Differences in opinion make a market.
Web-based inference of stock prices and volumes for a subset of systemically important banks

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Abstract

This paper analyses whether information coming from the web has some predictive power with respect to the stock market behavior of a set of systemically important European banks. Using the Europe Media Monitor (EMM) engine we scan the quantity of web-information related to HSBC, Barclays, BNP Paribas, Crédit Agricole, Royal Bank of Scotland and Deutsche Bank. Our working hypothesis is that the amount of web-info can be a proxy of the interest a given financial institution is attracting. This interest, in turn, should be linked to the stock price of the institution. The timing and evolution of web-buzz should also be able to give us an idea of the herding behavior arising, for example, in periods of economic turbulence. The findings of this paper are preliminary as the project is still ongoing.

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Introduction

Can the stock market be really predicted? This question always attracted the attention of economists and brokers. According to the Efficient Market Hypothesis (EMH, H. Fama 1965), stock markets are largely driven by new information (i.e. news rather than present and past prices). As prices are common knowledge, past prices are useless to predict current ones and today's information (again common knowledge) is useless to predict tomorrow's prices. As news is not predictable, stock market prices will follow a random walk pattern and cannot be anticipated with more than 50% accuracy. In the words of Malkiel a *blindfolded chimpanzee throwing darts at the Wall Street journal could select a portfolio that would do as well as the* (stock market) *experts* (Malkiel 2003, page 60).

Recent critical reading of the EMH, especially from the point of view of Socionomic Theory of Finance and Behavioral Finance (Malkiel, 2003), pointed to a certain degree of predictability showing that the golden assumption of EMH (prices follow a random walk) may not be realistic. The theory of noise trader (Schleifer and Summers, 1990) suggests persistent deviations of prices from their intrinsic value due to investors' sentiment (unrelated to fundamental data). Contemporaneously the geometric increase in supply of information via on line sources (on line journals, dedicated blogs, social networks, etc.) makes possible even for non-experts the access to financial information and facilitates market transactions. Barber and Odean (2001) show how internet changed the way in which information is delivered to investors and how investors can act on that information. Two opposite arguments seem to coexist. The orthodox vision whereby extensive web access is likely to favor information spreading and speeds up the formation of the "common knowledge" theorized in (neo) classical economic models, quickly eroding information rents (Malkiel, 2003). On the other hand, web-buzz incentives herding behavior and boosts volatility in periods of turbulences by amplifying rumors. This latter is particularly important for financial systems as perceived weakness of the system (or part of it) could produce a domino effect with dreadful consequences.

In the literature the evidence is mixed. Shiller (2000), for example, describes the bandwagon effect leading to the rise of US stock market in the 1999s. Among the first in exploring the link between news coverage and stock prices, Cutler et al., (1989)[3] find that important news do not seem to explain large movements in S&P500 as macroeconomic events instead do. DeBond and Thaler (1985) talk about investors subject to waves of optimism and pessimism, causing prices to deviate systematically from their fundamental values while Chan at al. (1996) suggest that markets respond only gradually to new information. Kahneman and Tversky (1979) portray investors as systematically overconfident in the ability to forecast future stock prices or earnings. The difficulty in validating these arguments is related to the complexity of modeling market dynamics: the degree of information possessed by agents and their interconnection, together with their inter-temporal optimization. What seems to be clear (or better obvious) is that information is important and the web is becoming the major source of information (or misinformation). In the words of Gloor et al. (2009) *the web has become part and a mirror of the real word*.

[3] and recently Cornell, 2013, who confirmed their findings.

The literature relating web mining with financial prediction is relatively recent. To the best of our knowledge the first study is due to Wysocki (1999). He proved that for the 50 firms with the highest message posting in Yahoo between January and August 1998, the posting volume did forecast next day trading volumes. About the opposite result, namely internet buzz cannot predict trading volume, is obtained by Tumarkin and Whitelaw (2001) and by Das and Chen (2001), among others. More recently Preis et al. (2012) show that weekly transactions volumes of S&P500 companies are correlated (at most 0.3 correlation) with weekly search volume of company names. Preis et al. (2013) analyzed the performance of 98 search terms in Google Trends finding that the term *debt* was associated to a return of the web-based trading strategy up to 2.31 standard deviations higher than the random strategy. They also find that decrease in Dow Jones Industrial Average is preceded by an increase in the search volumes for certain financially related terms, while less compelling evidence pushes to suppose that increased in Dow Jones were preceded by decrease in search. The same trading strategy is used by Moat et al., 2013 who analyse the prediction power of Wikipedia views or edits corresponding to the companies listed in the Dow Jones. They find an average log return from trading equals to 0.5, compared with 0.0002 of the random strategy only with wiki-views, while no gain is associated to the wiki-edit adjusted strategy (see Nardo et al, 2014, for a survey of stock market predictions using on-line financial news).

Web mining has been increasingly used as source of information for assessing a wide variety of economic or social phenomena. For example Doshi et al. (2009) Mishne and Glace (2006), Asur and Huberman (2010) and Goel et al. (2010) use web buzz to forecast box-office revenues of movies, videogame sales and Oscar winners. Tweets were considered as an alternative to election polls for forecasting the results of 2009 German Federal Election (Tumasjan et al. 2010). Choi and Varian (2011), show to what extent Google queries can be leading indicators of consumer purchases in selected sectors (automobiles sales, unemployment claims, travel destination planning, and consumer confidence). They show that web-based info assures gains from 5% to 20% with respect to autoregressive models. McLaren and Shanbhogue (2011) use Google Insights for Search data to nowcast the movements of unemployment and house prices in UK. Blog posts and blog sentiment proved to be related to product sales (Gruhl at al., 2005) and a Facebook's Gross National Happiness index is calculated by Mishne and Rijke (2006). Price et al. (2012) analyse the link between behavior on-line and real word economic indicators in 2010 for 45 countries, finding that the Future Orientation Index (a combination of Google searches for the terms 2009 –past– and 2011 –future–) has a 0.78 correlation with GDP.

This paper analyses whether information coming from the web has some predictive power with respect to the stock market behavior of a set of systemically important European banks. Using the Europe Media Monitor (EMM) engine we scan the quantity of web-information related to HSBC, Barclays, BNP Paribas, Crédit Agricole, Royal Bank of Scotland and Deutsche Bank. Our working hypothesis is that the amount of web-info can be a proxy of the interest a given financial institution is attracting. This interest, in turn, should be linked to the stock price of the institution. The timing and evolution of web-buzz should also be able to give us an idea of the herding behavior arising, for example, in periods of economic turbulence. The findings of this paper are preliminary as the project is still ongoing.

The paper is organized as follows. Section 1 provides a description of the EMM engine. Section 2 defines the main assumptions of the work and describes the data used while Section 3 illustrates the first results. Section 4 concludes and provides suggestions for future research.

1. The Europe Media Monitor

The Europe Media Monitor (EMM) was started in 2002 as a project to support the Commission with its Media Monitoring activities. The main purpose of EMM is to provide monitoring of a large (but selected) set of electronic media, reduce the information flow to manageable proportions by applying categorisation and to provide extra information by analysis of the retrieved texts in the form of entity recognition, entity extraction, recognitions of quotes, sentiment/tonality analysis etc.

EMM is designed as a near real-time monitoring system for new publications. The system generates the required information products continuously and does not rely on (and does not have) a big information archive. Although EMM does maintain an index of all retrieved material, allowing for limited historical research, the information products always refer to the original publication, mostly on the Internet.

At the core of the EMM system is a processing chain of lightweight extensible processes each running independently and chained together using robust and reliable in-house developed web service architecture. Articles begin their flow through the processing chain as thin RSS (Really Simple Syndication[4]) items that grow as meta-data gets added at each stage of the processing chain.

The first element of this processing chain, the scraper, monitors a number pages/RSS feeds on selected websites for the publication of items and produces a snapshot of all items currently being published on these pages. The selection of websites depends on the information domain to be monitored. For those sites that require 'near real time' monitoring (update frequency measured in minutes), EMM uses a technique which does not rely on 'crawling' the website. Instead, EMM monitors (scrapes) a selected set of HTML pages or RSS feeds on the website. For websites that do not have a clear 'publication' structure the system will crawl the website, but this will reduce the monitoring frequency to a number of times per day.

The second process in the chain receives the snapshot as produced by scraper, and determines the difference between the current snapshot and the previous snapshot (the delta). Based on this delta this process then 'grabs' the new items from the web and extracts the relevant text from the items. For a typical HTML page this is a non-trivial operation as the system tries to identify the 'main article' text from what can be a 'noisy' page. The system then constructs a basic RSS feed, containing the new articles from the source currently being monitored, and adds the extracted text as item metadata. This RSS feed, the basis of the information enhancement and filtering process, is then pushed to the next process in the chain.

[4]http://cyber.law.harvard.edu/rss/rss.html

Subsequent processes in the chain use the extracted text, and/or metadata added by previous processes, to further enrich the information in the RSS. The Entity Recognition process detects people and organizations in the article from a home grown information base of entities and organizations, populated by an automated (offline) entity recognition system. The next module in the chain performs geo-tagging of the articles, using a multilingual, classified geospatial information base of place names, provinces, regions and countries. The previously recognized entities are used to disambiguate the geo-tags (Clinton is also a place name in Arizona; Paris Hilton is not the Hilton in Paris). Another module extracts quotes from the text and assigns the quotes to the relevant entities in the article. The quote extraction module currently runs in 19 languages.

The tonality/sentiment of an article is determined using 4 sets of 'tonality' words per language, denoting highly positive, positive, negative and highly negative words. These tonality dictionaries are currently available in 14 languages, including the main EU languages (excluding Greek, Hungarian, Bulgarian, Baltic and Scandinavian languages but including Spanish, English, French, German, Dutch, Italian, Check, Slovak and Polish). The total score for an article is calculated by aggregating the score for all tonality words in the article. The score is then transformed using a logarithmic transformation and corrected using a source specific 'tonality bias' which is calculated using a long term 'rolling average' for the source. This ensures that the tonality is as much as possible comparable between sources. The score expresses a full article tonality and is not particularly meaningful as such. For further use, this tonality score is later transferred to any associated categories and aggregated per day. This aggregated value can be used to determine a tonality trend for a category.

The main component that determines the information streams from EMM is a powerful keyword based categorization system. The category definitions allow for word/weight lists, Boolean combinations, proximity and character wildcards. The system deals efficiently with 'overlapping' categories; it is not based on any hierarchical category structure. The system also deals efficiently with languages like Arabic (first character after whitespace is not the first character of the noun) and 'ideograph' languages like Chinese (no whitespace).

The (near) duplicate detection system uses a character trigram signature of the title and description of the articles to calculate a cosine distance measure between an article and all articles in a preceding 24 hour period in the same language. In order to reduce the (potentially huge) number of calculations, the system uses the assigned categories as a way of reducing the set of article signatures used for comparison. The assumption is that (near) duplicate articles share a large set of assigned categories.

Following the duplicate detection system the RSS flows through a second categorization system where new categories are constructed based on the now available article metadata. These new categories are typically defined as the co-occurrence of two or more 'content based' categories and restrictions based on source, language or source country. These new categories are assigned to the articles in an additive way, i.e. the original category information remains. For the purpose of further analysis these new categories are semantically equivalent to the keyword based categories.

All items, now enriched with metadata, are sent on to a number of downstream systems. Some of these downstream systems deal with the individual items, producing RSS feeds per category, per country/category, or sending a mail notifying interested users about new items in a category. All items are indexed to produce a free text searchable index of all articles that entered the system. An analyser module examines the article counts and produces alerts based on deviations from expected daily counts.

The articles also flow into the Clustering and Story Tracking Cache. Every 10 minutes the last 4 hours of articles are hierarchically clustered in every language individually. The clustering process is agglomerative and employs average group linkage to build the clusters using a simple cosine measure to calculate distance. The clustering process continues until the cosine measure falls below a certain set threshold. The article feature vectors are simple word count vectors with some additional ad-hoc rules. Using a sliding window approach the system tracks the evolution of stories over time. This makes it possible to detect 'breaking news', and furthermore to dynamically build (track) very large stories, without having to cluster a huge number of items.

The clustered articles, representing news stories, form the basis of another set of processing modules. These modules are no longer arranged in a pipeline but operate asynchronously and in parallel to each other in order to update the current news story metadata with extra information whenever it becomes available, without delaying the actual 'story'. Examples of these modules are: event metadata extraction, summarization and cross lingual cluster detection.

The results of the information harvesting and processing can be accessed in a number of ways. A website (e.g. http://emm.newsbrief.eu) allows for classical data browsing, and there is a full editorial and publishing system NewsDesk (not publicly accessible) that allows for the creation and publication of high level information products. EMM delivers emails and RSS feeds and there are (free) mobile applications for iPhone, iPad and Android tablets.

Examples of current applications of the EMM technology can be found in different application domains. EMM is used in a number of traditional media monitoring applications by various EU Institutions and Agencies. MedISys (http://medisys.newsbrief.eu) is an instance of EMM specifically developed for internet bio-surveillance and is used by a number of Health Agencies, including the WHO. Open source intelligence for humanitarian and conflict early warning is also covered by at least 3 instances of the EMM system.

At the moment of writing, the publicly accessible instance of EMM, used for the data retrieval described in this paper, monitors around 10000 RSS feeds/HTML pages from 4000 media websites and retrieves and processes around 200.000 new news articles per day. These articles are categorized in around 1500 categories. A selected subset of these categories and the results of the clustering process can be seen on the public EMM website http://emm.newsbrief.eu

2. Description of the data

On November 2013 the Financial Stability Board issued the list of globally systemically important banks. These are the banks that, from January 2016, will be required to possess higher loss absorbency requirements. The listed EU banks are (in decreasing order of tightness of additional loss absorbency): HSBC, Barclays, BNP Paribas, Deutsche Bank, Group Crédit Agricole, Royal Bank of Scotland, BBVA, ING Bank, Nordea, Santander, Société Générale, Unicredit Group.

In the first phase of this project the object of the analysis will be the banks requiring an additional loss absorbency up to 1.5% (this is the level of additional common equity loss absorbency as a percentage of risk-weighted assets), namely HSBC, Barclays, BNP Paribas, Deutsche Bank, Crédit Agricole and Royal Bank of Scotland. We nevertheless are gathering data for 26 EU banks, including all systemically important banks (the only exception is Standard Chartered as its main business is located outside EU in spite of being based in London) that will be included in the analysis at a later stage.

Daily data on stock prices (open, close, highest, lowest) and volumes exchanged are downloaded from Yahoo! finance for the main contracting markets: for Deutsche Bank we use stock values/prices of New York (NYSE) and Frankfurt stock exchanges, for HSBC, Royal Bank of Scotland, and Barclays we use NYSE and London data while for BNP Paribas and Crédit Agricole we only use Paris stock exchange data (as data on Frankfurt stock exchange does not report the volumes exchanged). Several summary variables have been constructed from stock data:

(1) close(t)- opening(t); (2) close(t)-close(t-1); (3) w(t)*(close(t)-opening(t)) where w is the volume exchanged in time t divided by the average volume exchanged the previous 5 days; (4) w(t)*close(t)-w(t-1)*close(t-1) ; (5) adjclose(t)-adjclose(t-1) , where adjclose is the close price adjusted for dividends and splits; (6) High(t)-low(t) where High (Low) is the highest (lowest) price reached during the contracting day, this variable is a proxy of the daily price volatility; (6) relative volume exchanged (daily volume divided by the average volume exchanged in the previous 5 days[5]); (7) volume exchanged.

Web data have been obtained by constructing *alerts* (one for each bank) each containing a variable number of keywords related to the bank (name, thicker, most common press mistakes for the name, abbreviations, etc.). A variable number of keywords with negative weight have been added to limit noise.[6] December 2013 has been used as test to properly calibrate EMM and all resulting web texts have been verified manually for anomalies.

Within the EMM architecture we had the possibility to influence the media websites (henceforth sources) scanned by the system by adding relevant or deleting irrelevant sources in order to minimize the noise. After analysing the corpus of texts retrieved from the web in December 2013 we opted for restricting the list of sources to financial and national journals, excluding local websites. We also excluded all non-European sources with the only exception of US, retained in the analysis for the New York stock exchange. From the 4000 media websites considered by EMM we finally retain about 1400.

When EU stock exchange data are analysed we explore two sets of web sources: all EU+US national and financial sources and only the sources of the country where the bank is located (e.g. Germany for Deutsche Bank, United kingdom for Royal Bank of Scotland, Barclays and HSBC and France for

[5] Ideally the volume of stocks exchanged should be divided by the share of bank capital represented by equities and sold in the stock market. This data is however not available for all the analyzed banks.
[6] For instance Barclays sponsors the UK football premiere league and it is also the name of a theater in Milan (Italy). In order to exclude irrelevant texts related to sport and theater we added appropriate. Notice that the weight of a keyword represents the number of times the keyword has to be found for the article to be selected. Negative keywords assure that the article will be never selected.

BNP Paribas and Crédit Agricole). Data are gathered from December 5th, weekends (and non-contracting days) are excluded.[7] Data collection is currently ongoing and results constantly updated.

EMM scans web sources periodically (the frequency, even few minutes, depending on the importance of the source) and updates its website with new results every 10 minutes. For the purpose of this exercise EMM supplies the following set of informations: a time-stamp indicating when the article has been detected (and not when the article has been published by the source), a measure of tonality, and the number of times the guiding keywords have been cited in the text (information not used in this analysis), plus a set of other textual information (article identifier and title). For the articles with missing tonality (corresponding to languages not considered by EMM) we set neutral tonality by default.

For each contracting day and each bank we tested several summary measures: number of articles, share of articles (with respect to the previous day), share of articles with respect to the total number of articles found by EMM that day, share of articles having positive (negative) tonality, average daily tonality, its standard deviation, polarity, subjectivity and disagreement, where:

polarity=(number_pos_ton-number_neg_ton)/(number_pos_ton+number_neg_ton);

subjectivity=(number_pos_ton+number_neg_ton)/number_articles;

disagreement=(number_pos_ton-number_neg_ton)/number_articles;

Polarity expresses whether the daily sentiment is positive or negative while disagreement is a measure of the overall polarity of visions on the daily occurrences. Both should be more related to the positive/negative behavior of stock prices, to price volatility and to the difference between the highest and lowest contracting price. Subjectivity indicates whether a sentiment (no matter its direction) has been expressed and should be more related to the volume exchanged.

The limited number of contracting days currently available (from 5th of December 2013 to the 7th of February 2014 with 44 data points) prevents sophisticated econometric analysis. In this preliminary version of the paper we will limit our analysis to cross-correlation (with at most 3 days of lag) and Granger causality for each of the combination of 8 stock prices variables and 12 web-buzz variables.

3. Analysis

The preliminary analysis is centered on the cross-correlation between trading and web variables and on the granger causality test. Tables are reported at the end of the paper.

Table 1. Daily average of web articles according to the source considered

[7] With an exception: in the calculating of the share of articles found by EMM in day t with respect to those found in t-1, weekends and non-contracting days are taken into account, so this variable on Monday is the difference in articles found by EMM with respect to Sunday.

	EU+US sources	Country sources
Barclays	43	8
BNP Paribas	54	15
Crédit Agricole	17	13
Deutsche Bank	82	34
HSBC	45	4
Royal B. Scotland	16	3

3.1 Cross-correlation

Let

2. Beyond trading volumes two other stock market variables stand out as the ones mostly related to web buzz: the difference between opening and closing trading prices (i.e. trade gains) and a proxy of daily trading volatility (the difference between the highest and the lowest trading price). This observation is in line with the literature. The relationship between intraday trading volatility and web-buzz is analysed by Lavrenko et al., (2000a,b) and Mittermayer (2004). They both find that an intraday trading strategy that uses web-buzz can produce an average gain ranging between 0.1% to 0.5% with respect to a random strategy with zero expected gain. Gidófalvi (2001) finds significant correlation between stock prices (for a set of 12 companies) and news articles 20 minutes before/after the news is made public. Increased trade (and increased returns) as the synchronous trading increases when the communication pattern is increasingly different from random is found by (Saavedra et al., 2011). In the literature probably the best result is obtained by Schumaker and Chen (2009). Web buzz, used to define a trading strategy, gives 71.18% prediction accuracy in detecting the direction of price change and a return of 8.5% for the simulated trading. The financial sector is especially predictive with a directional accuracy of 76.02%. A conflicting finding is that of Antweiler and Frank (2004). They analyse a set of posts in Yahoo!Finance and in Ranging Bull containing the name of the 45 firms and find that web messages do not successfully predict stock returns nor volatility.

3. For the Royal Bank of Scotland and the Deutsche Bank the best results in terms of the number (and magnitude) of significant cross-correlations is found when the European stock markets and country sources are considered, especially for Deutsche Bank, whose trading variables at the NYSE seem to mostly unrelated to past web buzz. The opposite holds for Barclays in the NYSE. Country sources seem informative also for Royal Bank of Scotland, and Barclays but not for HSBC. For both French banks considered the link between web buzz and trade volumes and prices seems rather week. However the average number of daily messages is low for the Crédit Agricole making tonality variables very sensitive to the tonality algorithm.

3.2 Granger causality test

We perform a Granger causality test on each pair of trade and web variables and for each set of sources and stock exchange data available. We test both the null H0: web does not Granger causes stock and the null H0: stock market does not Granger causes web and compare the results. Three lags for the dependent and the explanatory variables are taken into consideration and the lag length selection is chosen using the Bayesian Information Criterion. Given that Granger test presupposes stationary series, beforehand we check for unit root with the Augmented Dickey-Fuller test and differentiate series when unit root is not rejected.

Results for each case analysed are reported in Appendix (Table B.1-B.6). Below some preliminary conclusions for each bank.

1 Barclays. Web variables seem to have anticipatory power especially on trade gains (the difference between opening and closing prices), volumes and a proxy of volatility when data of the NYSE are considered. The null H0: stock market does not Granger causes web and compare the results is mostly rejected in favor of the opposite null. With the London stock exchange data the picture is less

clear. Some web variables seem to have anticipatory power on volumes but less on volatility and gains. The use of UK sources only to derive web-buzz slightly improves the results but does not supplies a clear picture on the leading role of web information.

2. BNP Paribas. Whether web information follows or anticipates trade is not clear using EU+US sources and trade data from Paris stock exchange. French sources for web-buzz improve slightly the picture for gains but not for volatility or volumes.

3. Crédit Agricole. Web-buzz and trade variables seem to be mostly unrelated when the first comes from EU+US media websites. Only in few cases granger test indicates that either web-buzz follows trade variables or the opposite. The situation improves slightly when French sources are considered but the anticipatory role of web information is not clear.

4. Deutsche Bank. When using EU and US media websites, web variables seem to follow rather than anticipate trade. Restrict the sources considered to German media websites improves slightly but does not reverse the conclusion.

5. HSCB. Web information seems to follow trade when the analysis is conducted using EU+US sources and trade data from NYSE. Anticipatory power of web-buzz improves when trade data come from the London stock exchange. In particular web information seems to be leading volatility (or at least the proxy we consider). The low number of daily web texts retained when UK sources are considered (on average 4) precludes any conclusion.

6. Royal Bank of Scotland. When NYSE data are used web-buzz seems to anticipate trade gains (difference between opening and closing prices) and volatility. The picture is less clear when London stock exchange data are used as no specific pattern appears and the Granger test fails to clearly identify whether web-buzz anticipates or follows trade. The limited number of web texts especially when UK sources are considered does not help (on average 16 articles per day for EU+US sources and 3 for UK sources).

The simple analysis performed so far triggers a number of observations. The trade variables where gains are weighted with the volume exchanged do not seem to be systematically related to web-variables. A stronger relation seems to exist for gains, volatility and volume of stock traded. Future analysis will focus on these latter variables. The picture however is far from clear and the ability of web-buzz to lead trade is mixed. The literature is not unanimous either. Gilbert and Karahalios 2010 and Bollen et al. 2011 apply Granger causality to test alternative causality direction and finding that web information is most likely causing price movements than the reverse. No prediction power for stock prices or volatility is found by Antweiler and Frank (2004) with Naïve Bayesian machine learning. De Choudhury et al. (2008) with Support Vector Machine, find out that only after the occurrence of "big" events web mining shows explanatory power (up to 87%). The typical explanation for this poor performance is that new information is rapidly incorporated into agents' information set so excessive returns rapidly vanish: only very short (ideally intra-day) stock price movements can be capitalized (Schumaker and Chen 2006, 2009).

Most likely in these times of financial turbulence announcements of the BCE or of other international or national authorities are likely to play a role in explaining trade behaviors. In order to capture this effect we set up an additional alert in EMM that collects web texts related to BCE and Fed liquidity and regulatory decisions. We will use explore this avenue in the coming months.

Our analysis does not suggest a clear advantage of measures of web-buzz based on tonality with respect to other count variables (e.g. share of messages). This could be partly due to the algorithm calculating tonality (especially when few we texts are selected by EMM). During the test phase we realized that the tonality failed to identify some important financial news (like for example the downgrade of Deutsche Bank on the 19th of Dec.). Currently the tonality algorithm is being upgraded.

Nonetheless tonality and sentiment analysis on financial texts are the latest and most promising advances in this type of literature. The first to analyse sentiment in financial messages have been (to the best of our knowledge) Das and Chen (2001): they compare texts classifiers testing their ability to extract messages expressing positive/negative feelings. A binary tonality is derived from the New York Times Annotated Corpus by Zhai, Cohen, and Atreya (2011) and from business webs by Tulankar S., Athale R., Bhujbal S. (2013). While Zahng, Fuehres, and Gloor (2010) summarize in a binary tonality different measures of general mood (hope happy, fear, worry, nervous, anxious, upset) taken from messages in Twitter. May be media are not the right place to look for information able to drive behavior. The project FEDRA (Financial Event Detection for Risk Assessment) to which this paper is related, will further refine the media sources possibly open to twitter and to financial blogs.

4. Conclusion

The sequence *economic event - investment decisions - stock price jumps* is far from being a stylized fact. Anecdotic comparison between economic news and ex-post movement in aggregated stock prices done by Culter, Poterba and Summers (1989) and updated by Cornell (2013) claims that the majority of the largest movements in S&P500 (Culter et al.) and CRSP Total Market Index (Cornell)[8] cannot be tied to *fundamental economic news sufficient to rationalize the size of the observed* [price] *move* (Cornell, 2013). As stated by Black (1986): *"… people sometimes trade on noise as if it were information"*. Is web buzzing an ingredient of the missing link of this sequence?

We explore this hypothesis by relating trading prices and volumes to web-buzz for a set of systemically important banks, HSBC, Barclays, BNP Paribas, Deutsche Bank, Crédit Agricole and Royal Bank of Scotland. Web-buzz is obtained by monitoring a number of selected European and US media websites and extracting the texts containing an exogenously supplied set of keywords. We compute cross-correlation and granger causality test.

The results of our analysis are not conclusive; we find that web-buzz leads trade gains, volatility and traded volumes only for a limited number of banks. In the coming months, for the cases where an anticipatory power seems to exist, we will analyse whether web-information leads trade with out-of sample analysis. Conditional to the availability of high frequency data we will also make some preliminary analysis on intra-day volatility issues.

[8] CRSP Total Market Index covers all New York, American, and NASDAQ stocks http://www.crsp.com/

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Appendix

Tables on Cross-Correlation

Cross correlation is reported only for positive values of the lag δ, i.e. for cases in which lagged values of web variables are associated to current values of trade variables. δ=0 refers to instantaneous correlations. The opposite case (lagged values of trade variables associated to current values of web variables) is not shown here but available on request.

The entries of each table have to be read as follows: 1(-)* indicates that the cross correlation at lag 1 is significant at 1% level and has negative sign; 0(+) means that cross correlations at lag 0 is significant at 5% and has positive sign. The highest cross-correlation (usually significant at 1%) is in red while the lowest cross-correlation (significant at 5%) is reported in the notes below the table.

Table A.1 Barclays

NYSE EU+US sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles						0(+)		
average_tonality	0(-) 3(+)	0(-) 3(+)	3(+)		3(+)		0(+)	
std_tonality								
number_neg_ton	3(-)	3(-)*	3(-)		3(-)			
share_neg_ton	0(+) 1(+)	0(+)	0(+)		0(+)		0(-)	
number_pos_ton	0(-)	0(-)*	0(-)		0(-)	0(+)		
share_pos_ton	0(-)	0(-)	3(+)		3(+)		0(+)	0(+)
polarity	0(-)*	0(-)*	3(+)		3(+)		0(+)	
subjectivity	1(+)	1(+)				0(-) 1(-)* 3(-)		
disagreement	0(-)	0(-)	3(+)		3(+)		0(+)	0(+)
share_wrt_totals			0(-)		0(-)			
share_wrt_previous_day	0(-)	0(-)*				0(+)		

* = significant at 1%
highest correlation = -0.45 (in red)
lowest correlation = -0.31

London EU+US sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles	0(-)	0(-)				0(+)*		
average_tonality			3(+)	3(-)	3(+)		1(+) 2(+)	
std_tonality						3(-)		
number_neg_ton			3(-)		3(-)	0(+)		
share_neg_ton			0(+) 1(+)		0(+) 1(+)	3(-)*	1(-) 2(-)	1(-) 2(-)*
number_pos_ton						3(+)		
share_pos_ton			3(+)		3(+)		1(+) 2(+)	
polarity						3(+)	1(+) 2(+)	1(+) 2(+)
subjectivity			0(+)		0(+)	3(+)		3(-)
disagreement						3(+)	1(+) 2(+)	1(+) 2(+)
share_wrt_totals	0(-)	0(-)		3(+)			3(+)	
share_wrt_previous_day								

* = significant at 1%
highest correlation = -0.435 (in red)
lowest correlation = 0.3

London UK sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles								
average_tonality			1(+)		1(+)	2(+)	2(+)	
std_tonality		1(-)				1(+)		1(+)
number_neg_ton			3(-)	3(+)	3(-)			
share_neg_ton				3(+)		2(-)*	1(-) 2(-)*	2(-)*
number_pos_ton								
share_pos_ton								
polarity							2(+)	2(+)
subjectivity						2(-)*	1(-) 2(-)	
disagreement							2(+)	2(+)
share_wrt_totals		3(+)		3(+)			3(+)*	
share_wrt_previous_day		3(+)		3(+)			3(+)*	

* = significant at 1%
highest correlation = -0.46 (in red)
lowest correlation = -0.32

Table A.2 BNP-Paribas

Paris, EU+US sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles							0(+)	
average_tonality								
std_tonality			1(+)					
number_neg_ton							0(+) 2(+)	
share_neg_ton			3(-)					
number_pos_ton							**0(+)***	
share_pos_ton								
polarity			3(+)					
subjectivity								
disagreement			3(+)				2(-)	
share_wrt_totals								
share_wrt_previous_day							3(+)	0(-)

* = significant at 1%
highest correlation = 0.4 (in red)
lowest correlation = 0.3

Paris, FR sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles				0(+)			0(+)* 1(+)	
average_tonality								
std_tonality						2(-)		0(-)* 2(-)
number_neg_ton							0(+) **1(+)***	
share_neg_ton	1(-)							
number_pos_ton				0(+)			0(+)	
share_pos_ton								
polarity	1(+)							
subjectivity								
disagreement	1(+)							
share_wrt_totals							0(+)	
share_wrt_previous_day				0(+)			1(+)	1(-)

* = significant at 1%
highest correlation = 0.43 (in red)
lowest correlation = -0.32

Table A.3 Crédit Agricole

Paris, EU+US sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles						0(+)* 1(+) 2(+) 3(+)		1(+) 2(+) 3(+)
average_tonality								
std_tonality								
number_neg_ton						0(+)*		0(+)
share_neg_ton								
number_pos_ton						1(+)		
share_pos_ton								
polarity								
subjectivity								
disagreement								
share_wrt_totals								
share_wrt_previous_day	1(+)*	**1(+)***	2(+)					

* = significant at 1%

highest correlation = 0.472 (in red)

lowest correlation = 0.3

Paris, FR sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles						0(+)* 1(+) 3(+)		1(+) 3(+)
average_tonality								
std_tonality							2(-)	
number_neg_ton	3(-)		3(-)	0(+)		**0(+)***	0(+)	0(+)*
share_neg_ton								
number_pos_ton								
share_pos_ton								
polarity								
subjectivity								
disagreement								
share_wrt_totals								
share_wrt_previous_day	1(+)	1(+)	2(+)				3(+)	

* = significant at 1%

highest correlation = 0.537 (in red)

lowest correlation = 0.3

Table A.4 Deutsche Bank

NYSE EU+US sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles	3(-)		2(-) 3(-)		2(-) 3(-)			
average_tonality								
std_tonality								
number_neg_ton								
share_neg_ton								
number_pos_ton		3(-)						
share_pos_ton						3(-)		3(-)
polarity								
subjectivity				3(-)		3(-)		3(-)*
disagreement								
share_wrt_totals			2(-)		2(-)			
share_wrt_previous_day				0(+) 1(-)*			**0(+)***	

* = significant at 1%

highest correlation = 0.564 (in red)

lowest correlation = -0.3

Frankfurt EU+US sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles			0(-)*	0(+) 1(-)	0(-)*	0(+)	0(+)	**0(+)***
average_tonality								
std_tonality							0(+)	
number_neg_ton			0(-)*	1(-)	0(-)*	0(+)	0(+)	
share_neg_ton								
number_pos_ton			0(-)	0(+) 1(-)*	0(-)	0(+)	0(+)	0(+)*
share_pos_ton						0(-)		
polarity								
subjectivity						0(-) 1(-) 3(-)		
disagreement								
share_wrt_totals			0(-)*	1(-)	0(-)*	0(+)	0(+)	0(+)*
share_wrt_previous_day				0(+)				0(+)

* = significant at 1%

highest correlation = -0.435 (in red)

lowest correlation = 0.3

Frankfurt DE sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles			0(-)*	0(+) 1(-)*	0(-)*	0(+)*	0(+)	**0(+)***
average_tonality	0(-)	0(-)*	0(-)*		0(-)*			
std_tonality			0(+)		0(+)			
number_neg_ton			3(-)	1(-)	3(-)			0(+)*
share_neg_ton		0(+)	0(+)		0(+)			
number_pos_ton			0(-)*	0(+) 1(-)*	0(-)*	0(+)*	0(+)	0(+)*
share_pos_ton	0(-)	0(-)*	0(-)		0(-)			
polarity	0(-)	0(-)	0(-)		0(-)			
subjectivity								
disagreement	0(-)	0(-)*	0(-)		0(-)			
share_wrt_totals			0(-)*	0(-)	0(-)*	0(+)	0(+)	0(+)*
share_wrt_previous_day				0(+)				

* = significant at 1%

highest correlation = 0.507 (in red)

lowest correlation = 0.3

Table A.5 HSBC

NYSE EU+US sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles	1(-)	1(-)	1(-)*		1(-)*	0(+)		
average_tonality				3(+)*			2(-)*	2(-)*
std_tonality								
number_neg_ton	1(-)	1(-)	1(-)*		1(-)*			2(+)
share_neg_ton			3(-)	3(-)*	3(-)		2(+)*	2(+)*
number_pos_ton								
share_pos_ton			1(+)*		1(+)*			
polarity			1(+)*	3(+)	1(+)*		2(-)	2(-)*
subjectivity			2(+)		2(+)		2(+)*	2(+)*
disagreement			1(+)*	3(+)	1(+)*		2(-)	2(-)*
share_wrt_totals								
share_wrt_previous_day	0(+)	0(+)* 2(+)						

* = significant at 1%

highest correlation = -0.564 (in red)

lowest correlation = 0.31

London EU+US sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles	1(-)		1(-)*		1(-)*	2(+)*		
average_tonality				1(-)*			1(-)	1(-) 2(-)
std_tonality		0(+)*		0(+)		0(+)	0(+)*	0(+)
number_neg_ton	1(-)		1(-)*		1(-)*	2(+)*		1(+)
share_neg_ton							1(+)	1(+) 2(+)*
number_pos_ton			1(-)*		1(-)*	2(+)		
share_pos_ton						2(-)		2(-)
polarity						2(-)		1(-) 2(-)*
subjectivity							1(+)	
disagreement						2(-)		1(-) 2(-)*
share_wrt_totals			1(-)*		1(-)*	2(+)*		
share_wrt_previous_day		3(+)					3(+)	

* = significant at 1%

highest correlation = -0.536 (in red)

lowest correlation = 0.3

London, UK sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles	2(-)		1(-)		1(-)			
average_tonality								
std_tonality			3(-)		3(-)			
number_neg_ton	2(-)		1(-)		1(-)	2(-)		
share_neg_ton								
number_pos_ton								
share_pos_ton								
polarity								
subjectivity		0(-)*		1(+)		2(+)		2(+)
disagreement								
share_wrt_totals								
share_wrt_previous_day	2(-)		1(-)		1(-)			

* = significant at 1%

highest correlation = -0.411 (in red)

lowest correlation = 0.3

Table A.6 Royal Bank of Scotland

NYSE, EU+US sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles		0(-)						
average_tonality								
std_tonality								
number_neg_ton								
share_neg_ton								
number_pos_ton		**0(-)***	0(-)		0(-)			
share_pos_ton								
polarity								
subjectivity								
disagreement								
share_wrt_totals		0(-)	0(-)		0(-)			
share_wrt_previous_day			1(+)		1(+)			

* = significant at 1%
highest correlation = -0.4 (in red)
lowest correlation = -0.31

London, EU+US sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles				2(+)		1(+)*	3(-)	**0(+)*** 1(+)*
average_tonality								
std_tonality							2(-)	0(+)
number_neg_ton						1(+)*	3(-)	0(+) 1(+)*
share_neg_ton								
number_pos_ton		2(-)	2(-)		2(-)	1(+)		0(+) 1(+)
share_pos_ton	2(-)	2(-)	2(-)		2(-)			
polarity								
subjectivity								
disagreement		2(-)						
share_wrt_totals				2(-)		1(+)		0(+) 1(+)
share_wrt_previous_day	1(+)	1(+)*				3(+)		

* = significant at 1%
highest correlation = 0.55 (in red)
lowest correlation = 0.3

London, UK sources

cross-correlation	close(t)-opening(t)	w(close(t)-opening(t))	close(t)-close(t-1)	w(close(t)-close(t-1))	adjclose(t)-adjclose(t-1)	high(t)-low(t)	Relative volume exchanged	Volume exchanged
number_articles		2(-)	2(-)		2(-)			
average_tonality				0(-) 2(+)			0(-)	0(-)
std_tonality						0(+)		**0(+)***
number_neg_ton								0(+)
share_neg_ton				0(+)		0(+)	0(+)	0(+)
number_pos_ton	1(-)	1(-)	1(-) 2(-)		1(-) 2(-)			
share_pos_ton								
polarity		1(-)				0(-)	0(-)	0(-)
subjectivity				0(+)				0(+)
disagreement						0(-)	0(-)*	0(-)
share_wrt_totals								
share_wrt_previous_day		2(-)	2(-)		2(-)			

* = significant at 1%
highest correlation = 0.42 (in red)
lowest correlation =- 0.3

Tables on Granger

Table B.1 Barclays

NYSE data

Does web Granger Cause stock? — if F > c_v we reject the null hypothesis that web does not Granger Cause stock

	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	6.49	2.86	3.68	2.86	3.05	2.86	5.76	2.86	3.88	2.86	4.69	2.86
w(close(t)-opening(t))	4.85	4.08	3.48	4.08	3.02	4.08	4.97	4.08	3.33	4.08	4.57	4.08
close(t)-close(t-1)	3.08	4.08	3.49	4.08	2.33	4.08	5.09	4.08	2.26	4.08	2.26	4.08
w(close(t)-close(t-1))	3.70	4.09	3.78	3.24	5.74	4.09	3.07	4.09	3.89	4.09	4.84	4.09
adjclose(t)-adjclose(t-1)	3.08	4.08	3.49	4.08	2.33	4.08	5.09	4.08	2.26	4.08	2.26	4.08
high(t)-low(t)	4.98	4.10	15.65	4.10	6.42	4.10	6.59	4.10	7.89	4.10	6.60	4.10
relative vol. exchanged	3.64	4.09	3.97	3.24	6.08	4.09	3.13	4.09	4.00	3.24	4.70	4.09
volume exchanged	3.79	2.86	3.93	3.24	4.72	4.09	3.79	2.86	4.36	4.09	4.04	4.09

Does stock Granger Cause web? — if F > c_v we reject the null hypothesis that stock does not Granger Cause web

	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	0.86	4.08	0.42	4.09	0.36	4.09	0.21	4.08	5.11	3.24	2.59	4.08
w(close(t)-opening(t))	0.55	4.08	0.50	4.09	0.35	4.09	3.60	2.85	4.70	3.24	1.26	4.08
close(t)-close(t-1)	0.79	4.08	0.56	4.09	1.37	4.09	3.11	2.85	4.92	3.24	0.93	4.08
w(close(t)-close(t-1))	0.90	4.08	3.38	3.24	0.01	4.09	0.23	4.08	1.07	4.08	1.12	4.08
adjclose(t)-adjclose(t-1)	0.79	4.08	0.56	4.09	1.37	4.09	3.11	2.85	4.92	3.24	0.93	4.08
high(t)-low(t)	0.71	4.08	9.30	4.09	0.07	4.09	0.22	4.08	0.17	4.08	2.72	4.08
relative vol. exchanged	0.84	4.08	3.45	3.24	0.01	4.09	0.22	4.08	1.35	4.08	1.03	4.08
volume exchanged	1.17	4.08	0.42	4.09	0.32	4.09	0.50	4.08	3.17	4.08	0.57	4.08

NYSE data

Does web Granger Cause stock? — if F > c_v we reject the null hypothesis that web does not Granger Cause stock

	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	3.92	2.86	3.50	2.86	3.84	2.86	3.47	2.86	5.12	2.86	7.00	2.86
w(close(t)-opening(t))	4.76	4.08	3.81	4.08	5.02	4.08	3.64	4.08	4.48	4.08	4.64	4.08
close(t)-close(t-1)	2.26	4.08	4.66	4.08	2.35	4.08	4.48	4.08	2.90	4.08	3.45	4.08
w(close(t)-close(t-1))	4.52	3.24	3.92	4.09	3.18	4.09	4.58	4.09	2.51	4.09	2.47	4.09
adjclose(t)-adjclose(t-1)	2.26	4.08	4.66	4.08	2.35	4.08	4.48	4.08	2.90	4.08	3.45	4.08
high(t)-low(t)	10.14	4.10	12.77	4.10	6.57	4.10	11.85	4.10	5.20	4.10	7.17	2.87
relative vol. exchanged	4.70	3.24	3.95	4.09	3.12	4.09	4.30	3.24	2.56	4.09	2.54	4.09
volume exchanged	3.63	3.24	3.20	3.24	3.25	4.09	3.95	3.24	1.93	4.09	1.91	4.09

Does stock Granger Cause Does stock Granger Cause web? — if F > c_v we reject the null hypothesis that stock does not Granger Cause web

	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	4.48	3.24	3.35	4.08	2.27	3.25	3.09	4.08	0.23	4.08	0.27	4.08
w(close(t)-opening(t))	3.40	3.24	1.71	4.08	2.65	3.25	1.75	4.08	0.19	4.08	0.43	4.08
close(t)-close(t-1)	4.09	3.24	0.88	4.08	3.04	2.87	1.22	4.08	0.07	4.08	2.08	4.08
w(close(t)-close(t-1))	1.06	4.08	1.72	4.08	2.74	2.87	2.21	4.08	0.02	4.08	0.21	4.08
adjclose(t)-adjclose(t-1)	4.09	3.24	0.88	4.08	3.04	2.87	1.22	4.08	0.07	4.08	2.08	4.08
high(t)-low(t)	0.71	4.08	2.26	4.08	4.62	2.87	2.49	4.08	0.76	4.08	8.90	4.08
relative vol. exchanged	1.38	4.08	1.71	4.08	2.25	3.25	2.17	4.08	0.02	4.08	0.23	4.08
volume exchanged	2.30	4.08	0.44	4.08	2.25	3.25	0.67	4.08	0.03	4.08	0.19	4.08

grey: not conclusive

LSE data and EU sources

Does web Granger Cause stock? — if F > c_v we reject the null hypothesis that web does not Granger Cause stock

	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.05	4.08	1.99	4.08	1.26	4.08	1.97	4.08	2.60	4.08	1.30	4.08
w(close(t)-opening(t))	0.71	4.08	1.05	4.08	0.84	4.08	1.96	4.08	1.21	4.08	0.68	4.08
close(t)-close(t-1)	2.59	4.08	2.78	4.08	2.42	4.08	4.92	4.08	2.52	4.08	1.63	4.08
w(close(t)-close(t-1))	3.55	3.24	2.83	3.24	0.89	4.09	2.23	3.24	0.07	4.09	2.24	4.09
adjclose(t)-adjclose(t-1)	2.59	4.08	2.78	4.08	2.42	4.08	4.92	4.08	2.52	4.08	1.63	4.08
high(t)-low(t)	0.05	4.09	0.59	4.09	0.37	4.09	0.08	4.09	1.15	4.09	4.63	3.24
relative vol. exchanged	3.45	3.24	3.09	3.24	0.96	4.09	2.27	3.24	0.09	4.09	2.39	4.09
volume exchanged	2.79	3.24	7.04	3.24	0.26	4.09	0.19	4.09	0.37	4.09	6.47	4.09

Does stock Granger Cause web? — if F > c_v we reject the null hypothesis that stock does not Granger Cause web

	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.05	4.08	0.44	4.08	1.12	4.09	0.43	4.08	2.95	4.08	0.31	4.08
w(close(t)-opening(t))	1.08	4.08	0.93	4.08	0.19	4.09	0.37	4.08	1.99	4.08	0.87	4.08
close(t)-close(t-1)	2.89	4.08	3.23	2.85	1.36	4.09	0.29	4.08	7.24	4.08	3.48	4.08
w(close(t)-close(t-1))	0.18	4.08	0.60	4.08	0.24	4.09	0.20	4.08	2.25	3.24	0.44	4.08
adjclose(t)-adjclose(t-1)	2.89	4.08	3.23	2.85	1.36	4.09	0.29	4.08	7.24	4.08	3.48	4.08
high(t)-low(t)	5.52	4.08	0.42	4.08	4.30	3.24	5.67	4.08	3.24	2.85	2.03	4.08
relative vol. exchanged	0.17	4.08	2.80	2.85	0.19	4.09	0.19	4.08	2.54	3.24	0.58	4.08
volume exchanged	0.94	4.08	2.26	4.08	0.02	4.09	1.40	4.08	0.33	4.08	0.14	4.08

LSE data and EU sources

Does web Granger Cause stock? — if F > c_v we reject the null hypothesis that web does not Granger Cause stock

	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.78	4.08	3.95	4.08	1.16	4.08	4.92	4.08	1.18	4.08	1.61	4.08
w(close(t)-opening(t))	1.01	4.08	2.13	4.08	0.68	4.08	2.61	4.08	0.78	4.08	1.24	4.08
close(t)-close(t-1)	3.01	4.08	6.69	4.08	1.84	4.08	7.41	4.08	2.66	4.08	2.13	4.08
w(close(t)-close(t-1))	0.02	4.09	1.71	4.09	0.05	4.09	1.51	4.09	0.89	4.09	2.02	3.24
adjclose(t)-adjclose(t-1)	3.01	4.08	6.69	4.08	1.84	4.08	7.41	4.08	2.66	4.08	2.13	4.08
high(t)-low(t)	0.23	4.09	0.40	4.09	3.29	3.24	0.01	4.09	0.03	4.09	3.71	3.24
relative vol. exchanged	0.03	4.09	1.90	4.09	0.06	4.09	1.73	4.09	0.95	4.09	1.89	3.24
volume exchanged	0.48	4.09	6.91	4.09	0.23	4.09	6.76	4.09	0.85	4.09	2.09	3.24

Does stock Granger Cause web? — if F > c_v we reject the null hypothesis that stock does not Granger Cause web

	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	2.03	4.08	0.06	4.08	0.30	4.10	0.12	4.08	0.62	4.08	1.26	4.08
w(close(t)-opening(t))	1.52	4.08	0.08	4.08	0.38	4.10	0.14	4.08	0.77	4.08	0.60	4.08
close(t)-close(t-1)	3.54	4.08	3.44	3.24	0.25	4.10	3.98	2.85	1.72	4.08	0.14	4.08
w(close(t)-close(t-1))	3.41	3.24	0.15	4.08	1.97	3.25	0.18	4.08	0.10	4.08	0.50	4.08
adjclose(t)-adjclose(t-1)	3.54	4.08	3.44	3.24	0.25	4.10	3.98	2.85	1.72	4.08	0.14	4.08
high(t)-low(t)	0.02	4.08	0.07	4.08	2.41	3.25	0.10	4.08	1.56	4.08	1.04	4.08
relative vol. exchanged	3.73	3.24	0.20	4.08	1.88	3.25	0.25	4.08	0.12	4.08	0.44	4.08
volume exchanged	2.75	3.24	0.78	4.08	2.49	3.25	0.92	4.08	0.22	4.08	0.71	4.08

grey: not conclusive

LSE data and GB sources

Does web Granger Cause stock? — if F > c_v we reject the null hypothesis that web does not Granger Cause stock

	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.33	4.08	1.40	4.08	1.05	4.08	1.90	4.08	1.07	4.08	1.13	4.08
w(close(t)-opening(t))	1.39	4.08	0.95	4.08	0.83	4.08	1.99	4.08	0.90	4.08	0.94	4.08
close(t)-close(t-1)	2.59	4.08	2.03	4.08	1.65	4.08	3.73	4.08	3.05	3.24	1.69	4.08
w(close(t)-close(t-1))	0.20	4.09	9.48	4.09	0.01	4.09	2.51	3.24	7.58	4.09	1.59	4.09
adjclose(t)-adjclose(t-1)	2.59	4.08	2.03	4.08	1.65	4.08	3.73	4.08	3.05	3.24	1.69	4.08
high(t)-low(t)	0.01	4.09	4.40	4.09	0.52	4.09	0.55	4.09	2.83	2.86	1.91	4.09
relative vol. exchanged	0.21	4.09	9.64	4.09	0.02	4.09	2.62	3.24	8.06	4.09	1.71	4.09
volume exchanged	0.22	4.09	9.34	4.09	0.51	4.09	0.31	4.09	4.17	4.09	1.42	4.09

Does stock Granger Cause web? — if F > c_v we reject the null hypothesis that stock does not Granger Cause web

	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	2.64	4.08	2.25	4.08	2.79	4.08	2.72	4.08	0.51	4.08	1.02	4.08
w(close(t)-opening(t))	2.88	4.08	1.32	4.08	4.71	4.08	2.21	4.08	0.49	4.08	1.74	4.08
close(t)-close(t-1)	1.77	4.08	5.42	4.08	2.54	4.08	1.93	4.08	0.49	4.08	0.82	4.08
w(close(t)-close(t-1))	0.61	4.08	0.25	4.08	0.98	4.08	0.01	4.08	5.49	2.85	1.88	4.08
adjclose(t)-adjclose(t-1)	1.77	4.08	5.42	4.08	2.54	4.08	1.93	4.08	0.49	4.08	0.82	4.08
high(t)-low(t)	0.65	4.08	2.52	3.24	0.70	4.08	2.12	4.08	5.52	2.85	0.16	4.08
relative vol. exchanged	0.68	4.08	0.20	4.08	1.10	4.08	2.43	2.85	5.49	2.85	1.95	4.08
volume exchanged	0.10	4.08	0.55	4.08	1.81	4.08	0.83	4.08	4.30	2.85	0.38	4.08

LSE data and GB sources

Does web Granger Cause stock? — if F > c_v we reject the null hypothesis that web does not Granger Cause stock

	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.05	4.08	1.34	4.08	1.63	4.08	1.39	4.08	1.58	4.08	1.35	4.08
w(close(t)-opening(t))	0.68	4.08	0.84	4.08	0.83	4.08	0.80	4.08	1.50	4.08	1.16	4.08
close(t)-close(t-1)	1.96	4.08	2.55	4.08	1.79	4.08	2.70	4.08	2.90	4.08	2.06	4.08
w(close(t)-close(t-1))	2.66	4.09	7.99	4.09	1.97	4.09	7.79	4.09	0.36	4.09	0.24	4.09
adjclose(t)-adjclose(t-1)	1.96	4.08	2.55	4.08	1.79	4.08	2.70	4.08	2.90	4.08	2.06	4.08
high(t)-low(t)	2.76	4.09	4.58	4.09	0.01	4.09	4.88	4.09	0.00	4.09	3.91	3.24
relative vol. exchanged	2.96	4.09	8.49	4.09	2.02	4.09	8.40	4.09	0.37	4.09	0.25	4.09
volume exchanged	3.94	4.09	7.30	4.09	0.24	4.09	7.58	4.09	0.23	4.09	0.31	4.09

Does stock Granger Cause web? — if F > c_v we reject the null hypothesis that stock does not Granger Cause web

	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	0.59	4.08	2.07	4.08	0.21	4.09	1.25	4.08	1.78	4.08	0.28	4.08
w(close(t)-opening(t))	0.17	4.08	1.57	4.08	0.04	4.09	0.91	4.08	2.02	4.08	0.44	4.08
close(t)-close(t-1)	0.99	4.08	2.52	4.08	0.12	4.09	1.75	4.08	1.10	4.08	0.61	4.08
w(close(t)-close(t-1))	0.17	4.08	0.17	4.08	3.94	3.24	0.40	4.08	4.65	2.85	3.97	2.85
adjclose(t)-adjclose(t-1)	0.99	4.08	2.52	4.08	0.12	4.09	1.75	4.08	1.10	4.08	0.61	4.08
high(t)-low(t)	0.51	4.08	0.78	4.08	4.46	3.24	1.05	4.08	0.12	4.08	0.41	4.08
relative vol. exchanged	0.17	4.08	0.15	4.08	3.80	3.24	0.37	4.08	4.69	2.85	3.74	2.85
volume exchanged	0.15	4.08	2.10	3.24	2.19	3.24	2.38	3.24	0.01	4.08	0.24	4.08

grey: not conclusive

Table B.2 BNP Paribas

EU sources Does web Granger Cause stock?					if F > c_v we reject the null hypothesis that web does not Granger Cause stock							
	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical valu	F-statistic	critical value	F-statistic	critical value	F-statistic	critical valu	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	3.76	2.85	4.10	2.85	5.35	2.85	3.69	2.85	3.77	2.85	1.76	4.08
w(close(t)-opening(t))	2.50	4.08	2.11	4.08	3.47	3.24	1.99	4.08	1.67	4.08	1.65	4.08
close(t)-close(t-1)	6.74	4.10	7.11	3.25	4.16	3.25	7.26	4.10	8.71	4.10	4.64	4.10
w(close(t)-close(t-1))	2.41	4.09	0.39	4.09	4.25	4.09	3.44	4.09	1.16	4.09	1.92	4.09
adjclose(t)-adjclose(t-1)	6.74	4.10	7.11	3.25	4.16	3.25	7.26	4.10	8.71	4.10	4.64	4.10
high(t)-low(t)	3.65	4.09	4.54	3.24	2.56	4.09	2.70	4.09	2.60	3.24	3.32	4.09
relative vol. exchanged	2.18	4.09	0.45	4.09	4.29	4.09	3.12	4.09	1.03	4.09	1.82	4.09
volume exchanged	1.24	4.09	0.63	4.09	2.63	4.09	2.01	4.09	0.36	4.09	0.51	4.09

Does stock Granger Cause web?					if F > c_v we reject the null hypothesis that stock does not Granger Cause web							
	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical valu	F-statistic	critical value	F-statistic	critical value	F-statistic	critical valu	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.64	4.09	6.45	2.87	0.73	4.10	0.42	4.08	2.84	4.09	0.30	4.10
w(close(t)-opening(t))	0.96	4.09	6.48	2.87	0.36	4.10	0.26	4.08	2.65	4.09	0.15	4.10
close(t)-close(t-1)	1.19	4.09	7.73	2.87	0.36	4.10	0.17	4.08	3.72	2.86	0.30	4.10
w(close(t)-close(t-1))	4.56	2.86	6.05	2.87	0.49	4.10	3.05	2.85	2.87	4.09	5.65	3.25
adjclose(t)-adjclose(t-1)	1.19	4.09	7.73	2.87	0.36	4.10	0.17	4.08	3.72	2.86	0.30	4.10
high(t)-low(t)	3.22	2.86	7.55	2.87	0.46	4.10	3.86	2.85	4.89	4.09	1.52	4.10
relative vol. exchanged	4.51	2.86	6.09	2.87	0.49	4.10	2.97	2.85	2.87	4.09	5.89	3.25
volume exchanged	0.15	4.09	6.22	2.87	0.44	4.10	0.01	4.08	2.71	4.09	1.50	4.10

EU sources Does web Granger Cause :	EU sources Does web Granger Cause stock?				if F > c_v we reject the null hypothesis that web does not Granger Cause stock							
	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical valu	F-statistic	critical value	F-statistic	critical value	F-statistic	critical valu	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	3.08	4.08	3.98	2.85	3.44	4.08	3.83	2.85	4.52	2.85	4.40	2.85
w(close(t)-opening(t))	1.90	4.08	2.50	4.08	2.71	4.08	2.62	4.08	3.22	3.24	2.92	3.24
close(t)-close(t-1)	5.27	3.25	9.86	4.10	4.12	4.10	9.34	4.10	4.86	3.25	5.87	3.25
w(close(t)-close(t-1))	0.05	4.09	0.49	4.09	1.44	4.09	0.13	4.09	1.87	4.09	0.42	4.09
adjclose(t)-adjclose(t-1)	5.27	3.25	9.86	4.10	4.12	4.10	9.34	4.10	4.86	3.25	5.87	3.25
high(t)-low(t)	3.95	4.09	1.54	4.09	1.79	4.09	1.61	4.09	2.93	4.09	1.18	4.09
relative vol. exchanged	0.08	4.09	0.41	4.09	1.59	4.09	0.10	4.09	1.73	4.09	2.17	3.24
volume exchanged	0.15	4.09	0.20	4.09	0.50	4.09	0.20	4.09	0.52	4.09	0.46	4.09

Does stock Granger Cause	Does stock Granger Cause web?				if F > c_v we reject the null hypothesis that stock does not Granger Cause web							
	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical valu	F-statistic	critical value	F-statistic	critical value	F-statistic	critical valu	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	0.77	4.10	3.76	2.87	0.46	4.10	2.91	4.08	0.01	4.08	3.19	4.09
w(close(t)-opening(t))	1.14	4.10	3.47	2.87	1.83	4.10	2.27	4.08	0.00	4.08	4.79	4.09
close(t)-close(t-1)	3.59	3.25	5.33	2.87	2.09	4.10	2.38	4.08	0.07	4.08	2.43	4.09
w(close(t)-close(t-1))	0.95	4.10	4.70	2.87	0.82	4.10	4.72	3.24	1.13	4.08	0.96	4.09
adjclose(t)-adjclose(t-1)	3.59	3.25	5.33	2.87	2.09	4.10	2.38	4.08	0.07	4.08	2.43	4.09
high(t)-low(t)	5.02	4.10	5.38	2.87	1.90	4.10	4.31	3.24	0.08	4.08	0.20	4.09
relative vol. exchanged	0.91	4.10	4.67	2.87	0.79	4.10	4.82	3.24	1.17	4.08	0.81	4.09
volume exchanged	0.84	4.10	3.43	2.87	1.18	4.10	3.58	3.24	0.01	4.08	0.95	4.09

grey: not conclusive

FR sources Does web Granger Cause stock?					if F > c_v we reject the null hypothesis that web does not Granger Cause stock							
	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical valu	F-statistic	critical value	F-statistic	critical value	F-statistic	critical valu	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.49	4.08	1.61	4.08	4.87	2.85	3.19	2.85	1.66	4.08	1.67	4.08
w(close(t)-opening(t))	1.34	4.08	1.64	4.08	2.12	4.08	1.78	4.08	1.68	4.08	1.70	4.08
close(t)-close(t-1)	3.90	4.10	4.60	4.10	6.48	3.25	4.91	4.10	5.26	4.10	4.15	4.10
w(close(t)-close(t-1))	0.93	4.09	0.05	4.09	0.05	4.09	1.36	4.09	0.03	4.09	0.56	4.09
adjclose(t)-adjclose(t-1)	3.90	4.10	4.60	4.10	6.48	3.25	4.91	4.10	5.26	4.10	4.15	4.10
high(t)-low(t)	4.27	4.09	3.99	4.09	1.21	4.09	2.72	4.09	3.06	4.09	3.44	4.09
relative vol. exchanged	0.88	4.09	0.07	4.09	0.07	4.09	1.22	4.09	0.04	4.09	0.61	4.09
volume exchanged	0.50	4.09	0.48	4.09	3.09	2.86	1.31	4.09	0.14	4.09	0.17	4.09

Does stock Granger Cause web?					if F > c_v we reject the null hypothesis that stock does not Granger Cause web							
	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical valu	F-statistic	critical value	F-statistic	critical value	F-statistic	critical valu	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.31	4.08	1.07	4.08	0.19	4.08	2.14	4.08	5.94	4.08	1.35	4.08
w(close(t)-opening(t))	1.19	4.08	0.47	4.08	0.30	4.08	2.50	4.08	4.91	4.08	1.41	4.08
close(t)-close(t-1)	1.23	4.08	0.28	4.08	0.38	4.08	1.03	4.08	3.95	4.08	1.20	4.08
w(close(t)-close(t-1))	1.92	4.08	0.21	4.08	4.26	2.85	3.49	2.85	1.51	4.08	3.23	4.08
adjclose(t)-adjclose(t-1)	1.23	4.08	0.28	4.08	0.38	4.08	1.03	4.08	3.95	4.08	1.20	4.08
high(t)-low(t)	1.87	4.08	1.22	4.08	0.31	4.08	3.38	2.85	1.61	4.08	3.27	4.08
relative vol. exchanged	1.99	4.08	0.22	4.08	4.43	2.85	3.37	2.85	1.63	4.08	3.41	4.08
volume exchanged	1.24	4.08	0.41	4.08	1.49	4.08	1.52	4.08	1.58	4.08	1.47	4.08

FR sources

Does web Granger Cause stock? — if F > c_v we reject the null hypothesis that web does not Granger Cause stock

	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	2.65	4.08	1.54	4.08	4.22	2.85	3.39	2.85	1.57	4.08	3.82	2.85
w(close(t)-opening(t))	1.82	4.08	1.59	4.08	1.51	4.08	2.67	4.08	1.38	4.08	1.35	4.08
close(t)-close(t-1)	4.73	4.10	4.96	4.10	4.28	2.87	6.79	4.10	3.96	4.10	4.73	2.87
w(close(t)-close(t-1))	0.05	4.09	0.10	4.09	0.09	4.09	0.12	4.09	0.93	4.09	0.56	4.09
adjclose(t)-adjclose(t-1)	4.73	4.10	4.96	4.10	4.28	2.87	6.79	4.10	3.96	4.10	4.73	2.87
high(t)-low(t)	4.85	4.09	3.49	4.09	1.18	4.09	3.65	4.09	3.61	4.09	1.23	4.09
relative vol. exchanged	0.09	4.09	0.13	4.09	0.12	4.09	0.17	4.09	0.89	4.09	0.58	4.09
volume exchanged	0.36	4.09	0.31	4.09	0.12	4.09	0.26	4.09	0.21	4.09	0.84	4.09

Does stock Granger Cause web? — if F > c_v we reject the null hypothesis that stock does not Granger Cause web

	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	3.87	3.25	6.80	4.08	2.44	4.10	5.89	4.08	0.78	4.08	0.88	4.09
w(close(t)-opening(t))	4.66	3.25	5.71	4.08	3.30	3.25	4.54	4.08	0.78	4.08	1.16	4.09
close(t)-close(t-1)	5.13	3.25	3.66	4.08	3.40	4.10	3.06	4.08	0.78	4.08	0.26	4.09
w(close(t)-close(t-1))	4.89	3.25	1.84	4.08	0.58	4.10	2.66	3.24	1.55	4.08	0.16	4.09
adjclose(t)-adjclose(t-1)	5.13	3.25	3.66	4.08	3.40	4.10	3.06	4.08	0.78	4.08	0.26	4.09
high(t)-low(t)	7.76	3.25	2.35	4.08	1.55	4.10	3.21	3.24	1.38	4.08	0.37	4.09
relative vol. exchanged	4.77	3.25	2.02	4.08	0.50	4.10	1.81	4.08	1.62	4.08	0.17	4.09
volume exchanged	5.42	3.25	2.03	4.08	1.67	4.10	2.70	3.24	0.88	4.08	0.17	4.09

grey: not conclusive

Table B.3 Crédit Agricole

EU sources

Does web Granger Cause stock? — if F > c_v we reject the null hypothesis that web does not Granger Cause stock

	number_articles		number_neg_ton		number_pos_ton		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	7.33	2.85	4.03	2.85	9.82	4.08	3.73	4.08	2.57	4.08
w(close(t)-opening(t))	5.16	4.08	1.20	4.08	3.47	4.08	1.82	4.08	0.84	4.08
close(t)-close(t-1)	8.44	4.08	3.39	2.85	8.91	4.08	4.89	4.08	2.76	4.08
w(close(t)-close(t-1))	0.53	4.09	0.61	4.09	0.55	4.09	0.56	4.09	5.00	2.86
adjclose(t)-adjclose(t-1)	8.44	4.08	3.39	2.85	8.91	4.08	4.89	4.08	2.76	4.08
high(t)-low(t)	1.95	4.10	1.72	4.10	0.88	4.10	1.01	4.10	4.74	2.87
relative vol. exchanged	0.66	4.08	1.11	4.08	0.63	4.08	0.41	4.08	0.28	4.08
volume exchanged	0.17	4.08	0.04	4.08	0.74	4.08	0.10	4.08	0.85	4.08

Does stock Granger Cause web? — if F > c_v we reject the null hypothesis that stock does not Granger Cause web

	number_neg_ton		subjectivity		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	4.26	2.85	1.93	4.10	9.48	3.24
w(close(t)-opening(t))	0.22	4.08	1.42	4.10	12.44	4.08
close(t)-close(t-1)	4.84	2.85	1.57	4.10	6.07	3.24
w(close(t)-close(t-1))	2.47	4.08	4.65	4.10	3.56	4.08
adjclose(t)-adjclose(t-1)	4.84	2.85	1.57	4.10	6.07	3.24
high(t)-low(t)	6.93	4.08	2.95	4.10	3.18	4.08
relative vol. exchanged	0.22	4.08	3.90	4.10	1.69	4.08
volume exchanged	2.58	4.08	3.96	4.10	1.57	4.08

grey: not conclusive

FR sources

Does web Granger Cause stock? — if F > c_v we reject the null hypothesis that web does not Granger Cause stock

	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton		polarity		share_wrt_totals		s_day	
	statistic	value	statistic	value	statistic	value	statistic	value	statistic	value	statistic	value	statistic	value	statistic	value	F-statistic	value
close(t)-opening(t)	7.17	2.85	4.69	2.85	1.47	4.08	4.76	2.85	2.86	4.08	11.74	4.08	2.69	4.08	2.99	4.08	2.78	4.08
w(close(t)-opening(t))	4.29	4.08	0.05	4.08	0.11	4.08	0.45	4.08	0.37	4.08	3.87	4.08	0.19	4.08	1.30	4.08	1.13	4.08
close(t)-close(t-1)	7.53	4.08	5.22	2.85	1.40	4.08	4.91	2.85	4.22	4.08	10.16	4.08	4.81	4.08	4.16	4.08	3.68	4.08
w(close(t)-close(t-1))	0.62	4.09	1.23	4.09	1.24	4.09	0.55	4.09	0.53	4.09	0.72	4.09	0.68	4.09	0.53	4.09	3.23	2.86
adjclose(t)-adjclose(t-1)	7.53	4.08	5.22	2.85	1.40	4.08	4.91	2.85	4.22	4.08	10.16	4.08	4.81	4.08	4.16	4.08	3.68	4.08
high(t)-low(t)	2.05	4.10	2.96	4.10	0.58	4.10	3.81	3.25	1.45	4.10	0.81	4.10	1.58	4.10	0.98	4.10	4.74	2.87
relative vol. exchanged	1.26	4.08	0.20	4.08	3.08	4.08	1.11	4.08	0.12	4.08	0.85	4.08	0.11	4.08	0.49	4.08	0.80	4.08
volume exchanged	0.30	4.08	2.33	3.24	3.43	2.85	0.02	4.08	1.90	3.24	0.80	4.08	0.22	4.08	0.12	4.08	2.09	3.24

Does stock Granger Cause web?	if F > c_v we reject the null hypothesis that stock does not Granger Cause web											
	number_articles		std_tonality		number_neg_ton		share_pos_ton		subjectivity		share_wrt_previous_day	
	F-statisti	critical v	F-statisti	critical	F-statistic	critical v	F-statistic	critical \	F-statistic	critical	F-statistic	critical value
close(t)-opening(t)	3.04	2.85	4.09	2.86	5.90	2.85	3.11	2.87	3.55	3.25	8.91	3.24
w(close(t)-opening(t))	1.02	4.08	5.92	2.86	3.50	2.85	2.68	2.87	3.49	4.10	6.10	4.08
close(t)-close(t-1)	0.94	4.08	4.26	2.86	6.32	2.85	3.82	2.87	3.31	4.10	5.58	2.85
w(close(t)-close(t-1))	0.31	4.08	4.00	3.24	4.37	2.85	0.20	4.10	4.84	4.10	1.95	4.08
adjclose(t)-adjclose(t-1)	0.94	4.08	4.26	2.86	6.32	2.85	3.82	2.87	3.31	4.10	5.58	2.85
high(t)-low(t)	1.44	4.08	4.35	2.86	8.42	4.08	0.14	4.10	3.55	4.10	2.88	4.08
relative vol. exchanged	1.70	4.08	5.03	2.86	3.73	2.85	0.32	4.10	5.25	4.10	0.89	4.08
volume exchanged	0.46	4.08	3.71	2.86	3.65	2.85	0.12	4.10	3.78	4.10	1.04	4.08

grey: not conclusive

Table A.4 Deutsche Bank

NYSE data Does web Granger Cause stock?	if F > c_v we reject the null hypothesis that web does not Granger Cause stock									
	number_articles		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	5.64	3.24	2.71	4.08	5.53	3.24	4.92	4.08	2.48	4.08
w(close(t)-opening(t))	0.53	4.08	1.22	4.08	2.49	3.24	2.27	4.08	0.53	4.08
close(t)-close(t-1)	1.58	4.08	2.72	4.08	1.59	4.08	2.11	4.08	1.57	4.08
w(close(t)-close(t-1))	1.74	4.08	3.10	4.08	1.96	4.08	0.30	4.08	0.23	4.08
adjclose(t)-adjclose(t-	1.58	4.08	2.72	4.08	1.59	4.08	2.11	4.08	1.57	4.08
high(t)-low(t)	11.08	3.24	4.91	4.08	9.05	3.24	1.63	4.08	4.03	3.24
relative vol. exchange	0.38	4.08	1.40	4.08	2.10	3.24	0.70	4.08	0.41	4.08
volume exchanged	2.47	4.10	7.67	4.10	2.90	3.25	1.30	4.10	1.34	4.10

Does stock Granger Cause web?	if F > c_v we reject the null hypothesis that stock does not Granger Cause web									
	number_articles		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	2.77	3.24	3.35	3.24	2.44	2.87	0.34	4.09	0.03	4.08
w(close(t)-opening(t))	2.75	3.24	5.09	3.24	1.97	3.25	2.97	3.24	0.03	4.08
close(t)-close(t-1)	6.01	3.24	3.59	2.86	5.06	3.25	4.41	3.24	2.69	3.24
w(close(t)-close(t-1))	2.39	3.24	4.14	3.24	0.98	4.10	3.66	3.24	0.11	4.08
adjclose(t)-adjclose(t-	6.01	3.24	3.59	2.86	5.06	3.25	4.41	3.24	2.69	3.24
high(t)-low(t)	3.60	3.24	3.98	3.24	3.33	3.25	2.83	3.24	0.18	4.08
relative vol. exchange	1.72	4.08	3.88	3.24	1.18	4.10	4.11	3.24	0.31	4.08
volume exchanged	3.35	3.24	5.67	3.24	1.14	4.10	3.94	3.24	0.31	4.08

NYSE data Does web Granger Caus Does web Granger Cause stock?	if F > c_v we reject the null hypothesis that web does not Granger Cause stock											
	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	2.40	4.08	2.86	4.08	4.76	4.08	2.81	4.08	5.39	3.24	7.71	4.08
w(close(t)-opening(t))	0.79	4.08	1.51	4.08	1.12	4.08	1.52	4.08	0.53	4.08	5.40	4.08
close(t)-close(t-1)	2.07	4.08	1.95	4.08	1.57	4.08	1.90	4.08	1.57	4.08	1.66	4.08
w(close(t)-close(t-1))	2.15	3.24	0.43	4.08	0.10	4.08	0.57	4.08	1.34	4.08	1.72	4.08
adjclose(t)-adjclose(t-1	2.07	4.08	1.95	4.08	1.57	4.08	1.90	4.08	1.57	4.08	1.66	4.08
high(t)-low(t)	0.44	4.08	0.41	4.08	0.76	4.08	0.31	4.08	7.42	3.24	0.40	4.08
relative vol. exchanged	0.40	4.08	0.46	4.08	0.57	4.08	0.39	4.08	0.38	4.08	0.43	4.08
volume exchanged	3.42	3.25	4.88	2.87	2.00	4.10	3.97	3.25	2.26	4.10	1.65	4.10

Does stock Granger Cause web?	if F > c_v we reject the null hypothesis that stock does not Granger Cause web											
	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	2.11	3.25	1.98	4.08	4.55	4.10	1.11	4.08	2.08	3.24	1.88	4.08
w(close(t)-opening(t))	2.04	3.25	1.02	4.08	4.80	4.10	0.54	4.08	2.05	3.24	1.10	4.08
close(t)-close(t-1)	3.49	3.25	3.55	3.24	5.23	4.10	2.06	4.08	6.43	3.24	1.37	4.08
w(close(t)-close(t-1))	2.43	3.25	0.91	4.08	8.45	3.25	0.77	4.08	0.24	4.08	12.01	4.08
adjclose(t)-adjclose(t-1	3.49	3.25	3.55	3.24	5.23	4.10	2.06	4.08	6.43	3.24	1.37	4.08
high(t)-low(t)	2.51	3.25	0.56	4.08	5.70	3.25	0.32	4.08	0.37	4.08	1.06	4.08
relative vol. exchanged	2.10	3.25	0.69	4.08	7.08	3.25	0.43	4.08	0.90	4.08	0.64	4.08
volume exchanged	2.21	3.25	0.55	4.08	9.83	3.25	0.28	4.08	0.77	4.08	3.82	4.08

grey: not conclusive

LSE data and EU sources

Does web Granger Cause stock? if F > c_v we reject the null hypothesis that web does not Granger Cause stock

	number_articles		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.21	4.10	3.92	4.10	1.24	4.10	1.22	4.10	1.53	4.10
w(close(t)-opening(t))	0.75	4.10	5.43	4.10	0.73	4.10	1.01	4.10	1.08	4.10
close(t)-close(t-1)	0.85	4.10	4.92	4.10	0.83	4.10	0.95	4.10	0.98	4.10
w(close(t)-close(t-1))	0.63	4.10	1.57	4.10	0.30	4.10	0.21	4.10	1.48	4.10
adjclose(t)-adjclose(t-1	0.85	4.10	4.92	4.10	0.83	4.10	0.95	4.10	0.98	4.10
high(t)-low(t)	2.60	3.27	2.41	3.27	2.58	3.27	0.59	4.11	3.18	3.27
relative vol. exchanged	0.69	4.10	1.73	4.10	0.33	4.10	0.21	4.10	1.59	4.10
volume exchanged	1.35	4.10	1.95	4.10	1.06	4.10	0.25	4.10	2.23	4.10

Does stock Granger Cause web? if F > c_v we reject the null hypothesis that stock does not Granger Cause web

	number_articles		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	0.84	4.10	7.65	2.87	1.19	4.10	3.17	3.26	0.65	4.10
w(close(t)-opening(t))	0.08	4.10	9.49	2.87	0.19	4.10	4.41	3.26	0.12	4.10
close(t)-close(t-1)	0.41	4.10	9.26	2.87	0.12	4.10	3.32	3.26	0.44	4.10
w(close(t)-close(t-1))	9.85	4.10	1.90	4.11	7.32	3.25	2.39	3.26	11.95	4.10
adjclose(t)-adjclose(t-1	0.41	4.10	9.26	2.87	0.12	4.10	3.32	3.26	0.44	4.10
high(t)-low(t)	4.11	4.10	1.86	4.11	3.78	4.10	3.24	3.26	7.73	4.10
relative vol. exchanged	9.28	4.10	2.05	4.11	6.68	3.25	2.28	3.26	11.50	4.10
volume exchanged	13.74	3.25	1.75	4.11	13.37	3.25	2.15	3.26	13.10	3.25

LSE data and EU sources **LSE data and EU sources**

Does web Granger Caus **Does web Granger Cause stock?** if F > c_v we reject the null hypothesis that web does not Granger Cause stock

	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.56	4.10	5.27	4.10	1.50	4.10	4.44	4.10	1.21	4.10	1.25	4.10
w(close(t)-opening(t))	0.78	4.10	3.87	4.10	1.37	4.10	2.90	4.10	0.75	4.10	1.22	4.10
close(t)-close(t-1)	0.95	4.10	3.10	4.10	1.38	4.10	2.33	4.10	0.85	4.10	0.86	4.10
w(close(t)-close(t-1))	0.01	4.10	0.25	4.10	0.17	4.10	0.31	4.10	0.79	4.10	0.66	4.10
adjclose(t)-adjclose(t-1	0.95	4.10	3.10	4.10	1.38	4.10	2.33	4.10	0.85	4.10	0.86	4.10
high(t)-low(t)	0.98	4.11	0.37	4.11	2.73	3.27	0.36	4.11	2.79	3.27	3.44	4.11
relative vol. exchanged	0.01	4.10	0.34	4.10	0.12	4.10	0.40	4.10	0.86	4.10	0.62	4.10
volume exchanged	0.13	4.10	0.07	4.10	0.03	4.10	0.09	4.10	1.48	4.10	0.98	4.10

Does stock Granger Cause web? if F > c_v we reject the null hypothesis that stock does not Granger Cause web

	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	5.10	4.11	3.10	4.10	4.15	3.26	2.24	4.10	1.13	4.10	1.51	4.10
w(close(t)-opening(t))	5.54	4.11	2.04	4.10	4.54	3.26	1.52	4.10	0.15	4.10	0.71	4.10
close(t)-close(t-1)	1.42	4.11	0.84	4.10	3.20	3.26	0.52	4.10	0.38	4.10	0.66	4.10
w(close(t)-close(t-1))	0.51	4.11	0.60	4.10	3.80	3.26	0.31	4.10	6.03	3.25	2.81	4.10
adjclose(t)-adjclose(t-1	1.42	4.11	0.84	4.10	3.20	3.26	0.52	4.10	0.38	4.10	0.66	4.10
high(t)-low(t)	2.19	4.11	0.46	4.10	6.03	3.26	0.22	4.10	2.98	4.10	1.76	4.10
relative vol. exchanged	0.50	4.11	0.59	4.10	3.72	3.26	0.30	4.10	5.54	3.25	2.41	4.10
volume exchanged	0.50	4.11	0.46	4.10	3.39	3.26	0.21	4.10	12.61	3.25	3.92	3.25

grey: not conclusive

LSE data and GB sources

Does web Granger Cause stock? if F > c_v we reject the null hypothesis that web does not Granger Cause stoc

	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.28	4.10	5.09	4.10	2.15	4.10	1.92	4.10	1.45	4.10
w(close(t)-opening(t))	0.76	4.10	5.10	3.25	2.59	4.10	0.89	4.10	2.78	3.25
close(t)-close(t-1)	0.94	4.10	2.56	4.10	4.95	4.10	1.05	4.10	1.14	4.10
w(close(t)-close(t-1))	0.59	4.10	2.07	4.10	0.04	4.10	0.24	4.10	6.69	4.10
adjclose(t)-adjclose(t-1	0.94	4.10	2.56	4.10	4.95	4.10	1.05	4.10	1.14	4.10
high(t)-low(t)	2.35	3.27	0.35	4.11	2.16	3.27	1.86	3.27	2.65	3.27
relative vol. exchanged	0.61	4.10	2.40	4.10	0.04	4.10	0.21	4.10	7.09	4.10
volume exchanged	0.86	4.10	0.71	4.10	0.08	4.10	0.12	4.10	4.09	2.87

Does stock Granger Cause web? if F > c_v we reject the null hypothesis that stock does not Granger Cause web

	number_articles		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.05	4.10	0.22	4.11	1.39	4.10	1.53	4.10	0.73	4.10
w(close(t)-opening(t))	0.24	4.10	0.18	4.11	0.46	4.10	2.00	4.10	0.14	4.10
close(t)-close(t-1)	0.44	4.10	1.84	3.27	2.52	2.87	0.85	4.10	0.50	4.10
w(close(t)-close(t-1))	10.81	4.10	0.96	4.11	7.34	3.25	0.44	4.10	9.51	4.10
adjclose(t)-adjclose(t-1	0.44	4.10	1.84	3.27	2.52	2.87	0.85	4.10	0.50	4.10
high(t)-low(t)	8.33	4.10	0.79	4.11	3.86	4.10	0.96	4.10	10.94	4.10
relative vol. exchanged	10.35	4.10	0.74	4.11	6.80	3.25	0.44	4.10	9.19	4.10
volume exchanged	17.04	4.10	3.50	4.11	11.06	3.25	0.37	4.10	14.97	4.10

LSE data and GB sources												
Does web Granger Cause stock?					if F > c_v we reject the null hypothesis that web does not Granger Cause stock							
	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	2.00	4.10	2.11	4.10	1.28	4.10	2.23	4.10	1.30	4.10	1.26	4.10
w(close(t)-opening(t))	1.93	4.10	3.27	3.25	1.50	4.10	3.42	3.25	0.78	4.10	0.94	4.10
close(t)-close(t-1)	1.16	4.10	2.18	4.10	2.79	4.10	2.37	4.10	0.99	4.10	0.88	4.10
w(close(t)-close(t-1))	2.60	4.10	5.29	4.10	4.06	4.10	5.44	4.10	0.72	4.10	0.07	4.10
adjclose(t)-adjclose(t-1	1.16	4.10	2.18	4.10	2.79	4.10	2.37	4.10	0.99	4.10	0.88	4.10
high(t)-low(t)	0.70	4.11	2.11	3.27	7.03	3.27	2.25	3.27	2.33	3.27	4.23	2.88
relative vol. exchanged	2.61	4.10	5.78	4.10	3.56	4.10	5.96	4.10	0.73	4.10	0.09	4.10
volume exchanged	4.03	4.10	3.73	4.10	1.45	4.10	3.52	4.10	0.98	4.10	0.08	4.10

Does stock Granger Cau	Does stock Granger Cause web?			if F > c_v we reject the null hypothesis that stock does not Granger Cause web								
	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	8.14	4.11	1.05	4.10	9.20	4.11	1.25	4.10	1.19	4.10	1.31	4.10
w(close(t)-opening(t))	10.67	4.11	1.03	4.10	7.84	4.11	1.12	4.10	0.35	4.10	1.12	4.10
close(t)-close(t-1)	3.17	4.11	0.31	4.10	1.72	4.11	0.45	4.10	0.50	4.10	1.12	4.10
w(close(t)-close(t-1))	2.73	2.87	0.23	4.10	7.66	4.11	0.22	4.10	10.00	4.10	3.78	4.10
adjclose(t)-adjclose(t-1	3.17	4.11	0.31	4.10	1.72	4.11	0.45	4.10	0.50	4.10	1.12	4.10
high(t)-low(t)	3.30	2.87	0.62	4.10	4.17	4.11	0.80	4.10	7.39	4.10	3.49	4.10
relative vol. exchanged	2.84	2.87	0.23	4.10	6.80	4.11	0.22	4.10	9.51	4.10	3.50	4.10
volume exchanged	1.15	4.11	0.14	4.10	7.80	4.11	0.23	4.10	10.82	3.25	4.98	3.25

grey: not conclusive

Table B.5 HSBC

NYSE data and EU+US sources												
Does web Granger Cause stock?					if F > c_v we reject the null hypothesis that web does not Granger Cause stock							
	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	3.60	4.09	0.83	4.09	2.46	4.09	1.49	4.09	0.17	4.09	5.43	4.09
w(close(t)-opening(t))	3.35	4.08	2.77	4.08	3.52	4.08	1.27	4.08	1.07	4.08	4.39	4.08
close(t)-close(t-1)	2.92	4.08	1.23	4.08	4.36	4.08	1.96	4.08	0.73	4.08	4.88	4.08
w(close(t)-close(t-1))	2.87	4.08	3.60	3.24	7.37	4.08	1.41	4.08	0.65	4.08	5.49	4.08
adjclose(t)-adjclose(t-1)	2.92	4.08	1.23	4.08	4.36	4.08	1.96	4.08	0.73	4.08	4.88	4.08
high(t)-low(t)	0.23	4.08	0.05	4.08	1.02	4.08	0.26	4.08	0.01	4.08	0.33	4.08
relative vol. exchanged	2.97	4.08	3.54	3.24	7.61	4.08	1.46	4.08	0.70	4.08	5.65	4.08
volume exchanged	2.18	4.09	3.83	3.24	4.51	4.09	1.07	4.09	0.31	4.09	3.02	4.09

Does stock Granger Cause web?					if F > c_v we reject the null hypothesis that stock does not Granger Cause web							
	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	7.49	4.08	1.49	4.08	0.01	4.10	6.95	4.08	2.46	4.08	3.49	4.08
w(close(t)-opening(t))	5.06	4.08	1.24	4.08	1.08	4.10	5.27	4.08	1.15	4.08	1.45	4.08
close(t)-close(t-1)	6.83	4.08	2.99	4.08	0.23	4.10	8.75	4.08	7.21	3.24	1.65	4.08
w(close(t)-close(t-1))	0.07	4.08	5.44	2.85	0.28	4.10	0.29	4.08	4.03	2.85	0.33	4.08
adjclose(t)-adjclose(t-1)	6.83	4.08	2.99	4.08	0.23	4.10	8.75	4.08	7.21	3.24	1.65	4.08
high(t)-low(t)	0.13	4.08	2.46	3.24	0.01	4.10	0.19	4.08	0.10	4.08	0.12	4.08
relative vol. exchanged	0.09	4.08	5.51	2.85	0.28	4.10	0.34	4.08	4.13	2.85	0.31	4.08
volume exchanged	0.43	4.08	4.82	3.24	0.88	4.10	0.90	4.08	4.33	3.24	0.12	4.08

NYSE data and EU+US sources												
Does web Granger Cause stock?					if F > c_v we reject the null hypothesis that web does not Granger Cause stock							
	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	0.09	4.09	0.07	4.09	0.33	4.09	0.28	4.09	2.38	4.09	0.85	4.09
w(close(t)-opening(t))	0.36	4.08	0.44	4.08	0.32	4.08	0.66	4.08	2.28	4.08	1.36	4.08
close(t)-close(t-1)	2.90	4.08	0.71	4.08	2.15	4.08	1.08	4.08	1.74	4.08	0.67	4.08
w(close(t)-close(t-1))	0.89	4.08	0.94	4.08	0.62	4.08	0.78	4.08	5.78	4.08	1.51	4.08
adjclose(t)-adjclose(t-	2.90	4.08	0.71	4.08	2.15	4.08	1.08	4.08	1.74	4.08	0.67	4.08
high(t)-low(t)	0.18	4.08	0.02	4.08	0.17	4.08	0.01	4.08	0.13	4.08	1.25	4.08
relative vol. exchange	0.96	4.08	1.00	4.08	0.66	4.08	0.84	4.08	5.89	4.08	1.49	4.08
volume exchanged	0.78	4.09	0.44	4.09	1.44	4.09	0.39	4.09	3.78	4.09	0.06	4.09

Does stock Granger Cause web?					if F > c_v we reject the null hypothesis that stock does not Granger Cause web							
	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	0.55	4.10	4.59	4.10	0.67	4.10	3.91	4.08	4.25	4.08	0.40	4.08
w(close(t)-opening(t))	0.66	4.10	2.49	4.10	0.59	4.10	3.44	4.08	2.60	4.08	3.03	3.24
close(t)-close(t-1)	0.71	4.10	8.24	3.25	2.94	4.10	7.52	3.24	3.23	4.08	0.37	4.08
w(close(t)-close(t-1))	1.27	4.10	2.37	2.87	3.32	3.25	3.40	2.85	0.21	4.08	0.43	4.08
adjclose(t)-adjclose(t-	0.71	4.10	8.24	3.25	2.94	4.10	7.52	3.24	3.23	4.08	0.37	4.08
high(t)-low(t)	3.84	4.10	2.78	3.25	0.21	4.10	2.84	3.24	0.33	4.08	1.47	4.08
relative vol. exchange	1.36	4.10	0.24	4.10	3.34	3.25	3.49	2.85	0.23	4.08	0.43	4.08
volume exchanged	1.83	4.10	1.45	4.10	5.73	3.25	3.36	4.08	0.73	4.08	0.38	4.08

grey: not conclusive

LSE data and EU+US sources												
Does web Granger Cause stock?				if F > c_v we reject the null hypothesis that web does not Granger Cause stock								
granger test	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.38	4.08	5.89	4.08	5.05	4.08	1.41	4.08	4.44	4.08	1.52	4.08
w(close(t)-opening(t))	0.65	4.08	4.12	4.08	14.59	4.08	0.78	4.08	5.65	4.08	0.53	4.08
close(t)-close(t-1)	1.99	4.08	3.70	4.08	5.25	2.85	1.85	4.08	3.06	3.24	1.02	4.08
w(close(t)-close(t-1))	0.12	4.09	0.02	4.09	1.79	4.09	0.08	4.09	0.11	4.09	0.92	4.09
adjclose(t)-adjclose(t-1)	1.99	4.08	3.70	4.08	5.25	2.85	1.85	4.08	3.06	3.24	1.02	4.08
high(t)-low(t)	3.97	3.24	4.03	3.24	3.97	3.24	3.77	3.24	4.10	3.24	3.86	3.24
relative vol. exchanged	0.35	4.08	0.88	4.08	11.62	4.08	0.26	4.08	0.90	4.08	0.23	4.08
volume exchanged	0.05	4.09	0.03	4.09	1.50	4.09	0.06	4.09	0.12	4.09	0.46	4.09

Does stock Granger Cause web?				if F > c_v we reject the null hypothesis that stock does not Granger Cause web								
granger test	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	4.34	4.08	0.57	4.08	1.55	4.10	3.93	4.08	0.25	4.08	2.77	4.08
w(close(t)-opening(t))	1.36	4.08	2.35	4.08	0.77	4.10	0.73	4.08	1.34	4.08	1.11	4.08
close(t)-close(t-1)	10.50	3.24	0.37	4.08	0.70	4.10	11.96	4.08	0.21	4.08	10.90	4.08
w(close(t)-close(t-1))	1.27	4.08	10.45	4.08	0.02	4.10	1.63	4.08	2.40	4.08	1.41	4.08
adjclose(t)-adjclose(t-1)	10.50	3.24	0.37	4.08	0.70	4.10	11.96	4.08	0.21	4.08	10.90	4.08
high(t)-low(t)	0.92	4.08	1.23	4.08	1.53	4.10	0.90	4.08	0.13	4.08	1.95	3.24
relative vol. exchanged	1.22	4.08	10.58	4.08	2.83	3.25	1.96	4.08	4.98	3.24	1.83	4.08
volume exchanged	1.11	4.08	9.57	4.08	1.85	3.25	1.42	4.08	2.44	4.08	1.19	4.08

LSE data and EU+US sources												
Does web Granger Cause stock?					if F > c_v we reject the null hypothesis that web does not Granger Cause stock							
granger test	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	3.64	2.85	5.50	3.24	1.67	4.08	4.76	3.24	1.52	4.08	1.95	4.08
w(close(t)-opening(t))	2.06	4.08	7.30	4.08	1.07	4.08	4.16	4.08	0.52	4.08	0.26	4.08
close(t)-close(t-1)	2.02	4.08	5.32	3.24	1.36	4.08	4.30	3.24	1.70	4.08	1.00	4.08
w(close(t)-close(t-1))	1.56	4.09	0.12	4.09	0.01	4.09	0.05	4.09	0.26	4.09	0.00	4.09
adjclose(t)-adjclose(t-	2.02	4.08	5.32	3.24	1.36	4.08	4.30	3.24	1.70	4.08	1.00	4.08
high(t)-low(t)	4.25	3.24	4.21	3.24	5.37	3.24	3.82	3.24	3.96	3.24	4.44	3.24
relative vol. exchange	0.00	4.08	1.81	4.08	0.80	4.08	0.79	4.08	0.38	4.08	0.12	4.08
volume exchanged	1.09	4.09	0.21	4.09	0.03	4.09	0.08	4.09	0.06	4.09	0.17	4.09

Does stock Granger Cause web?					if F > c_v we reject the null hypothesis that stock does not Granger Cause web							
granger test	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	3.77	2.86	0.07	4.10	0.72	4.08	0.09	4.10	2.42	4.08	0.35	4.08
w(close(t)-opening(t))	0.23	4.09	0.26	4.10	0.77	4.08	0.29	4.10	1.16	4.08	0.49	4.08
close(t)-close(t-1)	1.98	3.24	0.04	4.10	0.73	4.08	0.03	4.10	8.43	4.08	1.03	4.08
w(close(t)-close(t-1))	0.23	4.09	0.34	4.10	4.39	3.24	0.88	4.10	1.78	4.08	0.91	4.08
adjclose(t)-adjclose(t-	1.98	3.24	0.04	4.10	0.73	4.08	0.03	4.10	8.43	4.08	1.03	4.08
high(t)-low(t)	0.22	4.09	0.04	4.10	1.54	4.08	0.17	4.10	3.30	3.24	2.22	3.24
relative vol. exchange	0.93	4.09	4.15	3.25	3.22	3.24	3.03	4.10	1.40	4.08	2.98	2.85
volume exchanged	0.23	4.09	0.71	4.10	3.27	3.24	1.42	4.10	1.47	4.08	0.56	4.08

grey: not conclusive

LSE data and UK sources												
Does web Granger Cause stock?				if F > c_v we reject the null hypothesis that web does not Granger Cause stock								
granger test	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	2.72	4.08	2.29	4.08	3.89	4.08	1.51	4.08	4.88	4.08	2.67	4.08
w(close(t)-opening(t))	0.26	4.08	2.43	3.24	2.18	4.08	0.41	4.08	2.82	4.08	0.27	4.08
close(t)-close(t-1)	1.16	4.08	4.21	2.85	0.97	4.08	3.72	4.08	4.67	4.08	1.70	4.08
w(close(t)-close(t-1))	0.35	4.09	0.03	4.09	0.05	4.09	0.25	4.09	0.23	4.09	0.02	4.09
adjclose(t)-adjclose(t-1)	1.16	4.08	4.21	2.85	0.97	4.08	3.72	4.08	4.67	4.08	1.70	4.08
high(t)-low(t)	4.76	3.24	10.32	3.24	3.81	3.24	4.95	3.24	5.16	3.24	4.40	3.24
relative vol. exchanged	0.35	4.08	0.63	4.08	2.12	4.08	0.03	4.08	0.30	4.08	1.02	4.08
volume exchanged	0.70	4.09	0.09	4.09	0.08	4.09	0.60	4.09	0.47	4.09	0.05	4.09

Does stock Granger Cause web?				if F > c_v we reject the null hypothesis that stock does not Granger Cause web								
granger test	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.77	4.08	5.96	3.25	0.98	4.08	4.14	2.85	3.25	3.25	0.56	4.08
w(close(t)-opening(t))	1.04	4.08	4.73	3.25	0.23	4.08	1.43	4.08	1.48	4.10	0.47	4.08
close(t)-close(t-1)	6.37	4.08	6.68	3.25	0.70	4.08	5.59	4.08	2.04	4.10	2.06	4.08
w(close(t)-close(t-1))	1.32	4.08	5.65	3.25	1.04	4.08	1.93	4.08	3.79	4.10	0.81	4.08
adjclose(t)-adjclose(t-1)	6.37	4.08	6.68	3.25	0.70	4.08	5.59	4.08	2.04	4.10	2.06	4.08
high(t)-low(t)	0.63	4.08	7.29	3.25	0.32	4.08	3.33	2.85	1.68	4.10	0.35	4.08
relative vol. exchanged	1.35	4.08	5.86	3.25	0.67	4.08	1.38	4.08	3.70	4.10	1.50	4.08
volume exchanged	1.31	4.08	5.95	3.25	0.73	4.08	1.86	4.08	3.60	4.10	0.97	4.08

LSE data and UK sources												
Does web Granger Cause stock?					**if F > c_v we reject the null hypothesis that web does not Granger Cause stock**							
granger test	**share_pos_ton**		**polarity**		**subjectivity**		**disagreement**		**share_wrt_totals**		**share_wrt_previous_day**	
	F-statistic	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value
close(t)-opening(t)	1.54	4.08	2.04	4.08	2.38	4.08	1.96	4.08	3.36	4.08	2.71	4.08
w(close(t)-opening(t))	1.09	4.08	2.19	3.24	5.34	2.85	2.28	3.24	0.28	4.08	0.39	4.08
close(t)-close(t-1)	1.34	4.08	3.21	4.08	2.68	4.08	3.03	4.08	0.87	4.08	0.79	4.08
w(close(t)-close(t-1))	0.51	4.09	0.03	4.09	5.76	3.24	0.02	4.09	0.29	4.09	0.21	4.09
adjclose(t)-adjclose(t-	1.34	4.08	3.21	4.08	2.68	4.08	3.03	4.08	0.87	4.08	0.79	4.08
high(t)-low(t)	6.70	3.24	6.18	3.24	9.44	3.24	6.29	3.24	4.84	3.24	4.57	3.24
relative vol. exchange	0.33	4.08	0.02	4.08	5.66	2.85	0.00	4.08	0.31	4.08	0.47	4.08
volume exchanged	0.24	4.09	0.02	4.09	4.61	3.24	0.03	4.09	0.51	4.09	0.10	4.09

Does stock Granger Cause web?					if F > c_v we reject the null hypothesis that stock does not Granger Cause web							
granger test	**share_pos_ton**		**polarity**		**subjectivity**		**disagreement**		**share_wrt_totals**		**share_wrt_previous_day**	
	F-statistic	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value
close(t)-opening(t)	3.16	4.08	4.74	2.85	0.01	4.08	4.85	2.85	1.18	4.08	2.81	3.24
w(close(t)-opening(t))	2.31	4.08	4.00	2.85	1.62	4.08	4.21	2.85	0.73	4.08	0.77	4.08
close(t)-close(t-1)	3.02	4.08	3.56	4.08	2.35	4.08	3.52	4.08	3.19	4.08	5.56	4.08
w(close(t)-close(t-1))	2.09	4.08	2.29	4.08	3.30	3.24	2.54	4.08	1.39	4.08	2.63	4.08
adjclose(t)-adjclose(t-	3.02	4.08	3.56	4.08	2.35	4.08	3.52	4.08	3.19	4.08	5.56	4.08
high(t)-low(t)	2.22	4.08	1.90	4.08	0.15	4.08	2.00	4.08	0.72	4.08	0.68	4.08
relative vol. exchange	2.08	4.08	2.05	4.08	3.49	4.08	2.15	4.08	1.33	4.08	2.95	4.08
volume exchanged	2.06	4.08	3.30	2.85	0.02	4.08	3.53	2.85	1.25	4.08	2.75	4.08

grey: not conclusive

Table B.6 Royal Bank of Scotland

NYSE data												
Does web Granger Cause stock?					**if F > c_v we reject the null hypothesis that web does not Granger Cause stock**							
	number_articles		**average_tonality**		**std_tonality**		**number_neg_ton**		**share_neg_ton**		**number_pos_ton**	
	F-statistic	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value
close(t)-opening(t)	3.92	2.86	4.38	2.86	3.46	2.86	3.54	2.86	3.44	2.86	4.81	2.86
w(close(t)-opening(t))	1.57	4.08	4.57	4.08	4.65	4.08	2.04	4.08	2.02	4.08	2.25	4.08
close(t)-close(t-1)	1.18	4.08	1.07	4.08	1.07	4.08	1.33	4.08	0.99	4.08	0.88	4.08
w(close(t)-close(t-1))	1.29	4.09	2.37	4.09	0.43	4.09	0.89	4.09	2.04	4.09	2.61	4.09
adjclose(t)-adjclose(t-1)	1.18	4.08	1.07	4.08	1.07	4.08	1.33	4.08	0.99	4.08	0.88	4.08
high(t)-low(t)	7.38	4.10	7.38	4.10	8.48	3.25	7.61	4.10	7.83	4.10	7.34	4.10
relative vol. exchanged	2.39	4.09	1.96	3.24	0.71	4.09	3.63	4.09	2.01	3.24	2.49	3.24
volume exchanged	0.27	4.08	0.33	4.08	0.35	4.08	0.21	4.08	0.53	4.08	0.36	4.08

Does stock Granger Cause web?					if F > c_v we reject the null hypothesis that stock does not Granger Cause web							
	number_articles		**average_tonality**		**std_tonality**		**number_neg_ton**		**share_neg_ton**		**number_pos_ton**	
	F-statistic	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value
close(t)-opening(t)	2.77	3.24	0.50	4.10	1.54	4.09	2.60	4.10	1.39	4.08	0.46	4.08
w(close(t)-opening(t))	2.12	3.24	1.99	4.10	1.21	4.09	2.59	4.10	1.67	4.08	0.62	4.08
close(t)-close(t-1)	3.92	3.24	0.32	4.10	1.29	4.09	1.15	4.10	1.45	4.08	0.56	4.08
w(close(t)-close(t-1))	2.28	3.24	0.57	4.10	2.86	3.24	1.45	4.10	1.54	4.08	0.49	4.08
adjclose(t)-adjclose(t-1)	3.92	3.24	0.32	4.10	1.29	4.09	1.15	4.10	1.45	4.08	0.56	4.08
high(t)-low(t)	2.34	3.24	0.46	4.10	1.96	4.09	2.29	4.10	1.55	4.08	0.59	4.08
relative vol. exchanged	2.16	3.24	1.93	4.10	1.52	4.09	1.21	4.10	1.40	4.08	0.43	4.08
volume exchanged	2.41	3.24	1.46	4.10	0.99	4.09	1.43	4.10	1.75	4.08	0.45	4.08

NYSE data

Does web Granger Cause stock? — **if F > c_v we reject the null hypothesis that web does not Granger Cause stock**

granger test	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	4.65	2.86	4.33	2.86	3.49	2.86	4.08	2.86	3.86	2.86	3.78	2.86
w(close(t)-opening(t))	3.91	4.08	2.91	4.08	5.32	4.08	2.81	4.08	1.51	4.08	6.33	4.08
close(t)-close(t-1)	0.89	4.08	0.89	4.08	0.90	4.08	0.94	4.08	1.33	4.08	1.12	4.08
w(close(t)-close(t-1))	3.56	4.09	3.71	4.09	0.45	4.09	2.89	4.09	1.82	4.09	4.25	4.09
adjclose(t)-adjclose(t-1)	0.89	4.08	0.89	4.08	0.90	4.08	0.94	4.08	1.33	4.08	1.12	4.08
high(t)-low(t)	7.55	4.10	7.80	4.10	8.50	4.10	7.73	4.10	7.36	4.10	7.72	4.10
relative vol. exchanged	2.87	3.24	2.63	3.24	0.55	4.09	2.62	3.24	1.71	4.09	2.29	3.24
volume exchanged	0.86	4.08	1.62	4.08	0.33	4.08	0.73	4.08	0.40	4.08	0.11	4.08

Does stock Granger Cause web? — **if F > c_v we reject the null hypothesis that stock does not Granger Cause web**

granger test	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	0.99	4.08	0.78	4.08	0.40	4.08	1.37	4.08	1.84	4.09	0.82	4.08
w(close(t)-opening(t))	2.54	4.08	1.20	4.08	0.71	4.08	2.07	4.08	1.71	4.09	0.52	4.08
close(t)-close(t-1)	2.76	3.24	0.96	4.08	1.07	4.08	1.46	4.08	1.54	4.09	7.29	4.08
w(close(t)-close(t-1))	1.49	4.08	1.06	4.08	0.59	4.08	1.38	4.08	1.58	4.09	1.32	4.08
adjclose(t)-adjclose(t-1)	2.76	3.24	0.96	4.08	1.07	4.08	1.46	4.08	1.54	4.09	7.29	4.08
high(t)-low(t)	1.02	4.08	0.82	4.08	1.91	3.24	1.53	4.08	1.53	4.09	3.64	3.24
relative vol. exchanged	0.93	4.08	0.86	4.08	0.57	4.08	1.38	4.08	1.51	4.09	1.67	4.08
volume exchanged	0.94	4.08	0.77	4.08	0.12	4.08	1.45	4.08	1.59	4.09	3.27	4.08

grey: not conclusive

LSE data and EU sources

Does web Granger Cause stock? — **if F > c_v we reject the null hypothesis that web does not Granger Cause stock**

	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	1.37	4.08	0.55	4.08	0.35	4.08	0.95	4.08	0.45	4.08	0.99	4.08
w(close(t)-opening(t))	1.03	4.08	3.79	2.85	0.25	4.08	0.47	4.08	0.62	4.08	1.09	4.08
close(t)-close(t-1)	2.81	4.08	3.45	2.85	1.12	4.08	2.37	4.08	1.08	4.08	2.04	4.08
w(close(t)-close(t-1))	2.88	4.09	3.32	4.09	2.47	4.09	2.50	4.09	3.38	4.09	2.81	4.09
adjclose(t)-adjclose(t-1)	2.81	4.08	3.45	2.85	1.12	4.08	2.37	4.08	1.08	4.08	2.04	4.08
high(t)-low(t)	2.01	4.08	3.19	4.08	1.70	4.08	0.72	4.08	1.83	4.08	8.08	4.08
relative vol. exchanged	3.32	4.09	3.47	4.09	2.72	4.09	2.82	4.09	3.63	4.09	3.23	4.09
volume exchanged	5.08	4.09	2.62	4.09	3.78	4.09	3.37	4.09	2.21	4.09	5.03	4.09

Does stock Granger Cause web? — **if F > c_v we reject the null hypothesis that stock does not Granger Cause web**

	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	3.33	3.24	0.50	4.08	0.06	4.09	1.34	4.10	2.33	4.08	0.75	4.08
w(close(t)-opening(t))	3.60	3.24	0.35	4.08	0.08	4.09	1.31	4.10	2.47	4.08	2.53	3.24
close(t)-close(t-1)	4.10	3.24	0.35	4.08	0.17	4.09	2.25	4.10	1.91	4.08	2.06	4.08
w(close(t)-close(t-1))	7.63	3.24	1.07	4.08	7.85	3.24	4.09	2.87	0.05	4.08	2.81	3.24
adjclose(t)-adjclose(t-1)	4.10	3.24	0.35	4.08	0.17	4.09	2.25	4.10	1.91	4.08	2.06	4.08
high(t)-low(t)	6.98	3.24	1.34	4.08	2.46	3.24	4.33	3.25	0.39	4.08	2.55	3.24
relative vol. exchanged	7.67	3.24	1.10	4.08	7.99	3.24	4.22	2.87	0.07	4.08	2.73	3.24
volume exchanged	7.74	3.24	1.02	4.08	6.41	3.24	6.17	2.87	0.35	4.08	0.74	4.08

LSE data and EU sources

Does web Granger Cause stock? — **if F > c_v we reject the null hypothesis that web does not Granger Cause stock**

granger test	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	0.46	4.08	0.33	4.08	0.58	4.08	0.33	4.08	2.12	4.08	2.81	4.08
w(close(t)-opening(t))	0.96	4.08	0.67	4.08	0.39	4.08	0.62	4.08	1.96	4.08	1.58	4.08
close(t)-close(t-1)	1.29	4.08	1.09	4.08	1.91	4.08	1.07	4.08	2.94	4.08	3.76	4.08
w(close(t)-close(t-1))	4.38	3.24	3.34	3.24	2.00	4.09	3.52	3.24	2.99	4.09	4.74	2.86
adjclose(t)-adjclose(t-1)	1.29	4.08	1.09	4.08	1.91	4.08	1.07	4.08	2.94	4.08	3.76	4.08
high(t)-low(t)	4.74	3.24	4.05	3.24	0.90	4.08	4.21	4.08	2.33	4.08	1.79	4.08
relative vol. exchanged	4.46	3.24	3.46	3.24	2.18	4.09	3.66	3.24	3.48	4.09	4.74	2.86
volume exchanged	2.31	4.09	2.71	4.09	2.29	4.09	2.51	4.09	4.30	4.09	4.80	2.86

Does stock Granger Cause web? — **if F > c_v we reject the null hypothesis that stock does not Granger Cause web**

granger test	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value	F-statistic	critical value
close(t)-opening(t)	4.32	2.85	2.35	3.24	0.62	4.08	2.60	3.24	0.35	4.08	7.28	4.08
w(close(t)-opening(t))	5.56	2.85	2.55	3.24	0.43	4.08	3.19	3.24	0.47	4.08	8.36	4.08
close(t)-close(t-1)	3.37	2.85	0.54	4.08	0.37	4.08	0.96	4.08	0.56	4.08	3.56	4.08
w(close(t)-close(t-1))	0.89	4.08	0.52	4.08	2.60	4.08	1.04	4.08	4.23	3.24	0.78	4.08
adjclose(t)-adjclose(t-1)	3.37	2.85	0.54	4.08	0.37	4.08	0.96	4.08	0.56	4.08	3.56	4.08
high(t)-low(t)	1.68	4.08	1.06	4.08	0.95	4.08	1.31	4.08	7.02	3.24	9.81	4.08
relative vol. exchanged	0.87	4.08	0.51	4.08	2.67	4.08	1.03	4.08	4.34	3.24	0.74	4.08
volume exchanged	0.84	4.08	0.50	4.08	2.07	4.08	0.91	4.08	4.44	3.24	0.57	4.08

grey: not conclusive

LSE data and GB sources												
Does web Granger Cause stock?						if F > c_v we reject the null hypothesis that web does not Granger Cause stock						
	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value
close(t)-opening(t)	0.35	4.08	3.43	4.08	0.38	4.08	1.12	4.08	7.08	4.08	2.51	4.08
w(close(t)-opening(t))	0.33	4.08	1.94	4.08	0.26	4.08	1.15	4.08	5.42	4.08	1.45	4.08
close(t)-close(t-1)	1.31	4.08	2.47	4.08	1.19	4.08	2.42	4.08	5.59	4.08	1.79	4.08
w(close(t)-close(t-1))	3.04	4.09	4.17	4.09	2.47	4.09	3.89	4.09	5.45	4.09	1.97	4.09
adjclose(t)-adjclose(t-1)	1.31	4.08	2.47	4.08	1.19	4.08	2.42	4.08	5.59	4.08	1.79	4.08
high(t)-low(t)	2.77	4.08	1.00	4.08	7.27	4.08	2.87	4.08	0.74	4.08	2.18	4.08
relative vol. exchanged	3.46	4.09	4.41	4.09	2.74	4.09	4.44	4.09	5.95	4.09	2.13	4.09
volume exchanged	4.59	4.09	3.45	4.09	3.82	4.09	6.45	4.09	4.26	4.09	2.14	4.09

Does stock Granger Cause web?						if F > c_v we reject the null hypothesis that stock does not Granger Cause web						
	number_articles		average_tonality		std_tonality		number_neg_ton		share_neg_ton		number_pos_ton	
	F-statistic	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value
close(t)-opening(t)	2.70	3.25	4.67	2.85	0.43	4.09	0.23	4.10	3.34	3.24	5.22	4.08
w(close(t)-opening(t))	1.75	4.10	4.40	2.85	3.00	2.86	0.22	4.10	3.96	3.24	5.13	3.24
close(t)-close(t-1)	2.97	4.10	3.74	2.85	1.15	4.09	0.73	4.10	1.37	4.08	5.83	3.24
w(close(t)-close(t-1))	0.14	4.10	7.10	2.85	5.92	3.24	2.79	2.87	3.62	4.08	1.07	4.08
adjclose(t)-adjclose(t-1)	2.97	4.10	3.74	2.85	1.15	4.09	0.73	4.10	1.37	4.08	5.83	3.24
high(t)-low(t)	1.88	3.25	5.29	2.85	3.96	2.86	2.32	3.25	4.00	2.85	0.96	4.08
relative vol. exchanged	0.15	4.10	7.25	2.85	5.47	3.24	2.77	2.87	3.80	4.08	1.27	4.08
volume exchanged	0.14	4.10	6.36	2.85	5.42	3.24	3.48	2.87	3.98	4.08	1.10	4.08

LSE data and GB sources												
Does web Granger Cause stock?						if F > c_v we reject the null hypothesis that web does not Granger Cause stock						
granger test	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value
close(t)-opening(t)	1.74	4.08	7.55	4.08	3.59	4.08	7.60	4.08	0.54	4.08	0.41	4.08
w(close(t)-opening(t))	0.95	4.08	5.74	4.08	3.14	4.08	5.31	4.08	0.62	4.08	0.23	4.08
close(t)-close(t-1)	2.08	4.08	5.70	4.08	3.34	4.08	5.88	4.08	1.36	4.08	1.13	4.08
w(close(t)-close(t-1))	5.20	3.24	5.32	4.09	3.99	4.09	5.12	4.09	3.14	4.09	1.97	4.09
adjclose(t)-adjclose(t-1)	2.08	4.08	5.70	4.08	3.34	4.08	5.88	4.08	1.36	4.08	1.13	4.08
high(t)-low(t)	2.90	3.24	0.84	4.08	2.61	3.24	1.12	4.08	2.26	4.08	0.83	4.08
relative vol. exchanged	5.38	3.24	5.63	4.09	4.48	4.09	5.43	4.09	3.61	4.09	2.12	4.09
volume exchanged	4.35	3.24	4.70	4.09	3.29	4.09	4.23	4.09	4.05	4.09	2.16	4.09

Does stock Granger Cause web?						if F > c_v we reject the null hypothesis that stock does not Granger Cause web						
granger test	share_pos_ton		polarity		subjectivity		disagreement		share_wrt_totals		share_wrt_previous_day	
	F-statistic	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value	**F-statistic**	critical value
close(t)-opening(t)	3.82	4.09	4.24	2.85	0.89	4.08	3.60	4.08	1.53	4.10	2.66	3.24
w(close(t)-opening(t))	4.76	4.09	5.55	2.85	2.33	3.24	4.40	2.85	1.64	4.10	2.98	2.86
close(t)-close(t-1)	4.40	4.09	2.88	4.08	0.47	4.08	2.59	4.08	2.27	4.10	4.16	2.86
w(close(t)-close(t-1))	1.04	4.09	4.01	4.08	1.40	4.08	3.32	4.08	0.18	4.10	0.88	4.09
adjclose(t)-adjclose(t-1)	4.40	4.09	2.88	4.08	0.47	4.08	2.59	4.08	2.27	4.10	4.16	2.86
high(t)-low(t)	0.31	4.09	3.70	2.85	2.94	3.24	3.16	3.24	2.99	3.25	0.65	4.09
relative vol. exchanged	1.15	4.09	4.24	4.08	1.44	4.08	3.54	4.08	0.24	4.10	0.93	4.09
volume exchanged	0.97	4.09	5.23	4.08	1.67	4.08	3.86	4.08	2.46	2.87	0.71	4.09

grey: not conclusive