluminum with respect to Turkey. This was retweeted approximately 36.1k times. The news conveyed through the tweet arguably contributed to a massive 15.86% drop in the value of the Turkish Lira compared to the day before.

This should not necessarily come as a surprise. With the help of social media, news travel much faster and wider compared to the recent past. Indeed, social media have become a popular open forum for analyzing economic/financial issues and, equally important, they reflect public sentiment minute by minute. It has long since become essential for economic commentators, policymakers and their faithful followers. For instance, New York Times Columnist and 2008 Nobel Laurate Paul Krugman run a Twitter account with some 1m followers during the Greek-related Eurozone crisis in early 2013; his followers have now risen to approximately 4.5m. Also updating in real time are dedicated websites such as Real Time Economics of The Wall Street Journal (with its twitter account having approximately 776k followers) that discuss hot economic topics in detail. Not surprisingly, people pay attention. This is more so in the case of US President Donald Trump who currently has some 55.8m Twitter followers and what he writes makes a(n) (financial) impact. In fact, in an interview with The Financial Times on April 2, 2017 President Donald Trump noted “without the tweets, I wouldn’t be here”.

This paper differentiates from existing literature on how media influence financial markets in the sense that it compares news from Twitter with news appearing in traditional news outlets and emphasizes their differential impact on sovereign bond markets. More specifically, we examine the following two questions: First, is there a

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1 See: https://twitter.com/realdonaldtrump/status/102789286586109955.
2 See: https://www.bloomberg.com/quote/TRY:CUR.
3 Krugman is the top economist in terms of followers (see: https://ideas.repec.org/top/top.person.twitter.html).
4 See: https://www.ft.com/content/9ae777ea-17ac-11e7-a53d-df096373be87.
two-way channel of information flow between Twitter and traditional news outlets? Second, given that one source of news dissemination (i.e. the feeder) feeds in content more systematically the other source (i.e. the receiver), is the predictive capacity of the feeder towards the bond market above and beyond that of the receiver? We focus on the Greek debt crisis as it relates to a set of characteristics that allow “apples-to-apples” comparison. These characteristics are as follows: first, the time persistence of the crisis that permits collection of data for a reasonable duration; second, the global interest for the crisis that creates adequate volume of resources and, third, the existence of the unique and untranslated acronym “Grexit” that directly refers to the Greek debt crisis. By considering the above characteristics, we focus on the sovereign bond market since sovereign risk affects not only the ability of governments to borrow, repay and indeed rollover their debt obligations in international markets but also because it affects borrowing costs of banks and the private sector operating in that sovereign.

Most of us would probably find it very hard to believe that information on social media might have the power to influence financial markets, but there is evidence of this. In November 2015, for instance, the Scottish financial trader James Alan Craig was charged in the US for allegedly using Twitter to manipulate share prices (it is not Twitter per se that affects markets but instant news which is proxied by Twitter). According to the US Department of Justice, the 62-year-old caused shareholders to lose more than $1.6m after allegedly spreading “fraudulent” information about companies on the social network. In fact, academic research (see e.g. Hasan et al., 2013) shows that negative press rumors impact on financial markets more than fundamentals.

Social media popularity might explain why Twitter has recently decided to double the length of the classic 140-character tweet to 280. In fact, Twitter has grown over the years as an extremely valuable source of information. Twitter is organized across the so-called “interest graph”; this means that professionals and the public follow accounts that provide valuable information, whether they have met or not. Twitter is extremely popular with journalists and is considered “more or less their

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7 Contrast this with Facebook’s “social-graph” structure which means that most people follow people they have met; see https://multimedia.journalism.berkeley.edu/tutorials/twitter/.

8 Journalists were making up nearly a quarter (24.6 percent) of Twitter’s authenticated users according to a 2015 report (see: https://www.poynter.org/news/report-journalists-are-largest-most-active-verified-group-twitter).
Journalists tend to tweet immediately when a news story is breaking and often let their audience know that full coverage will appear on the newspaper’s site soon. Since 2013, at least half of Twitter users in the US have reported getting news on the site; in 2017, however, that share went up to 74% and then fell slightly to 71% in 2018. It is also interesting to note that Bloomberg has recognized the rapidly growing importance of Twitter in releasing financial information by integrating, since 2013, real-time Twitter feeds in its financial platform. In 2018, Bloomberg and Twitter expanded their relationship so that enterprise clients could incorporate Twitter-relevant news to their advanced trading strategies. Despite the popularity of Twitter, a recent survey by Shearer and Gottfried (2017) notes that “many social media news consumers still get news from more traditional platforms”. This is not to say that traditional news platforms are ignored. For instance, 55% of Twitter users often get news from news websites and 11% of Twitter users often get news from print newspapers.

Consequently, an important question is whether the information content on Twitter differentiates from the respective content on traditional news outlets. There are good reasons to expect differences. In terms of speed, for instance, reports published on social media sites can be accessed instantly whereas traditional media takes time to disseminate information (this is limited to once a day for newspapers; obviously television or radio can update their reports more frequently). In terms of creation and dissemination of content, traditional media work on the ‘one-to-many’ principle; an Editor decides what is news and the news consumers (readers and viewers) do not play a role in the creation or dissemination of content. Contrast this with the ‘many-to-many’ principle of social media where any individual can create and share content. In terms of interactivity, all comments in social media occur in real time; traditional media instead is tightly patrolled. Further, social media connects

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12 Although Facebook is the first among social media as news source, we focus on Twitter. This is justified by the nature of the topic. As the topic is about the sovereign risk of a country, the ideal user profile demands high education with capacity to comprehend economic topics. Twitter users fit better this profile as they are more educated relative to the users of other social media (Mitchell et al., 2012). Dergiades et al. (2015) confirm, for the same topic as in our study, that the number of Grexit mentions mainly come from Twitter rather than Facebook.
billions of individuals across the globe whereas traditional media limit their reach to the number of readers or viewers that individual newspapers or channels may have.\footnote{Worldwide, weekly social media use for news has enjoyed a steady increase over the 2013-2017 period (only to drop slightly in 2018); for 2018, the use was 45% in the US, 39% in the UK, 36% in France and 31% in Germany. See: \url{http://www.digitalnewsreport.org/survey/2018/overview-key-findings-2018/}.}

From a theoretical point of view, media not only reflects but also drives the expectations of managers and investors alike; expectations in turn feed into asset pricing. To the extent that media content works as a proxy for investment sentiment, it carries predictive power for financial assets; at the same time, media visibility and content can increase an asset’s investor base and also direct investment attention (see the discussion in Tetlock, 2015 and references therein and the empirical evidence, from a historical perspective, in Turner \textit{et al.}, 2018). A growing empirical literature identifies significant social media effects on stock returns, stock volatility and earnings surprises (see, among others, Boudoukh \textit{et al.}, 2018; Ben-Rephael \textit{et al.}, 2017; Chen \textit{et al.}, 2014 and Sprenger \textit{et al.}, 2013). Media tone through a textual analysis of the content across newspaper articles has significant predictive power for future house prices (Soo, 2018). Dergiades \textit{et al.} (2015) identify significant social media effects in sovereign bond markets. Gennaioli \textit{et al.} (2014) use data for 46 countries to focus on the dire consequences of sovereign default on aggregate financial activity in the defaulting country; the impact is stronger in countries where domestic banks hold more public debt. Gennaioli \textit{et al.} (2018) use a dataset of over 20,000 banks in 191 countries to quantify a significant negative relationship between a bank’s holdings of government bonds and its lending during sovereign defaults. Altavilla \textit{et al.} (2017) flag the amplification effect of sovereign stress on bank lending to domestic firms for a sample of Euro-area banks. Augustin \textit{et al.} (2018), Wolski (2018) and Bedendo and Colla (2015) identify spillover effects from sovereign to corporate risk across Europe.

To compare Twitter with traditional news media, we construct a unique dataset based on “Grexit” related news. The comparison is conducted within a context that grants, for both news sources, topic homogeneity, global geographic coverage and inclusion of all potential languages. By pre-selecting a topic that is described by the untranslatable term “Grexit” (adopted by financial reporters, commentators and individuals), we establish, to a great extent, topic homogeneity. Twitter readily allows for global coverage. In order to establish the same geographic coverage for the traditional news outlets, we collect full-text documents from around the world based
on more than 3,700 news sources (newspapers, magazines, broadcast transcripts from TV and radio as well as wire services). Finally, the untranslatable nature of the term “Grexit” allows us to identify tweets and text documents irrespective of their language. Methodologically, the two news sources are compared by conducting the Dufour et al. (2006) causality test that relies on the estimation of multiple-horizon Vector AutoRegressive (VAR) specifications, while the associated impulse response analysis is executed by the Jordà (2005, 2009) local projections approach, relying also on multiple-horizon VAR specifications.

The paper then examines the impact of both news sources on Eurozone’s sovereign bond market. More specifically, we focus on the borrowing costs of Eurozone’s peripheral countries (namely Greece, Ireland, Italy, Portugal and Spain; hereafter the GIIPS). For comparison reasons, we also consider France as a core Eurozone country. In particular, we look at the differential impact of the “Grexit” mentions coming from Twitter and traditional news media on the sovereign spreads, over and above the impact of economic/financial fundamentals, namely measures of default risk, liquidity risk and global financial risk. Sovereign bond spreads are defined as the difference between the 10-year government bond yield in each of the GIIPS and France relative to the German government bond yield.

We have three main findings. First, there is a bidirectional information flow between Twitter and traditional news outlets with the impact of Twitter on traditional news being consistently more prolonged and more robust in terms of significance, especially in high-activity periods. Second, the impact of Twitter’s “Grexit” mentions on the Greek sovereign spread is positive and of higher magnitude than that of the traditional news outlets; in addition, the predictive power of Twitter persists even by taking out the effects of the traditional news (in terms of orthogonalizing the Twitter variable on the traditional news variable). Third, our analysis shows weak contagion effects primarily for the case of Portugal and Ireland.

Overall, our results suggest that the information that appears and is shared on Twitter plays a vital role over and above the traditional news outlets. This brings into the picture the importance of regulating social media; we return to this very issue in Section 5 where we discuss our main findings more in detail.

The paper proceeds as follows: Section 2 provides an outline of our methodology. Section 3 discusses the dataset used in this paper whereas Section 4
reports our empirical results. Finally, Section 5 provides a discussion of our findings and concludes.

2. Methodology

2.1. Non-causality at various horizons

To compare Twitter with traditional news media and examine their impact on the sovereign bond market, we rely on the Dufour et al. (2006) causal framework, which permits inferences on the causal linkages of a multivariate process not only at a single horizon but also at a multiple horizons framework. For finite order VAR processes, impediment in testing the non-causality hypothesis, at horizons different from one, is the non-linear nature of the imposed restrictions. Hence, the typical Wald-type statistics do not conform to the standard asymptotic theory. To alleviate these complications, Dufour et al. (2006) introduce a multiple-horizon VAR. After correcting for serial correlation in the error term, the validity of the restrictions is examined via a Wald-type test statistic (hereafter DPR).

Within this context, for the \( W(t) = (w_{1t}, \ldots, w_{mt})' \) vector of random variables, the projection of a VAR process of order \( p \) at horizon \( h \) (\( VAR(p, h) \)) can be written as follows:

\[
W(t + h) = \mu^{(h)} + \sum_{i=1}^{p} \pi_{i}^{(h)} W(t + 1 - i) + \sum_{j=0}^{h-1} \psi_{j} \alpha(t + h - j)
\]  

(1)

where \( \mu^{(h)} \) is the constant term at horizon \( h \) \( (h = 1, 2, \ldots, H) \), \( \pi_{i}^{(h)} \) are \( m \times m \) coefficient matrices at horizon \( h \) and finally, \( \psi_{j} \) are \( m \times m \) coefficient matrices that correspond to components of the MA(\( h-1 \)) process assumed for the error-term. The derivation of \( \pi_{i}^{(h)} \) and \( \psi_{j} \) matrices is described in Dufour and Renault (1998). Eq. 1 is rewritten as follows:

\[
W(t + h)' = \mu^{(h)}' + \sum_{i=1}^{p} W(t + 1 - i)' \pi_{i}^{(h)}' + u^{(h)}(t + h)'
\]  

(2)

with \( u^{(h)}(t + h)' = \sum_{j=0}^{h-1} \alpha(t + h - j) \psi_{j}' \). Using matrix notation Eq. 2 is represented as:

\[
W(t + h) = \overline{W}(h) \Pi^{(h)} + U(t + h)
\]  

(3)

where \( \Pi^{(h)} \) is a matrix of coefficients and \( \overline{W}(h) \) the matrix of the variables.
The multiple-horizon VAR system in Eq. 3 is estimated by OLS. Once the estimate $\hat{\Pi}^{(h)}$ of $\Pi^{(h)}$ is attained, we may impose zero restrictions to test the non-causality hypothesis at horizon $h$. Suppose that it is of our interest to know whether the variable $W_{st}$ cause at horizon $h$ another variable, say $W_{qt}$ ($1 \leq s \leq m$, $1 \leq q \leq m$ and $s \neq q$). To test whether $W_{st}$ does not cause $W_{qt}$ given the available information set $\{W_{st} \leftrightarrow W_{qt}\}$, we need to impose the following zero restrictions:

$$
H^{(h)}_{w_{st} \rightarrow w_{qt}} : \pi^{(h)}_{w_{st}} = 0, \quad i = 1, \ldots, p
$$

(4)

The non-causality hypothesis illustrated in Eq. 4 is tested through the Wald-type test statistic \( W^{(h)} \) (DPR statistic) that follows the \( \chi^2 \) distribution with \( p \) degrees of freedom.

$$
W^{(h)} = T(R\hat{\beta}_q(h) - r)\left[R\hat{V}_q(\hat{\beta}_q)R^\top\right]^{-1}(R\hat{\beta}_q(h) - r)
$$

(5)

where, $R_{pm(n+pm)}$ is selection matrix, $\hat{\beta}_q(h)$ is the $(n + pm) \times 1$ vector of OLS estimates for the $q^{th}$ equation of the VAR system, $r_{pm1}$ is a vector of zeros and $\hat{V}_q(\hat{\beta}_q)$ is the Newey-West estimate of the $(n + pm) \times (n + pm)$ variance-covariance matrix. Finally, as it is noted in Dufour et al. (2006), failure to reject the null hypothesis consistently up to horizon $L = (m - 2)p + 1$ is an adequate condition to verify absence of long-run causality.

Under the Dufour et al. (2006) framework, the testing procedure is adjusted to account for integrated processes up to order $d \geq 1$. The proposed adjustment follows the lines of the lag-extension practice introduced by Toda and Yamamoto (1995). Hence, if the involved process is integrated of order $d$, the optimal lag structure of the system illustrated in Eq. 2 is augmented by adding $d$ extra lags. Once augmentation is done, the null hypothesis of no causality is examined by imposing restrictions on the optimal lag structure of the system (the extra lags are ignored).

Unfortunately, the asymptotic distribution of the $W^{(h)}$ statistic proves to perform quite poorly in small samples. The performance of the test deteriorates further when the testing procedure is conducted in VAR systems with large order and with large number of variables. Furthermore, inference of non-causality at long horizons also disturbs the size and the power of the test as a consequence of the observed serial
correlation. To control for these concerns, Dufour et al. (2006) assess the validity of the null hypothesis by implementing a parametric bootstrap procedure. The bootstrap technique performs asymptotically considerably better in small samples, provided that the asymptotic distribution of $\mathcal{W}[H_0(h)]$ is nuisance-parameter-free.

### 2.2. Local projections

Starting from the VAR process of order $p$ at horizon $h$ (VAR$(p, h)$), illustrated in Eq. 2, we further compute impulse responses based on local projections, as proposed by Jordà (2005). To circumvent the algebraic complexity involved in the estimation of the impulse responses within a standard VAR framework (introduced by the unique set of the VAR coefficients estimates), Jordà (2005) suggests obtaining a new set of coefficients estimates for each horizon $h$ of Eq. 2. For instance, at horizon $t + h$, local projections constitute the response of the vector $W(t + h)$ to an experimental shock on the VAR reduced form residuals $e$ at time $t$, given the available information set $I_t$.

Such a response is formally presented below:

$$\mathcal{J}_h^p = E(W(t + h) | e_t = 1; I_t) - E(W(t + h) | e_t = 0; I_t)$$

(6)

The structural impulse response is given by the following structural decomposition:

$$\Theta_h^p = \mathcal{J}_h^p A_0^{-1}$$

(7)

Hence, to construct $\hat{\Theta}_h^p$, we need an estimate of $\mathcal{J}_h^p$ which is attained by the coefficient matrix $\hat{\Theta}_h^{(h)}$ of Eq. 2, while the impact matrix $A_0^{-1}$ is recovered from the standard VAR$(p)$ specification, after implementing an appropriate identification scheme.

To assess the shape of the response trajectories, given by (7), and the individual significance of each response, we construct the Scheffe’ and the conditional confidence bands respectively, as proposed by Jordà (2009). By letting $\hat{\theta}_{ij}$ to denote the estimated response of the variable $i$ to a shock on variable $j$ up to horizon $h$, then the Scheffe’s confidence interval is defined as:

$$\hat{\theta}_{ij} \pm \hat{A}_{ij} \hat{D}_{ij} \left( c^2_\alpha / H \right) i_{ij}$$

(8)

where, $\hat{A}_{ij}$ is a lower triangular matrix and $\hat{D}_{ij}$ is diagonal matrix (both are estimated through Cholesky decomposition), $c^2_\alpha$ is the critical value that corresponds to the $\chi^2$
with $H$ degrees of freedom and $1_H$ is a vector of ones. Additionally, the conditional confidence bands are constructed as follows:

$$\hat{\theta}_i \pm z_{\alpha/2} \text{diag} \left( \hat{D}_i^{1/2} \right)$$

(9)

where, $z_{\alpha/2}$ is the critical value that corresponds to the standard normal distribution and $\text{diag} \left( \hat{D}_i^{1/2} \right)$ is the vector with the diagonal elements of $\hat{D}_i^{1/2}$. The benefits of using local projections over the standard VAR impulse analysis are as follows: first, the robustness over potential model misspecification; second, the joint inference for the impulse response coefficients and, third, the applicability of the approach to non-linear models. These advantages are discussed more analytically in Jordà (2005; 2009). The disadvantages of the local projections approach are summarized as follows: first, the impulse responses derived from small samples may be less precise compared to the standard VAR responses (although asymptotically local projections remain superior); second, the responses in the long-run may be quite volatile, and third, the associated standard errors may be serially correlated. A comprehensive criticism on the use of local projections is provided by Kilian and Kim (2009).

3. Data

Carrying out a comparison between Twitter and traditional news media is not a trivial task because of a set of emerging challenges that do not permit “apples-to-apples” evaluation. For instance, the discovery and classification of a topic both necessitate the implementation of natural language processing algorithms, which reduce its efficiency when the text size is short, as is the case of Twitter. Hence, topic homogeneity is a concern. Other challenges, especially for topics of global interest, are the geographic coverage and the language coverage. Thus, a direct and meaningful comparison between the two news sources demands topic homogeneity and the same geographic and language coverage.

To examine whether the information content on Twitter feeds/leads the information content on the traditional news outlets (and vice versa), by pre-selecting a topic related to sovereign bonds markets, we construct a unique dataset based on the “Grexit” mentions coming from the two news sources. Among the existing community-based content sharing social media (e.g. Twitter, Facebook, Digg,
Google+, Reddit), Twitter is used extensively as a platform for spreading news and principally economic/financial news. Hence, Twitter is used as one source of information with global coverage. On the other hand, to establish global coverage for the traditional news outlets, we collect full-text documents from around the world based on more than 3,700 news sources (newspapers, magazines, broadcast transcripts from TV and radio and wire services).

The term “Grexit” has been inaugurated in February 2012 by two Citigroup economists (Willem Buiter and Ebrahim Rahbari). As such, the sample starts from the first week of March 2013 (3/5/2012) and ends in June 2016 (6/24/2016), including 1,573 daily observations. For the above period, using as source of data the premium Twitter historical database of Followthehashtag, we collect 936,837 unique tweets that contain the keyword “Grexit” or “#Grexit”. By defining the number of followers of each tweet contributor as a measure of influence, then the average influence per tweet is 8,024 and the cumulative influence of the 936,837 tweets is 7.5 billion. Our sample covers geographically all countries around the globe (collected tweets come from 195 countries) and all languages (collected tweets are written in 14 different languages). In more detail, 76.1% of the sample tweets are written in English, Spanish and German (42.6%, 22.9% and 10.6%, respectively), while the countries ranked at the 95th percentile and above (see in Figure 1 countries in red color) contribute 79% to the total number of the collected tweets. Figure 1 groups the 195 countries in percentiles according to the density of tweets contributed. Countries in white color signify no contribution to the sample. “Grexit” seems to be an issue of discussion for Twitter users from North America and Europe.

To build the series that captures the intensity of the “Grexit” discussion in Twitter, we count for the collected tweets, on a daily basis, the total number of mentions for both terms “Grexit” and “#Grexit” and we assign each value to the respective day. In total, we identify 1,338,086 mentions. The created time series is presented in Figure 2.

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14 Kümpel et al. (2015) mention that 69% of the studies dealing with news sharing use Twitter as a source platform. Twitter is in the lead of Facebook (17%), YouTube (12%) and Digg (8%).

15 See: http://www.followthehashtag.com. The dataset is available from the website for a fee.
To construct the respective time-series with a daily frequency for the traditional news outlets we use as source the LexisNexis Academic database. The coverage of the database is worldwide offering access to multilingual text sources coming from newspapers, magazines, broadcast transcripts from TV and radio news as well as wire services. Hence, for the same sample period, (3/5/2012 - 6/24/2016), we collect 40,341 unique text sources (e.g. newspaper articles) containing the keyword “Grexit” at least
one time. Our sample covers geographically all countries around the globe (the collected text sources come from 83 countries) and all languages (collected text sources are written in 18 different languages). In more detail, 84.5% of the text sources from the traditional news are written in English, German, Dutch and French (42.5%, 22.7%, 10.8% and 8.5%, respectively), while the countries ranked at the 95th percentile and above (see red areas in Figure 3) contribute 63% of the total number of collected text items. Figure 3, groups the 83 countries in percentiles according to their text item contribution in the sample. Countries in white color signify no contribution to the sample. For the traditional news outlets, “Grexit” appears to be a topic of discussion mostly in Europe.

![Figure 3. Traditional news density per country.](image)

For the traditional news, we follow the same procedure as in the case of Twitter. To build the series that captures the intensity of the topic in the traditional news outlets, we count the “Grexit” mentions for the collected text items on a daily basis and we assign each value to the respective day. In total, we identify 66,246 mentions. The constructed time-series is illustrated in Figure 4.
The two independently constructed time-series (Twitter and traditional news) (see Figures 2 and 4), present a high degree of positive linear correlation (the respective correlation coefficient is equal to 0.89). This high degree of linear association can be perceived as a signal of robustness towards the procedures used to build the series. From Figures 2 and 4, we identify two high-activity periods for both series. The first high-activity period (sub-sample) starts with the beginning of the full-sample (3/5/2012 – right after the introduction of the “Grexit” term) and ends at 10/12/2012. In particular, following the declaration of Mario Draghi to “do whatever it takes to preserve the euro (7/26/2012),\textsuperscript{16} the lower “Grexit” media activity after 10/12/2012 had to do with ECB’s announcement for the unlimited bond buying plan on the secondary market (9/9/2012) and the Greek parliamentary vote on the 2013 budget (10/11/2012), which foresaw €13.5 billion budget cuts as a precondition to secure a new bailout loan from the European Union and the International Monetary Fund (discussed on the 10/12/2012 Eurogroup by the Eurozone finance ministers).

The second high-activity (sub-sample) period starts on 12/28/2014 and terminates at the end of the full-sample on 6/24/2016. The main reason for the reignited “Grexit” discussion was the snap general national election announcement triggered by failure of the Greek parliamentarians to elect a new head of state.

The revealed prospect by opinion polls that the election outcome might bring into power the radical left party of Syriza was sufficient to revive in a keenly manner the “Grexit” discussion.

Descriptive statistics for both series referring to the full-sample and to the two sub-samples, are reported in Table 1. The activity on Twitter is more intense than that on traditional news, as the “Grexit” mentions in Twitter illustrate in all samples higher means and higher volatilities. Moreover, in all samples both constructed series appear to deviate vastly from normality as this can be judged from the respective values of the skewness and the kurtosis. Hence, our empirical analysis is executed based on the logarithmic transformation of both constructed time-series, as a convenient way to move from highly skewed variables to variables that are closer to normal.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Twitter mentions</th>
<th>Traditional news mentions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$S^d$</td>
<td>$S^I$</td>
</tr>
<tr>
<td>mean</td>
<td>850.65</td>
<td>247.76</td>
</tr>
<tr>
<td>median</td>
<td>49.00</td>
<td>70.50</td>
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<tr>
<td>minimum</td>
<td>0.00</td>
<td>0.00</td>
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<tr>
<td>maximum</td>
<td>67948.00</td>
<td>2448.00</td>
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<td>st. deviation</td>
<td>4263.59</td>
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<tr>
<td>skewness</td>
<td>9.77</td>
<td>2.86</td>
</tr>
<tr>
<td>kurtosis</td>
<td>113.53</td>
<td>11.62</td>
</tr>
</tbody>
</table>

Notes: $S^I$, $S^d$ and $S^{II}$ denote the full sample, the first and the second high-activity samples, respectively.

The considerably higher maximum values observed for Twitter mentions reflect Twitter’s ultra-speed in disseminating news. In a failed Eurogroup meeting that took place on 7/11/2015, (that is, a shortly after the 7/5/2015 Greek referendum), “Grexit” was closer than ever following Germany’s proposal for Greece to take a ‘time-out’ of the common currency block for five years. After the end of the meeting in the early hours of 7/12/2015, it was Jeroen Dijsselbloem’s (President of the Eurogroup) exit doorstep comment “it is still very difficult” that triggered the “Grexit” mentions in Twitter to reach at their highest value (67,948 – 98% increase compared to the previous day). Traditional news reached their maximum value (2,312 – 120% increase compared to the previous day) a day later, on 7/13/2015.

4. Empirical findings

4.1. Does Twitter lead traditional news outlets?

To examine whether there is a two-way information flow between the Twitter ($T_t$) and traditional news ($N_t$) series, we implement the Dufour et al. (2006) non-causality testing approach. By identifying the causal dynamics, at horizons greater than one, we can assess not only the nature of the relationship between Twitter and traditional news outlets, but also the persistence/strength of the predictive content over time. To conduct the causal testing, we estimate Eq. 2 for the bivariate vector $W(t) = (T_t, N_t)'$ by specifying the optimal lag-length through the Schwarz Information Criterion. Eq. 2 is estimated repetitively to obtain the $H_0(h)$ (or DRP) statistics up to twenty horizons (or days) ahead ($h = 1, 2, ..., 20$). The significance of the statistics is evaluated through bootstrapped $p$-values with 1000 replications. Moreover, starting from Eq. 2, we estimate the twenty periods response trajectory of $T_t$ after a shock on $N_t$ (and vice versa), under the Jordà (2005) local projections approach. The overall shape and the individual significance for each point on the impulse response path, are assessed by calculating respectively, the Scheffe’ and the conditional confidence bands. Furthermore, we test the significance of the impulse responses’ twenty-period cumulative sum as proposed by Jordà (2009). This way, we assess the direction (positive or negative) and the significance of the overall impact of the shock on the target variable. Finally, the full-sample analysis (3/5/2012 to 6/24/2016) is re-estimated for the two sub-samples of high-activity (3/5/2012 to 10/12/2012 and 12/28/2014 to 6/24/2016).

The full-sample $p$-values, for both hypotheses, are presented jointly in Figure 5. The $p$-values for the hypothesis of no-causality running from Twitter to the traditional news outlets ($T_t \leftrightarrow N_t$) and vice versa ($N_t \leftrightarrow T_t$) are depicted by the red and the black line, respectively. The dark grey area and the light grey area imply significance at the 0.05 and 0.01 levels, respectively. Furthermore, all DPR statistics are reported in Table A1 (Appendix 2). From Figure 5, we infer that the first hypothesis ($T_t \leftrightarrow N_t$) is rejected at the 0.01 significance level for all horizons, except the last horizon where the rejection takes place at the 0.05 significance level. For the reversed hypothesis ($N_t \leftrightarrow T_t$), the rejection is the regular decision up to the ninth horizon, mainly at the 0.05 significance level, while for longer horizons, the non-rejection is the dominant
inference. The full-sample results reveal a two-way predictive capacity between $T_t$ and $N_t$, with the effect of $T_t$ on $N_t$ being more prolonged and more robust in terms of significance.

When we implement the Dufour et al. (2006) test in the first sub-sample, a different conclusion is drawn. The $p$-values for the first sub-sample are communicated visually in Figure 6 and the respective DPR statistics in Table A1 (Appendix 2). From Figure 6, $T_t$ appears to lead significantly, mainly at the 0.01 significance level, $N_t$, up to horizon 15, while $N_t$, for the conventional levels of significance, has no predictive power on $T_t$ at any horizon. It seems that in the first sub-sample, which can be characterized as high information flow period, Twitter, as a faster platform of news dissemination, leads traditional news outlets, whilst the reverse cannot be verified.

For the second high-activity period, the results appear to corroborate the inference of the first-sample. The derived $p$-values are illustrated in Figure 7 and the respective DPR statistics in Table A1 (Appendix 2). Figure 7 shows that $T_t$ causes significantly, mainly at the 0.01 significance level, $N_t$, up to the nineteenth horizon. On the other hand, for the $N_t$ variable the no-causality hypothesis is rejected sporadically at various horizons, mostly at the 0.05 significance level. For once more,
for the second sub-sample of high information flow we find evidence that Twitter systematically leads traditional news outlets.

We further construct the twenty periods ahead impulse response of $T_t (N_t)$ following a generalized one standard deviation shock on $N_t (T_t)$. Figures 8 to 10 show how a shock on $T_t (N_t)$ is transmitted to $N_t (T_t)$, for the full-sample and the two sub-samples of high-activity (in “Grexit” mentions). For the full-sample, Figure 8.a, shows the response of $N_t$ to a shock on $T_t$ (continuous black line) along with the 95% Scheffe’ confidence interval (grey area) and the 95% conditional confidence interval (blue area). In this case, the conditional confidence band supports consistently a positive trajectory, while the corresponding Scheffe’ confidence band provides additional evidence that the impulse response is expected to fluctuate above zero. Furthermore, at the bottom left hand-side of Figure 8.a, we report the twenty-horizon cumulative sum (C. sum) of the responses with the respective $p$-value for testing the significance (C. sum $p$-value). Moreover, the magnitude of the responses implies that a 1% increase in the activity of $T_t$ would lead to a 1.29% increase in the activity of $N_t$ at the first horizon and to a 15.77% (and significant) cumulative increase after twenty-horizons.

Figure 8.b illustrates the response of $T_t$ to a shock on $N_t$. The conditional confidence band does not include zero for any but three horizons, whilst the Scheffe’ confidence band suggests a positive trajectory up to horizon nine. The twenty-horizon cumulative impact is significant (at the 0.01 level), while a 1% increase in the activity

Notice that $p$-values below the selected value of $\alpha$ imply that a shock on Twitter has a significant twenty days cumulative impact on the activity of the traditional news outlets.
of $N_t$ leads to a 0.71% increase in $T_t$ at the first-horizon and to a 6.66% cumulative increase. The full-sample impulse response results provide evidence in favor of: (i) a positive relationship between Twitter and the traditional news media, (ii) a significant bidirectional cumulative impact, (iii) a positive and significant impact of Twitter on the traditional news outlets, that is more prolonged compared to the respective impact of the reverse direction, and (iv) empirical evidence that the twenty-horizon impact of Twitter (for a 1% increase in mentions) on the traditional news is approximately 2.37 (=15.77%/6.66%) times higher than the reverse impact. Overall, these findings come to enhance the validity of the Dufour et al. (2006) testing results.

![Figure 8](image.png)

**Figure 8.** Full-sample local projections impulse responses

*Notes:* C. sum (20) refer to the twenty-horizon (days) cumulative sum of the impulse responses, while C. sum p-value is the resulting $p$-value for testing the hypothesis that the C. sum (20) is equal to zero. Finally, *** denote rejection of the null hypothesis at the 0.01 significance level.

Turning to the results of the first sub-sample, the conditional confidence band in Figure 9.a implies that the response of $N_t$ to a shock on $T_t$ is always positive, whereas the Scheffe’s confidence band suggests fluctuation above zero for the first eleven horizons. Furthermore, we infer that a 1% increase of $T_t$ leads to a 1.56% increase $N_t$ at the first horizon and to a 23.85% increase (significant at 0.01) cumulatively. On the other hand, Figure 9.b shows that the response of $T_t$ to a shock on $N_t$, wiggles around zero for the majority of the examined horizons. Thus, the twenty-horizon cumulative impact is 3.42% and not significant, while a 1% increase in the activity of $N_t$ leads to a 0.98% increase of $T_t$ at the first horizon.
The impulse response analysis for the first sub-sample reveals: (i) a positive relationship between Twitter and traditional news outlets, (ii) a significant twenty-horizons cumulative impact that runs from Twitter to the traditional news and not vice versa, (iii) an impact of Twitter to the traditional news that is again more prolonged compared to the respective impact of the reverse direction, and (iv) empirical evidence that the twenty-horizon impact of Twitter (for a 1% increase in mentions) to the traditional news outlets is approximately 6.97 (=23.85%/3.42%) times higher than the reverse impact. These results confirm the causal testing inference of this section.

Figure 9. First sub-sample local projections impulse responses

Notes : see notes of Figure 8.

Finally, for the second sub-sample, the conditional confidence band in Figure 10.a shows that the trajectory of $N_t$ to a shock on $T_t$ is always positive. The region of all potential trajectory paths, defined by the Scheffe’ confidence band, implies that the trajectory is anticipated to fluctuate above zero for the first eleven horizons. The twenty periods cumulative sum of the responses is significant, while a 1% increase in $T_t$ leads to a 1.56% increase in $N_t$ at the first horizon and to a 15.81% increase after twenty horizons. In Figure 10.b the conditional confidence band implies that the response of $T_t$ to a shock on $N_t$ is positive, with the Scheffe’ confidence band to imply positive trajectory for the first three days. The twenty periods cumulative impact of the responses is significant, while a 1% increase in the activity of $N_t$ leads to a 0.90% increase in the activity of $T_t$ at the first horizon and to a 10.37% increase after twenty horizons.

The impulse response analysis for the second high-activity sub-sample shows (i) a positive relationship, (ii) a bidirectional significant twenty-horizons cumulative
impact, (iii) that the effect of Twitter on the traditional news outlets is more prolonged than the reverse and (iv) empirical evidence that the twenty-horizon impact of Twitter to the traditional news outlets is \(1.52 (=15.81%/10.37\%)\) times higher than the opposite impact.

From the executed causal and impulse response analysis (a summary of the results is presented in Figure A.1 in Appendix 1), we provide evidence in favor of the first examined research question. We reveal that the information flow between Twitter and the traditional news outlets is bidirectional. We also find that the impact of Twitter on the traditional news is more prolonged and more robust in terms of significance, especially in high-activity periods. Finally, in all examined samples (full sample and the two sub-samples), a shock on Twitter impacts on traditional news media to a greater extent compared with the reverse impact.

### 4.2. Twitter, traditional news and sovereign spreads in the GIIPS

#### 4.2.1. Full-sample analysis

The previous section provides evidence of a bidirectional content feed between the two sources of news dissemination; furthermore, Twitter feeds in content the traditional news outlets more systematically than the other way around. In this section, we move on to examine whether the predictive capacity of Twitter towards the bond market is above and beyond the respective capacity of the traditional news media. More specifically, we assess the predictive capacity of the two news sources...
over the sovereign bond spreads \( (S_{jt}, S_{jt}, S_{jt}) \) for the GIIPS (Greece, Ireland, Italy, Portugal, Spain) and France (hence, \( j = 1, \ldots, 6 \)) by estimating Eq. 2 for the multivariate vector \( W(t) = (S_{jt}, M_{kt}, L_{jt}, D_{jt}, E_{jt}, G_{jt}) \).\(^{19}\) We follow Dergiades et al. (2015) in capturing country-specific idiosyncratic risk by two types of risk, that is, the credit or default risk, \( D_{jt} \), and the liquidity risk, \( L_{jt} \), while the international risk is quantified by the common Eurozone risk, \( E_{jt} \), and the global financial risk, \( G_{jt} \).

In more detail, the sovereign bond spread is defined as the difference between the 10-year government bond yield in country \( j \) and the German government bond yield. All series come from Datastream (see Figure A.4 in Appendix 1). We construct for each country \( j \) the default risk as the difference between the 10-year Credit Default Swap (CDS) premia in country \( j \) and the 10-year German CDS premia (all series come from Datastream; see Figure A.5 in Appendix 1). The liquidity risk for each country \( j \) is approximated by the difference between the bid-ask spread of the 10-year bond in country \( j \) and the bid-ask spread of the respective German bond (all series come from Datastream; see Figure A.6 in Appendix 1). As in De Santis (2014), the Euro area common risk factor is identified by the difference between the return on the 10-year KfW (Kreditanstalt für Wiederaufbau) bond and the respective return on the 10-year German government bond (all series come from Datastream; see Figure A.7 in Appendix 1). Finally, to capture global financial risk we use the Global Financial Stress Index constructed by the Bank of America Merrill Lynch Global Research Division (available from Bloomberg; see Figure A.7 in Appendix 1).

For each country, \( j \), we estimate three different versions of the multivariate vector \( W(t) \) depending on the news information source \( M_{kt} \) \((k = 1, 2, 3)\). The first specification contains the “Grexit” mentions in Twitter (that is, \( M_{kt} = T_t \)). The second specification contains the “Grexit” mentions in the traditional news outlets (that is, \( M_{kt} = N_t \)). The final specification contains the orthogonalized Twitter variable (that is, \( M_{kt} = T_t - \), after taking out any effect of \( N_t \) from \( T_t \)).\(^{20}\) For all three specifications and for every country \( j \), we obtain the DPR statistics up to twenty horizons (or days) ahead by calculating bootstrapped \( p \)-values based on 1000 replications.

\(^{19}\)The lag-length in all specifications is determined based on the Schwarz Information Criterion.

\(^{20}\)After regressing the Twitter variable on the traditional news media variable, the orthogonalized variable is obtained from the residuals.
The \( p \)-values are analytically presented in Figure 11, while the values of the DPR statistics for selected horizons (due to space constraints) are illustrated in Table A2 in Appendix 2. Starting with Greece, the hypothesis of no-causality running from \( T \) to the Greek sovereign spread (red-line in Figure 11.a) is rejected at the conventional levels of significance (0.01, 0.05 and 0.1) up to the eighteenth horizon. When the \( T \) is replaced by \( N \) (black-line in Figure 11.a), the rejection of the null hypothesis, at the 0.1 significance level, is verified only up to the sixth horizon (exception is the first horizon where the rejection takes place at the 0.05 significance level). Finally, in the case where the orthogonal Twitter variable \( (T,^\perp) \) is used (red-dashed line in Figure 11.a), the rejection of the null hypothesis at the conventional levels of significance persists up to the seventh horizon (exception is the fifth horizon). The full-sample testing results reveal that the effect of \( N \) on the Greek sovereign spread is more short-lived (6 days) compared to \( T \) (18 days), while \( T \) continues to cause the Greek spread for several horizons (7 days), even when it is orthogonal to \( N \).

To examine possible contagion effects from the news related to the Greek debt crisis towards the remaining countries, we perform the same testing procedure by replacing the Greek sovereign spread by each country’s respective sovereign spread. The causality results indicate evidence of contagion mainly for the case of Portugal. In the case of Ireland, the evidence is weak, while there is even weaker and only circumstantial evidence for the remaining countries. In particular, for Portugal the hypothesis of no-causality running from the \( T \) to the sovereign spread (red-line in Figure 11.d) is rejected at the conventional levels of significance for sixteen out of the twenty horizons. Similar inference is obtained for the \( N \) variable, with rejection occurring for nineteen out of the twenty periods (black line in Figure 11.d). Furthermore, for the \( T,^\perp \) variable, we fail to reject the null hypothesis at any horizon, implying that Twitter conveys no additional information relative to the traditional news outlets.

Focusing on Ireland, only the \( T \) variable appears to predict the Irish spread for the first three horizons (red-line in Figure 11.b). In all other cases, we are unable to reject the no-predictability hypothesis. For the remaining three countries (that is, Italy, Spain and France) the derived inference is uniform; no effect on the spreads can be
traced no matter the variable used, or the horizon examined (Figures 11.c, 11.e and 11.f).

Moreover, we construct the twenty periods ahead impulse response trajectory of each country’s spread following a generalized one standard deviation shock on $T$, $N$ and $T^\perp$. Figure 12 shows the transmission of these shocks to each country’s spread (see Figure 12.r) which points to flight-to-safety considerations.

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21 Exception is France, where sporadic rejections (for four horizons) take place only when the orthogonalized Twitter variable is used (red-dashed line in Figure 11.f). It is worth mentioning that the cumulative twenty periods impulse response is negative, suggesting reduction in the spread (see Figure 12.r) which points to flight-to-safety considerations.
spread for the full-sample. All impulse trajectories (continuous black line) are accompanied with the 95% Scheffe’ confidence interval (grey area) and the 95% conditional confidence interval (blue area). At the bottom left hand-side of each graph, the twenty-period cumulative sum (Cum sum) of the responses and the resulting p-value for testing the significance (Cum p-value) are reported.

Starting with Greece, the spread trajectories are consistently positive no matter the origin of the shock (\(T\), \(N\), or \(T\perp\)); at the same time, the respective conditional bands do not include zero (see Figures 12.a to 12.c). Focusing on Scheffe’s confidence band, the spread response to a \(T\), \(N\), and \(T\perp\) shock is positive up to the seventh, third and fifth horizon, respectively (see Figures 12.a to 12.c). In addition, the cumulative impact of the responses is positive and significant at the 0.01 significance level in all three cases. The magnitude of the Greek sovereign spread response following a shock on \(T\) is an 11 basis points increase at the first horizon and a 329 basis points cumulative increase (see Figure 12.a). Following a shock on \(N\), the spread increases by 8 basis points during the first horizon and by 215 basis points cumulatively (see Figure 12.b). Finally, the increase in the spread following a shock on \(T\perp\) is 7 basis points during the first horizon and 220 basis points cumulatively (see Figure 12.c).

The impulse response analysis for the rest of the countries confirms the derived causal inference discussed above. For the case of Italy and Spain, although the impulse trajectories in all occasions are primarily positive, the Scheffe’s confidence bands embrace zero immediately after the second horizon (see Figures 12.g to 12.i and Figures 12.m to 12.o, respectively). Moreover, for both countries and all instances, the cumulative effects (ranging between 1 and 12.9 basis points) are statistically insignificant. In Ireland, (see Figures 12.d and 12.e), both sources of news dissemination affect the spread in a comparable fashion as: (i) the impulse trajectories evolve similarly; (ii) the Scheffe’s confidence bands after the second horizon imply insignificance and (iii) the \(T\perp\) delivers responses that are indistinguishable from zero. Finally, the cumulative impact of \(T\) on the Irish spread is 12.5 basis points (being significant at the 0.1 significance level), while the respective impact of \(N\) is 7.9 basis points (being insignificant).
Figure 12. Full-sample impulse responses (3-5-12 to 6-24-16).

Notes: C. sum (20) refer to the twenty-horizon (days) cumulative sum of the impulse responses, while C. sum p-value is the resulting p-value for testing the hypothesis that the C. sum (20) is equal to zero. Finally, *, ** and *** denote rejection of the null hypothesis at the 0.1, 0.05 and 0.01 significance level, respectively.
For Portugal and after the first horizon, the Scheffe’s confidence bands support, in all cases, responses that wiggle around zero (see Figures 12.j to 12.l). Moreover, all cumulative effects on the Portuguese sovereign spread are insignificant. Finally, France is the only country where all the derived trajectories for the spread are in principle negative, although not different from zero (see Figures 12.p to 12.r). The twenty periods cumulative impact of both news sources is negligible and insignificant (-2.2 and -1.9 basis points), while significance occurs only after a shock on \( t \) (see Figure 12.r and footnote 21).

Overall, based on the full-sample findings, we may argue that the impact of Twitter on the Greek sovereign spread is positive and of higher magnitude than that of the traditional news outlets (both appear to significantly affect the Greek spread in the short-run). Further, the predictive power of Twitter still persists even when we account for the effects of the traditional news outlets. Finally, the combined inference from the causality testing and the impulse response analysis indicate some weak contagion effects for the case of Portugal and Ireland. The full-sample summary results are illustrated in Figures A.2 and A.3 in Appendix 1.

4.2.2. First-sample analysis

We repeat the analysis of the previous sub-section for the first sub-sample of high-activity (3-5-12 to 10-12-12). The Dufour et al. (2006) testing results are illustrated in Figure A.8 and Table A3 (both presented in Appendix 2). Figure A8.a illustrates that the no-predictability hypothesis running from \( t \) to the Greek sovereign spread (continuous red line) is rejected at the conventional levels of significance for the first fourteen horizons. On the same figure, and for the \( N \) variable, predictability is verified up to the ninth horizon (black line). Finally, for the \( T,^+ \) variable (dashed red line), predictability is traced from the first up to the eighth horizon, and sporadic predictability at some higher horizons. Hence, Twitter continues to cause the Greek spread for several horizons, even when it is orthogonal to the traditional news outlets.

For the rest of the countries, the results indicate some evidence of contagion towards Portugal and Ireland, while this is not the case for Italy, Spain and France. Specifically, the non-predictability hypothesis running from \( T \) to the Portuguese spread (red line in Figure A8.d) is rejected up to the sixteenth horizon. For the \( N \), variable, the rejection is less frequent and at higher significance levels as predictability
is established up to the twelfth horizon (black line in Figure A8.d). Finally, for the $T_i$ variable, predictability is verified for nine out of the twenty periods (red dashed line in Figure A8.d).

Our findings for Ireland show that $T_i$ predicts the sovereign spread at the first ten horizons (red line in Figure A8.b). In contrast, $T_i$ conveys predictive power towards the Irish spread only at the first horizon and from the seventh up to the tenth horizon (black line in Figure A8.d). For the $T_i^\perp$ variable, predictability is supported from the second up to the fifth horizon (red dashed line in Figure A8.d). In the case of Italy, the sovereign spread is predicted only by $T_i$ and the $T_i^\perp$ variables at the very short-run (see Figure A8.c). In France, sporadic rejections of the null hypothesis take place (at four out of twenty horizons) only for the $T_i^\perp$ (see the red dashed line in Figure A8.f). Finally, for Spain the results show no effect on the spread (see Figure A8.e).

Again, we proceed by estimating the impulse response trajectory of each country’s spread following a generalized one standard deviation shock on $T_i$, $N_i$, and $T_i^\perp$. The derived impulse responses are presented in Figure A.9 and Table A3 (both presented in Appendix 2). For the case of Greece (see Figures A9.a to A9.c), the impulse response trajectories are positive with the respective conditional confidence bands (blue area) indicating individual significance. The wider Scheffe’s confidence bands, following a $T_i$ shock, indicate a positive trajectory up to the thirteenth horizon (see Figure A9.a). When the shock is attributed to $N_i$, the Scheffe’s confidence bands imply a positive path only for the fifth and up to the ninth horizon (see Figure A9.b). When the shock is attributed to $T_i^\perp$, positive trajectories emerge for the first eight horizons (see Figure A9.c). Moreover, in all cases the twenty-periods cumulative responses are positive and significant at the 0.01 significance level.

The Scheffe’s confidence bands for the response of the Portuguese spread following a shock on $T_i$ and $N_i$ suggest a positive path up to the seventh and fourth horizon, respectively (see Figures A9.j and A9.k). At the same time, no clear positive path can be verified after a $T_i^\perp$ shock (see Figure A9.l). In all cases, the twenty periods cumulative responses of the Portuguese spread are positive, while significance is established only after a shock on $T_i$ and $T_i^\perp$ (see Figure A9.l). In Ireland, the Scheffe’s confidence bands support a positive reaction of the spread up to the third and second
horizon following a shock on \( T \) and \( N \), respectively (see Figures A9.d and A9.e). A \( T,^+ \) shock leads to changes that are indistinguishable from zero (see Figure A9.f). The cumulative response of the spread is positive but not statistically significant.

In Spain and Italy, no matter the source of the shock, the Scheffe’s confidence bands suggest a positive reaction of the spreads only in the very short-run; at the same time, all cumulative spread responses are insignificant for both countries (see Figures A9.m to A9.o and A9.g to A9.i). For France (see Figures A9.p to A9.r), the impulse responses are mainly negative and the respective Scheffe’s confidence bands include the value of zero. Most interestingly, the cumulative twenty periods spread response following a shock on \( T \) and \( T,^+ \) is negative and statistically significant which points to flight-to-safety effects.

Overall, the first sample results reveal again that the impact of Twitter on the Greek sovereign spread is of higher magnitude than that of the traditional news outlets. Moreover, the predictive power of Twitter persists even when we account for the effects of the traditional news. Additionally, the impact of the two news sources on the Greek spread is considerably higher than the respective impact in the full sample. Finally, there is evidence of contagion for the case of Portugal and weaker evidence for Ireland. It is worth mentioning for the case of France that while the causal testing and the impulse response analysis imply no significant responses, the twenty horizons cumulative sum is negative and statistically significant. The first sample summary results are illustrated in Figures A.2 and A.3 in the Appendix.

**4.2.3. Second-sample analysis**

We conclude the empirical results by repeating the analysis of the previous two subsections for the second sub-sample (12-28-14 to 6-24-16). The causal testing results are shown in Figure A.10 and Table A4 (both presented in Appendix 2). The continuous red line in Figure A.10a, shows that the hypothesis of no-predictability running from \( T \) to the Greek sovereign spread is rejected (at the conventional level of significance) up to the fifth horizon. For \( N \), predictability can be verified only for the first horizon (black line in Figure A10.a). Finally, for \( T,^+ \) predictability is still present from the first up to the sixth horizon (dashed red line in Figure A10.a). Hence, the second-sample results show that the effect of Twitter on the Greek spread is more long-lived compared to traditional news outlets and robust in terms of significance, while Twitter
continues to predict the Greek spread, even when it is orthogonalized to the traditional news outlets.

The results for the rest of the countries show only circumstantial evidence of contagion effects. Specifically, the non-predictability hypothesis running from $T_t$ to the Italian sovereign spread (red line in Figure A10.c) is rejected only for the first two horizons. For $N_t$, there is no rejection at any horizon (black line in Figure A10.c), while for the $T_{T_t}$, predictability exists up to the fifth horizon but only at the 0.1 significance level (red dashed line in Figure A10.c). The results for Ireland imply that $T_t$ predicts (at the 0.1 significance level) the sovereign spread at three sporadic horizons (red line in Figure A10.b), while for $N_t$, the rejection is verified only at the first horizon (red line in Figure A10.b). For the case of Spain (Figure A10.e), predictability exists for both news sources and $T_{T_t}$ only at the first horizon. Finally, for Portugal (Figure A10.d) and France (Figure A10.f), we fail to reject the null hypothesis in any case.

The impulse responses for each country are illustrated in Figure A11 (in the Appendix). Starting with Greece (Figures A11.a to A11.c), when the shock takes place in $T_t$ or in $N_t$, the response paths are positive and individually significant (see blue area). When the shock is introduced in $T_{T_t}$, the responses turn negative after the seventeenth horizon. In response to a $T_t$ shock, the Scheffe` bands suggest a positive trajectory up to the fourth horizon. Following a shock on the traditional news, the Scheffe` bands suggest a positive trajectory up to the second horizon. Following a $N_t$ shock, a positive trajectory emerges for the first four horizons. Finally, all twenty periods cumulative effects, in response to a shock on $T_t$, $N_t$, and $T_{T_t}$, are statistically significant.

In the case of Italy (see Figures A11g, A11.h and A11.i), and following a shock on $T_t$ and $T_{T_t}$, the Scheffe` confidence bands support a significant positive trajectory for the first three horizons. On the other hand, following a $N_t$ shock, the trajectory is indistinguishable from zero. In the case of Ireland, the Scheffe` confidence bands imply a significant positive trajectory up to the third, second and first horizon in response to a shock on $T_t$, $N_t$, and $T_{T_t}$, respectively (Figures A11d, A11.e and A11.f). The findings for Spain indicate a significant positive trajectory only in the very short-run (Figures A11.m to A11.o). Lastly, the Scheffe` confidence bands for Portugal (Figures A11.j to
A11.l) and France (Figures A11.p to A11.r) show a significant positive trajectory up to the first and fourth horizon only in response to a $T_1$ shock. For Portugal and France, the cumulative twenty horizons responses are not significant.

Overall, the second-sample results reveal that the impact of Twitter on the Greek sovereign spread is of higher magnitude than that of the traditional news media and that the predictive power of Twitter persists even when we take out the effects of the traditional news. Furthermore, the impact of the two news sources on the Greek spread is lower compared to the first-sample and the full-sample. Finally, there is evidence of contagion in the first-sample for Portugal and Ireland; such evidence disappears in the second-sample. The second-sample summary results are illustrated in Figures A.2 and A.3 in the Appendix.

5. Discussion of results and conclusions

This paper considers the differential impact of social media, Twitter in particular, and traditional news on the sovereign bond market to reach the following findings. First, there exists a bidirectional information flow between Twitter and traditional news outlets with the impact of Twitter on the traditional news being consistently more prolonged and more robust in terms of significance, especially in high-activity periods. Second, the impact of Twitter’s “Grexit” mentions on the Greek sovereign spread is positive and of higher magnitude than that of the traditional news outlets in all examined samples; in addition, the predictive power of Twitter persists even when we take out the effects of the traditional news (by orthogonalizing the Twitter variable on the traditional news variable). Third, our analysis shows weak contagion effects for the case of Portugal and Ireland in both the full-sample and first high-activity sample whereas, in the second high-activity sample, contagion effects disappear.

In more detail, our full-sample results (in Figures A2-A3) show that the informational content on Twitter (Traditional news outlets) significantly affects the Greek spread for eighteen (six) days; the cumulative twenty days impact is 329 (215) basis points. The effect of Twitter persists even when it is orthogonal to Traditional news outlets as it continues to impact significantly on the Greek spread for seven days; the respective cumulative impact is 220 basis points. Evidence of contagion effects are traced for Portugal (for the first sample) and Ireland (for the full sample). In particular, Twitter significantly affects the Portuguese spread for sixteen days; the cumulative
twenty days impact is 119 basis points. Further, orthogonal Twitter significantly affects
the Portuguese spread for nine days; the cumulative twenty days impact is 250 basis
points. In the case of the full sample, the information content of Twitter predicts the
Irish spread for three days; the twenty days cumulative impact is 12.5 basis points. For
Italy and Spain and the full sample, the information content of Twitter or traditional
news is not statistically significant in affecting the borrowing costs at any horizon; for
both countries, the cumulative twenty days impact is indistinguishable from zero.
Similar findings (to Italy and Spain) emerge for France with the only difference being
that the cumulative impact on the French spread is negative and almost always
statistically insignificant. Our evidence of weak contagion effects might be related to the exposure of
banks to Greek public and private debt. Recall that we find some evidence mainly for
Portugal\textsuperscript{22} and Ireland. Figure 13 reports Bank of International Settlements (BIS) data
which shows that prior to the crisis, Portuguese banks had the highest exposure to
Greek public and private debt (reaching 6.79\% of their total exposure around the world
in 2010Q1). In terms of timing, we observe that Irish banks decided to reduce notably
their exposure to Greek debt earlier than everybody else in 2010Q4, that is, when
Ireland itself was bailed-out for €85bn.\textsuperscript{23} We also note that the exposure of banks in
Spain to Greek debt had always been negligible. As the crisis evolved, the exposure of
all banks to Greek public and private debt became negligible which arguably offers
support to our empirical finding that contagion effects drop to great extent as we move
from the first high-activity sample to the second one.

Our results highlight the importance of social media platforms, Twitter in
particular, in predicting bond market movements over and above the impact of
economic/financial fundamentals and more so, compared to traditional news. Taking
into account the instantaneous manner in which social media information is spread,
social media contribute to the efficient functioning of financial markets. Unless, of
course, misinformation finds its way through social media platforms. In a recent
paper, for instance, Fan \textit{et al.} (2018) find that automated Twitter accounts (known as
‘bots’) can pump out messages that have the ability to affect public opinion and the

\begin{footnotes}
\item[22] Using a composite indicator that measures multidimensional sovereign bond market stress
in the euro area from September 2000 to August 2018, Garcia-de-Andoain, and Kremer (2018)
find spill-over effects from Greece to Portugal and vice versa.
\end{footnotes}
stock market. In addition, the case of Scottish trader James Alan Craig serves as a reminder that Twitter has the power to predict future market movements and, at the same time, can be used to manipulate markets for ill gain.

![Figure 13. Exposure of IIPS and France to Greek debt](image)

**Figure 13.** Exposure of IIPS and France to Greek debt

*Notes:* The data for the exposure of the IIPS banks to the Greek public and private debt (% of their total exposure around the world) come from the Bank of International Settlements (BIS) and cover the period 2007Q1 to 2018Q1.

All these raise the important issue of regulating social media. The responsibility lies with media companies, journalists and governments. Worldwide, there seems to be more consensus among consumers that media businesses, journalists and companies like Google or Facebook need to do more to combat misinformation. When it comes to government intervention, however, a more mixed picture emerges with sentiment towards government intervention being stronger in Europe than in the US which raises the issue of how effective government intervention might turn out to be in the absence of coordinated government action across the world.  

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24 According to The Reuters Institute Digital News Report 2018, 60% of responders in Europe favor increased government intervention compared to 41% in the US (see: [http://www.digitalnewsreport.org/](http://www.digitalnewsreport.org/)).
References


Appendix 1. Summary of the results

**Figure A1. Summary results for section 4.1**

*Notes*: The bar length shows the twenty-periods cumulative response of one news source after a shock on the other news source; *** indicate the 0.01 significance of the cumulative response; finally, the number right before the letter h, imply the number of horizons for which the null hypothesis of no causality is rejected at the conventional levels of significance.

**Figure A2. Summary results for section 4.2**

*Notes*: The bar length shows the twenty-periods cumulative response of the spreads after a shock on the respective news source; ***,** and * indicate the 0.01, 0.05 and 0.1 significance of the cumulative response; finally, the number right before the letter h, imply the number of horizons for which the null hypothesis of no causality is rejected at the conventional levels of significance.
Figure A3. Summary results for section 4.2

Notes: The bar length shows the twenty-periods cumulative response of the spreads after a shock on the orthogonal Twitter; ***, ** and * indicate the 0.01, 0.05 and 0.1 significance of the cumulative response; finally, the number right before the letter h imply the number of horizons for which the null hypothesis of no causality is rejected at the conventional levels of significance.
Appendix 2. The data and causality results

Figure A4. Sovereign Spreads for GIIPS and France

Figure A5. Default risk proxy for GIIPS and France
Notes: The Euro area common risk proxy is identified by the difference between the return of the 10-year KfW (Kreditanstalt für Wiederaufbau) bond and the respective return of the 10-year German government bond. The Global Financial Stress Index is provided by the Bank of America Merrill Lynch Global Research Division.
Figure A8. First sub-sample DPR p-values for the GIIPS and France.
Figure A9. First sub-sample impulse responses (3-5-12 to 10-12-12).

Notes: C. sum (20) refers to the twenty-horizon (days) cumulative sum of the impulse responses, while C. sum p-value is the resulting p-value for testing the hypothesis that the C. sum (20) is equal to zero. Finally, * ** and *** denote rejection of the null hypothesis at the 0.1, 0.05 and 0.01 significance level, respectively.
Figure A10. Second sub-sample DPR p-values for the GIIPS and France.
Figure A11. Second sub-sample impulse responses (12-28-14 to 6-24-16).

Notes: See notes of Figure A9.
Table A1. Twitter activity predictability from the respective activity on Traditional news outlets and vice versa.

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Panel B

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Notes: Dufour et al. (2006) Wald statistics (DPR) are reported. The symbol $\rightarrow$ denotes the null hypothesis of non-causality that runs from the left-hand variable to the right-hand variable. $T$ is the logarithm of the Grexit mentions in Twitter and $N$ is the logarithm of the Grexit mentions in the traditional news outlets. The sequence of stars (*, ** and ***), signify rejection of the null hypothesis at the 0.1, 0.05 and 0.01 significance level, respectively.
Table A2. Sovereign spreads predictability in the GIIPS from Twitter and Traditional news (Full-sample: 3-5-12 to 6-24-16).

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Notes: Dufour et al. (2006) Wald statistics (DPR) are reported. The symbol $\leftarrow$ denotes the null hypothesis of non-causality that runs from the left-hand variable to the right-hand variable. $T$ is the Grexit mentions in Twitter (logarithm), $N$ is the Grexit mentions in the traditional news outlets (logarithm), $T^c$ is the orthogonal Twitter and $S$ is the sovereign spreads. $EGLD$ suggests conditioning on euro-zone risk, global financial risk, liquidity risk and default risk. Finally, *, ** and *** signify rejection of the null hypothesis at the 0.1, 0.05 and 0.01 significance level, respectively.
### Table A3. Sovereign spreads predictability in the GIIPS from Twitter and Traditional news (First-sample: 3-5-12 to 10-12-12).

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Notes: Dufour et al. (2006) Wald statistics (DPR) are reported. The symbol $\rightarrow$ denotes the null hypothesis of non-causality that runs from the left-hand variable to the right-hand variable. $T$ is the Grexit mentions in Twitter (logarithm), $N$ is the Grexit mentions in the traditional news outlets (logarithm), $T^c$ is the orthogonal Twitter and $S$ is the sovereign spreads. EGLD suggests conditioning on euro-zone risk, global financial risk, liquidity risk and default risk. Finally, *, ** and *** signify rejection of the null hypothesis at the 0.1, 0.05 and 0.01 significance level, respectively.
Table A4. Sovereign spreads predictability in the GIIPS from Twitter and Traditional news (Second-sample: 12-28-14 to 6-24-16).

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<td>8.49*</td>
</tr>
<tr>
<td>France</td>
<td>$T \rightarrow S_{EGLD}$</td>
<td>1.91</td>
</tr>
<tr>
<td></td>
<td>$N \rightarrow S_{EGLD}$</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>$T^c \rightarrow S_{EGLD}$</td>
<td>0.97</td>
</tr>
</tbody>
</table>

Notes: Dufour et al. (2006) Wald statistics (DPR) are reported. The symbol $\rightarrow$ denotes the null hypothesis of non-causality that runs from the left-hand variable to the right-hand variable. $T$ is the Grexit mentions in Twitter (logarithm), $N$ is the Grexit mentions in the traditional news outlets (logarithm), $T^c$ is the orthogonal Twitter and $S$ is the sovereign spreads. $EGLD$ suggests conditioning on euro-zone risk, global financial risk, liquidity risk and default risk. Finally, *, ** and *** signify rejection of the null hypothesis at the 0.1, 0.05 and 0.01 significance level, respectively.