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Intraday News Trading: The Reciprocal Relationships Between the Stock Market and Economic News

Nadine Strauß[1], Rens Vliegenthart[1], and Piet Verhoeven[1]

Abstract

This study investigates the interdependent relationships between the stock market and economic news in the U.S. context. 2,440 economic tweets from Reuters and Bloomberg published in September 2015 were analyzed within short-term intervals (5 minutes, 20 minutes, and 1 hour) as well as 50 influential Bloomberg market coverage stories distributed via their terminals for the same period of time. Using Vector Auto Regression analyses, it was found that news volume, news relevance, and expert opinion in tweets seem to influence the fluctuation of the Dow Jones Industrial Average (DJI) positively, while economic news appears to respond to market fluctuation with less coverage, including fewer retweets, favorites, updates, or expert opinions conveyed. Inspecting the influential market stories by Bloomberg, the results imply that while Bloomberg terminals provide firsthand information on the market to professionals, tweets rather seem to offer follow-up reporting to the public. Furthermore, given that the effect of economic tweets on the DJI fluctuations was found to be strongest within longer time intervals (i.e., 1 hour), the findings imply that public traders need more time to evaluate information and to make a trading decision than professional investors.

Keywords

economic news, intraday trading, news agencies, Twitter, time series, stock market

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Globalization and digital technologies have led to the delivery of economic news in real time (Barber & Odean, 2001; Hope, 2010). Microblogging platforms, such as Twitter, provide news on stocks and the financial market instantly, making it a useful and accessible information source for investors. Indeed, several examples of the dissemination of economic news on Twitter, leading to severe fluctuations of share prices, suggest that tweets can exert a considerable influence not only on stocks but also on the coverage on those incidents thereafter (e.g., Tesla's new product line, April 2015: Sheffield, 2015). Although these relationships might be expected in light of public agenda-setting (McCombs & Shaw, 1972) and media agenda-setting theory (Rogers, Dearing, & Bregman, 1993), it still needs to be empirically examined whether general agenda-setting patterns also apply in the economic news context. It is still up for discussion to what extent tweets influence the stock market, or whether tweets are mainly follow-up reports on recent market events.

Scholars in finance, information systems, and communication science have increasingly devoted attention to the supposed effect of social media and online news on the stock market (e.g., Antweiler & Frank, 2004; Bollen, Mao, & Zeng, 2011). However, some of these studies lack in terms of external validity and practical implications for investors in explaining why certain news drives the stock market while other does not. In addition, only few studies have been seeking the reversed relationship, scrutinizing whether and how stock market reactions drive news reporting (e.g., Kleinnijenhuis, Schultz, Utz, & Oegema, 2015; B. Scheufele, Haas, & Brosius, 2011). And only slowly, scholars start to take a step beyond looking at daily stock market and news data, investigating high-frequency data and stock market reactions at lower time intervals (e.g., Groß-Klußmann & Hautsch, 2011).

In accounting for these shortcomings, this study contributes to existent work in three ways: First, we study the mutual relationships between economic news (i.e., tweets released by Reuters and Bloomberg accounts) and the stock market (i.e., fluctuation of the Dow Jones Industrial Average [DJI]) in September 2015, providing tentative evidence for both public agenda-setting and media agenda-setting theory. Second, in coding the tweets manually, we account for the multidimensionality of economic news and the actual content. More specifically, we unravel the interdependent relationships of various facets of economic news, on one hand (e.g., news volume, relevance, expert opinion), and stock market fluctuation of the DJI, on the other hand. And third, by applying adequate time series analyses, we investigate intraday interactions (5-minute, 20-minute, 1-hour interval), revealing the dynamic relationships between economic news and the stock market within short-term intervals. Eventually, we contextualize our findings by analyzing market-moving Bloomberg news articles, the so-called "influential market coverage," that are distributed through Bloomberg terminals—the main source of financial news for professional investors (cf. Davis, 2005).

Theoretical Background

The Role of Media

Media are powerful tools to spread information on the financial market and to reflect the consensus market opinion (Davis, 2006). Following mass communication theory, organizational and management research has highlighted the crucial role of media in informing the market (Deephouse, 2000). Based on intermediaries, such as financial news or financial analysts, the media create an interpretative context for investors and other market participants (cf. Shiller, 2000). In turn, the information provided by the media serves as the foundation for market opinions and trading decisions, which become eventually manifested in investor behavior (cf. Pollock & Rindova, 2003).

The mechanism behind information conveyed in the media triggering stock market reactions can be substantiated by public agenda-setting theory (e.g., Hügel, Degenhardt, & Weiss, 1989). Representatives of this theory assume that the effect of media coverage on the public's agenda is contingent on individual characteristics of the media audience (Erbring, Goldenberg, & Miller, 1980). In this sense, not all media messages are considered to be equally relevant to every person. Whereas economic news might be crucial for traders and individual investors, others might be less interested in news about the economy or a specific firm. Hence, following the idea of agenda-setting theory (McCombs & Shaw, 1972), media are assumed to direct investors' attention to economic news and listed firms by increasing news coverage about the economy and corporations.

Besides creating pure attention, the media are also considered to trigger impression formations among the audience by reporting in a certain tone or associating actors with particular issues (D. A. Scheufele, 2000). This relates to framing theory (McCombs, Llamas, Lopez-Escobar, & Rey, 1997) and the priming hypothesis (D. A. Scheufele, 2000). While priming research investigates how issue salience affects judgments of public personalities by the public (e.g., Iyengar & Kinder, 1987), scholars investigating frame-settings are interested how media frames of certain issues become reflected among perceptions of the audience (e.g., Huang, 1995). Hence, not only the extent to which but also the way a firm or the economy is reported in the news might potentially impact investors' evaluations of these firms or the market as a whole (cf. Pollock & Rindova, 2003).

Intraday News Trading

Professional investors particularly rely on real-time news wire services (e.g., Reuters or Bloomberg) to stay updated on economic news and to anticipate market movements (cf. Antweiler & Frank, 2004; Davis, 2005; Thompson, 2009). However, intraday stock market trading based on information is questioned in light of the efficient market hypothesis (EMH; Fama, 1970), which implies that all publicly available information is instantaneously incorporated in stock market prices. In this sense, the prediction of the stock market based on news or historical data is unsustainable. Although several studies have provided results that are in line with the EMH (e.g., B. Scheufele et al., 2011; Strauß, Vliegenthart, & Verhoeven, 2016), other studies in finance have questioned it, implying that information might indeed drive stock market reactions. Behavioral finance scholars contend in particular that market behavior is not fully based on rational decision making but also influenced by emotions and herd-like behavior (e.g., Nofsinger, 2005).

We furthermore argue that one of the major reasons why some studies might not have found the media to have a significant effect on the stock market is due to the level of data aggregation. A number of studies in this field of research have mainly investigated news information aggregated on a daily level (e.g., Fang & Peress, 2009). However, given that information is nowadays distributed and updated constantly via various media channels while stock market traders execute trades within (micro)seconds (Lewis, 2014), looking at daily time intervals does not seem to be adequate anymore. Therefore, following previous research (e.g., Groß-Klußmann & Hautsch, 2011), we assume the stock market to respond to economic news within a trading day, and differently with regard to varying time windows.

Arguing from a psychological stance, we might expect different effects of news on the stock market for different time intervals. In fact, Thaler, Tversky, Kahneman, and Schwartz (1997) showed in an experimental test that investors who received most feedback—in other words, more time and information—were least likely to take risk and invest money in stocks. Tversky and Kahneman (1992) defined this as the "myopic loss aversion." The concept implies two aspects: on one hand, that people are more sensitive to losses than to gains; and, on the other hand, that they tend to assess outcomes more frequently over time.

Following this reasoning, it can be expected that traders who receive more information—hence, taking more time to gather and process information—are more likely to rethink their trading decisions in a risk-averse direction. Thus, we pose the first research question:

> **Research Question 1 (RQ1):** What differences in relations of economic news and stock market fluctuations can be observed for various intraday time intervals?

The influence of economic news on investors' trading decisions might depend not only on the time frame but also on the content and characteristics of the news. To remain in the field of psychology, it is well known that the cognitive processing of stimuli (i.e., economic information) is based on a range of dimensions that affect decision-making processes (Suedfeld & Tetlock, 1977). Varying aspects of the stimuli might be considered in different ways, dependent on the receiver and context. Therefore, the response of a receiver to a stimulus (i.e., economic information) is assumed to be more complex, the more dimensions the receiver identified and perceived as important (cf. Kleinnijenhuis, Schultz, & Oegema, 2015).

Following this reasoning, it does not suffice to only investigate one dimension of stimuli (e.g., either news volume, or sentiment, or news relevance) when aiming at making predictions of trading behavior based on information. Trading decisions are manifold and might vary depending on the assessment of specific characteristics of a news item (cf. Davis, 2006). Hence, we need to analyze news from a wide-ranging perspective, accounting for different dimensions and characteristics of information. Originating from a literature review on studies dealing with online information, social media, news, and the stock market, we have identified five dimensions of economic news that are assumed to trigger stock market reactions.

Dimensions of Economic News

Behavioral finance scholars assume that investors do not act rationally when making trading decisions, but are biased by emotions, social mood (Nofsinger, 2005), and subject to herd-like behavior (Davis, 2006). It is argued that "rational, self-interested individuals can, collectively, behave in mass, irrational ways, and in response to common sources of media and communications" (Davis, 2006, pp. 621-622). In turn, investors might react to new information—although not yet verified—simply because they anticipate the market might perceive it as important. This is in line with the theory of availability heuristics (Tversky & Kahneman, 1973). Based on this theory, it can be assumed that investors are especially prone to respond to information that is more salient. Building on this argumentation, we assume the following hypothesis for intraday stock market trading within various time intervals:

Hypothesis 1 (H1): News volume of economic news is related to stock market fluctuations.

In a similar vein, Groß-Klußmann and Hautsch (2011) found stock markets to react stronger to news items that are identified as highly relevant, implying that news items send a stronger signal to the market when being repeated, confirmed, or more elaborated (see also Davis, 2005). Thus, *news relevance* can be reflected by the extent to which the news event is novel or an update of a news release. Ensuing from this line of thinking, it is important to distinguish news items based on their novelty character. Hence, the extent to which a news provider attributes relevance to specific news items—for example, by repeatedly reporting on news—might affect stock market reactions. We therefore hypothesize the following:

Hypothesis 2 (H2): Relevant appearing economic news is related to stock market fluctuations.

Given that not all information might be equally relevant for investors, we follow the expertise effect theory (e.g., Thomas-Hunt, Ogden, & Neale, 2003) in expecting that news covering analysts' and experts' recommendations might be more influential in evoking market reactions than general news (cf. Li, Ramesh, Shen, & Wu, 2015). Moreover, Bar-Haim, Dinur, Feldman, Fresko, and Goldstein (2011) argued that the distinction between expert and nonexpert market opinion is crucial to rule out noise in estimating market predictions. Consequently, we assume:

Hypothesis 3 (H3): The presence of expert opinions in economic news is related to stock market fluctuations.

Not only might expert opinions and news that appears "relevant" induce market reactions, a number of studies in psychology and behavioral finance have provided evidence that stock market decisions are also affected by *emotions* (e.g., Bollen et al., 2011). More specifically, it is assumed that investors' trading behavior is primarily determined by their feelings toward the development of the financial markets; in other words, whether investors are optimistic (bullish) or pessimistic (bearish) toward market movements (Nofsinger, 2005). Nofsinger proposes that positive social mood (e.g., hope) gets integrated into stock market prices by increasing trades and the buying of stocks, whereas negative social mood (e.g., fear) gets reflected in declining stock market prices and higher volatility (e.g., Gilbert & Karahalios, 2010). Based on these findings, the fourth hypothesis reads:

> **Hypothesis 4 (H4):** The presence of hope or fear in economic news is related to stock market fluctuations.

Eventually, literature dealing with the effects of information on the stock market generally distinguishes between marketwide and firm-specific information. Findings indicate that firm-specific news has a positive effect on market indicators (e.g., Berry & Howe, 1994), whereas macroeconomic news announcements (e.g., unemployment) were found to have an influence on stock returns (e.g., Birz & Lott, 2011). To account for varying effects with regard to the *focus of the news* item, we pose the following open research question:

> **Research Question 2 (RQ2):** To what extent do the relations of economic news and stock market fluctuations vary with regard to the focus of the news?

Reversed Effect

Referring back to the EMH, however, it is likely that economic news does not have an effect on fluctuations of the stock market after all. In fact, we find explanations for this assumption in mass communication theories. Studies in the field of media agenda-setting theory, for example, consider the agenda of the mass media as the main dependent variable in their models (Rogers et al., 1993). Following this, scholars are inclined to find out how the media agenda is set. In this regard, not only sources of news, organizational and extramedia forces, but also individual characteristics of journalists are considered as factors that shape the news media (Shoemaker & Reese, 1996). Hence, examining economic news as a response to market reactions might not only give us useful insights into what drives economic news reporting, but might also reveal the complex temporal interrelationships between real-world events, news reporting, and market reactions.

The influence of external factors on the media agenda is closely related to news value theory (Galtung & Ruge, 1965). Whereas Galtung and Ruge have provided 12 factors to determine how events overseas become foreign news in Norwegian newspapers, Harcup and O'Neill (2001) have tested these factors in light of domestic and foreign news in the United Kingdom, suggesting a more contemporary overview of news values. Their findings imply that events are more likely to be selected to become news when they contain certain factors such as relevance, bad or good news, or surprise. Therefore, it could be argued that unexpected or severe negative or positive shifts of the stock market (i.e., high fluctuation) are more likely to be reported in the news. This in turn could be reflected in the magnitude of various news dimensions as selected in this article, such as the repeated reporting on events, negative or positive emotions, or the usage of expert opinion. Hence, based on media agenda-setting and news value theory, we pose the third research question:

> **Research Question 3 (RQ3):** To what extent do stock market fluctuations relate to the presence of the dimensions of economic news (news volume, relevance, expert opinion, and emotions) within a trading day?

Data and Method

Twitter Accounts of Reuters and Bloomberg

To investigate the interrelationships between economic news and the stock market, we chose the Twitter accounts by Reuters and Bloomberg as objects of analyses. Microblogging platforms, such as Twitter, excel as online sources for investors, as they can provide real-time information on the market and the economy, evaluations on firm performances, and up-to-date financial analyses, also having the potential to go viral (cf. herd behavior: Yu, Duan, & Cao, 2013).[1] While the financial news wire sources Reuters and Bloomberg are said to have the widest acceptance in the financial community (cf. Yang, Mo, & Liu, 2015), Twitter has recently become endorsed by the U.S. Securities and Exchange Commission (SEC; 2013) as a distribution channel for listed firms to announce market relevant information. In this regard, the social media accounts of the most relevant news wire services, Bloomberg and Reuters, can be considered as proxies for market relevant information and news, likely to affect investors' trading behavior. For our analysis, we focused on all major accounts of Reuters and Bloomberg on Twitter, including news about real-world events such as mergers and acquisitions, investments, or global and emerging market developments (see Online Appendix A for the distribution of tweets per Twitter account for the month of investigation, September 2015).[2]

Intraday Stock Market Data

Given that reactions toward economic information aggregated from Reuters and Bloomberg tweets are more likely to be detected on global stock indices than on individual stocks, we decided to investigate one of the major U.S. stock market indexes, namely, the DJI (cf. Uhl, 2014).[3] The fact that most news from our Twitter sample deals with the U.S. market, U.S. companies, or U.S.-related topics substantiates our selection of the DJI (see Online Appendix B).

We downloaded the closing prices for the DJI on a 5-minute time interval, which allowed us to aggregate the data also to 20-minute and 1-hour time intervals for further analyses. We chose these three time intervals, as previous studies in finance have shown that stock prices do not react instantly to the release of information, but take some time to become integrated in prices (cf. Nassirtoussi, Aghabozorgi, Wah, & Ngo, 2014). Chordia, Roll, and Subrahmanyam (2005), for example, suggested that it takes at least 5 minutes but less than 60 minutes until the market has converged to efficiency again. Gidófalvi (2001) has shown that there is a time window of approximately 20 minutes before and after a financial news article was released to predict the stock market price before equilibrium. To investigate the fluctuations of the DJI, we used the absolute values of the differenced series of the closing prices of the DJI.

Data Management

We automatically retrieved tweets by means of a python script[4] from seven Reuters[5] and six Bloomberg[6] Twitter accounts for the U.S. trading hours (9:30 a.m. to 16:00 p.m.) for all trading days in September 2015. In total, 4,186 tweets were downloaded for the period of analysis. 13 tweets were deleted from the sample because they were not completely downloaded or had too few characters to be correctly identified.

Manual coding. To account for criticism on automated content analyses, and particularly with regard to Twitter (e.g., to understand informal language; Bar-Haim et al., 2011), we decided to use manual coding for our sample. By reading all tweets of the sample in depth and looking up the hyperlinks of the online news by Reuters and Bloomberg, it was possible for us to trace back what the tweets were in fact about. Two coders coded the tweets based on a prespecified codebook[7] between January 2016 and March 2016. After several rounds of discussions on ambiguous tweets, the adjustment of the codebook and two intercoder reliability tests, the alignment between the two coders was assessed. See Online Appendix C for an overview of the coded items, examples, and their reliability scores. Each coder was randomly assigned to code tweets published by Reuters and Bloomberg for 10 or 11 days in September 2015. After finishing the coding, the data set was cleaned by removing duplicates as well as adjusting some miscoded tweets,[8] which left us with 4,114 tweets. Given that our theoretical assumptions are mainly based on news dealing with the economy, only tweets that dealt with economic news were subject of the subsequent analyses ($N = 2,440$).

Measurements

To prepare the Twitter data set for time series analyses, the coded variables had to be aggregated in an appropriate manner. *News volume* was calculated by the number of tweets that were released by all Reuters and Bloomberg accounts within the given time interval (5 minutes, 20 minutes, 1 hour).[9] To measure the *relevance* of a specific tweet, we followed Sprenger, Tumasjan, Sandner, and Welpe (2014) and measured the number of *retweets* and *favorites* for each tweet.

Furthermore, following Groß-Klußmann and Hautsch (2011), we coded news items based on their novelty character by making use of an *update indicator* (initial news item = 0; updates on the news item > 0). To catch the updates of news in the trading month September, we had to manually write down the topic of each tweet after coding. Having the overview of the topics of each tweet, one coder wrote a tally list and indicated which topic occurred more than one time, and noted in the data set and in the tally list the number of updates (see Online Appendix B for the most occurring topics). The variable *updates* is eventually based on the sum of the number of updates per time interval (5 minutes, 20 minutes, 1 hour).

Expert opinion was coded for tweets that explicitly dealt with the view of an expert on the market, stock, or industry (e.g., financial analyst), or when there was an explicit sell or buy recommendation expressed (cf. Bar-Haim et al., 2011). For the analyses, the variable *expert opinion* is based on the number of expert opinions that was coded per time interval (5 minutes, 20 minutes, 1 hour).

The measurement of the *emotions fear* and *hope* was aimed at capturing the positive or negative outlook for a stock, company, industry, or the market as a whole. As such, it was evaluated whether the tweet reflected *optimistic (i.e., hope), pessimistic (i.e., fear) prospects, both* or *none*. To make the coding more comprehensible, we asked the coders to write down the words that triggered the coding decision. Furthermore, a number of examples in the codebook worked as a guideline for the coders. For the analyses, we estimated one variable for *fear* (Σ of fear coded per interval), and one for *hope* (Σ of hope coded per interval).

Following previous studies (e.g., Berry & Howe, 1994), we also differentiated whether the Reuters or Bloomberg tweets dealt with *firm-specific* (*listed firms/stocks, nonlisted firms*) or *marketwide information* (*international market, national market, industry*, or *others*). To test the differences between the two foci in comparison to all economic news in the analyses, we split the data set into firm-specific and marketwide news.

Vector Auto Regression (VAR) Models

Given that our hypotheses and research questions assume interdependence (endogeneity) of economic news and the stock market, an adequate method of time series had to be used. We opted for VAR models, as these are particularly useful to examine the dynamic effects between two or more variables. More specifically, within VAR analyses, a separate equation is estimated for each variable that is considered to be dependent (Vliegenthart, 2014), also including lags of both variables to control for the past of the dependent and independent variables. In our VAR models, this is the closing price of the DJI per time interval (5 minutes, 20 minutes, 1 hour), and one of the variables of the dimensions of economic news (news volume, retweets, favorites, novelty, expert opinion, hope, fear). Furthermore, the VAR models were constructed 3 times: 1 time based on all economic tweets, and the other 2 times using either the data sets for firm-specific or marketwide news.[10] Online Appendix E shows the means and standard deviations of the variables included in the VAR models.

Procedure. We followed the procedure according to Vliegenthart (2014) when constructing the VAR models. In the first step, the Augmented Dickey–Fuller (ADF) test was conducted to check whether the time series were stationary and did not contain a unit root. All series were stationary after differencing them. In case only one of the two series was nonstationary (e.g., DJI) at the first stage, the same level of integration had to be chosen by differencing the other series (e.g., news volume) as well.

Second, the optimal lag structure for the VAR models was defined by means of selection-order criteria. For the 5-minute intervals, we specified the maximum lag number with 24, equaling two trading hours; for the 20-minute intervals, a maximum lag number of 12, equaling 4 hours; and for the 1-hour interval, a maximum lag number of seven was chosen, accounting for a little bit more than one trading day. The given selection-order statistics, including the final prediction error (FPE), Akaike's information criterion (AIC), the Hannan and Quinn information criterion (HQIC), and the Schwarz's Bayesian information criterion (SBIC), were consulted to chose the optimal number of lags for each VAR model.

After estimating the VAR models, *Granger causality tests* were performed to evaluate whether the dimensions of the economic tweets (e.g., Δnews volume) predict the fluctuation of the DJI above and beyond the past values of the DJI, or vice versa. Technically, Granger causality tests indicate whether one series (X(t)) is better explained by the history of both X(t) and Y(t), instead of its own past (X(t)) solely (Vliegenthart, 2014). For reasons of clarity and space, only significant Granger causality findings are discussed in this article; but all other tables can be requested from the corresponding author.

To get a clearer picture of the dynamic effects of the VAR processes, the *cumulative impulse response functions* (CIRF) were estimated, which indicate the response of the dependent variable after a one-unit increase in the independent variable (shock) after n-steps, that is, the number of lags chosen for the respective VAR model (cf. Luo & Zhang, 2013). Furthermore, the forecast error variance (FEV) was estimated to get insights of how much variance of the dependent variable (e.g., |Δ|DJI) is explained by its own past and how much by the independent variable (e.g., Δnews volume) (cf. Luo & Zhang, 2013). Results for both CIRF and FEV are discussed for the number of lags each particular VAR model was constructed. The graphs for the CIRFs and FEVs can be found in the Online Appendices F and G.

VAR robustness checks. To make sure that the VAR models are stable, and not misinterpreted due to autocorrelation of a non-White noise process of residuals, a number of robustness checks were conducted. First, the Lagrange-multiplier (LM) test was performed, which tests the null hypothesis of no autocorrelation at the lag order chosen for the specific VAR model. Second, it was tested for serial correlation by means of the Portmanteau (Q) test for autocorrelation of residuals up to the lag order of 20 (Vliegenthart, 2014). In no models, the null hypothesis of no residual autocorrelation had to be rejected. In addition, the stability condition of the VAR estimates was checked to see whether the Eigenvalues lie inside the unit circle. All our VAR models satisfied the stability condition.[10]

Contextualization of VAR Results

Bloomberg influential market coverage. To put our findings from the VAR analyses in context, we have collected the "influential market coverage" by Bloomberg. These are articles written by Bloomberg and released via their terminals. Hence, these are the news stories that professional traders who have subscribed to the Bloomberg terminal services usually receive first during a regular trading day. A total of 50 news articles were found that were identified as influential market coverage in September 2015. Bloomberg marks these news stories itself based on the fact that Bloomberg was the first outlet that has reported on the specific news and has thereby considerably moved the market in terms of a change of stock market prices. For each article, we wrote down the topic of the news story and calculated the percentage change of the share prices of the companies that were object of these stories.[11] In doing so, we do not only give insights in the sort of news that are driving stock market reactions and to what extent, we also compare the difference in content between the Bloomberg influential market coverage and the Reuters and Bloomberg tweets.

Expert interview. Furthermore, to get insights into the news production processes at Bloomberg itself and how Bloomberg news gets distributed via different channels (i.e., terminal vs. tweets), we conducted an expert interview with a manager and editor at Bloomberg with more than 20 years of experience in the job. By means of this interview, we were not only able to make sense of the results of our VAR analyses in comparison to the findings for the influential market coverage by Bloomberg, but we also learned about the different information mechanisms that are at play on financial markets.

Results

News Volume

The first hypothesis stated that *news volume* of economic news is related to stock market fluctuations. Although we found no evidence for this supposition on the 5-minute intervals, we could evidence strong relationships of DJI with *news volume* for the 1-hour and 20-minute intervals (see Table 1). Inspecting the endurance of the effects (cf. CIRF; see Online Appendix F), it was found that an additional one-unit increase of economic tweets within 1 hour, leads to a significant increase of the fluctuations of the DJI by 2.168 points after 2 hours, increases sporadically, but stays significant up to 7 trading hours (CIRF: 2.776). Hence, the effect persists even until the next day, explaining 6.3% of the variance of the DJI fluctuations. This effect is even more pronounced for tweets dealing only with marketwide information, but slightly smaller for 20-minute intervals. Here, the amount of economic tweets by Reuters and Bloomberg only Granger causes the fluctuations of the DJI for marketwide news (see Table 1). Similar to all economic news, the CIRF only becomes significant after two steps (40 minutes) and increases slowly up to 3.468, explaining 5.6% of the variance of the DJI

Table 1. Results of VAR Models for 1-Hour Intervals (DJI Dependent Variable).

		News relevance				Emotions	
	News volume	Retweets	Favorites	Updates	Expert opinion	Hope	Fear
1 hour							
All news	L(7) χ^2 = 16.226* CIRF = 2.776 FEV = .063 N = 139	L(7) χ^2 = 23.22** CIRF = .074 FEV = .1 N = 139		L(7) χ^2 = 34.733*** CIRF = .061 FEV = .169 N = 139	L(7) χ^2 = 16.723* CIRF = 6.199 FEV = .099 N = 139		
Marketwide news	L(7) χ^2 = 23.022** CIRF = 3.802 FEV = .099 N = 139	L(7) χ^2 = 27.724*** CIRF = .105 FEV = .123 N = 139	L(7) χ^2 = 22.111** CIRF = .209 FEV = .104 N = 139	L(7) χ^2 = 36.774*** CIRF = .063 FEV = .179 N = 139	L(7) χ^2 = 26.451*** CIRF = 7.931 FEV = .142 N = 139		
20 minutes							
All news				L(5) χ^2 = 11.26* CIRF = .027 FEV = .025, ns N = 414			
Marketwide news	L(6) χ^2 = 23.656** CIRF = 3.468 FEV = .056 N = 413	L(12) χ^2 = 43.226*** CIRF = .062, ns FEV = .083 N = 407		L(5) χ^2 = 15.944** CIRF = .035 FEV = .036 N = 414			
5 minutes							
All news			L(13) χ^2 = 28.176** CIRF = .048, ns FEV = .012 N = 1,624	L(18) χ^2 = 52.637*** CIRF = .028, ns FEV = .021 N = 1,619	L(18) χ^2 = 31.643* CIRF = −1.168, ns FEV = .014 N = 1,619		

Note. Significances for Granger causality tests: *$p < .05$. **$p < .01$. ***$p < .001$; all time series were differenced; CIRF and FEV for n-lag steps. CIRF = cumulative impulse response functions, FEV = forecast error variance.

ns	CIRF < −1.000	CIRF > −1.000 and < −5.000	CIRF > −5.000
ns	CIRF < 1.000	CIRF > 1.000 and < 5.000	CIRF > 5.000

fluctuations. These results lead us to confirm H1 with regard to 1-hour intervals, and partly for 20-minute intervals, but to reject H1 for 5-minute intervals. In other words, the amount of Reuters and Bloomberg tweets is positively related to the fluctuations of stock market prices (i.e., DJI), particularly when considering tweets within 1-hour intervals.

Inspecting effects in the opposite direction, namely, the fluctuations of the DJI affecting economic news (i.e., number of tweets per interval), we find significant Granger causality effects for all time intervals (see Table 2). Furthermore, except for firm-specific news within 1-hour intervals, all CIRFs are negative and significant, meaning an increase in the fluctuations of the DJI leads to fewer economic Reuters and Bloomberg tweets. Interestingly, these effects increase in their scope from 5-minute intervals, over 20-minute intervals to 1-hour intervals (see Table 2). This increasing effect is also reflected in the character of the CIRFs (see Online Appendix G). While for the 5-minute and 20-minute intervals the CIRFs switch from significant to nonsignificant over the long run, the CIRFs stay significant for all steps within the 1-hour intervals.

Relevance

The second hypothesis suggested that *relevant* appearing economic news is related to the fluctuations of the stock market. As a reminder, relevance was operationalized by means of three variables: *favorites, retweets*, and *updates* per time interval. Overall, we partly find support for the second hypothesis. *Updates* Granger causes the fluctuations of the DJI within all time intervals and for both marketwide and all economic news (see Table 1). For *retweets*, we find a Granger causality effect within the 20-minute intervals for marketwide news and within 1-hour intervals for both all economic news and marketwide news. The Granger causality effects are less pronounced for *favorites*, however. *Favorites* only Granger causes the fluctuations of the DJI within 5-minute intervals for all economic news and within 1-hour intervals for marketwide news (see Table 1).

Similar to the findings with regard to news volume, the endurance of the effects (CIRF) becomes stronger within 1-hour intervals when compared with 5-minute intervals. For example, an additional increase in *updates* for all economic tweets leads to .027 unit increase of the DJI fluctuations after 5 steps (i.e., 100 minutes) within 20-minute intervals, while there is .061 unit increase within 1-hour intervals. In addition, the explained variance of the DJI fluctuations by *updates* increases from 2.5% within 20-minute intervals to 16.9% within 1-hour intervals. However, it should be noted that the CIRFs for the news relevance variables are less stable within the 5-minute intervals when compared to the 20-minute or 1-hour intervals (see Online Appendix F). Hence, it seems that the more often a topic gets covered in Reuters and Bloomberg tweets and the more it is *retweeted* within an hour, the stronger the fluctuations of the DJI as a response.

Investigating the reversed effects, we find the fluctuations of the DJI to have a significant Granger causality effect on almost all news relevance variables (see

Table 2. Results of VAR Models for 1-Hour Intervals (DJI Independent Variable).

		News relevance				Emotions	
	News volume	Retweets	Favorites	Updates	Expert opinion	Hope	Fear
1 hour							
All news	L(7) χ^2 = 39.354*** CIRF = −.056 FEV = .062 N = 139	L(7) χ^2 = 21.273** CIRF = −1.849 FEV = .058 N = 139	L(7) χ^2 = 17.229* CIRF = −.73 FEV = .039 N = 139	L(7) χ^2 = 24.022** CIRF = −3.201 FEV = .028 N = 139	L(7) χ^2 = 14.544* CIRF = −.019 FEV = .011 N = 139		
Marketwide news	L(7) χ^2 = 32.326*** CIRF = −.048 FEV = .039 N = 139	L(7) χ^2 = 27.724*** CIRF = −1.564 FEV = .033 N = 139	L(7) χ^2 = 18.041* CIRF = −.666 FEV = .028 N = 139	L(7) χ^2 = 24.661** CIRF = −3.114 FEV = .026 N = 139	L(7) χ^2 = 17.349* CIRF = −.019 FEV = .010 N = 139		
Firm-specific news	L(7) χ^2 = 16.785* CIRF = −.002, ns FEV = .098 N = 139					L(7) χ^2 = 17.496* CIRF = .004, ns FEV = .048 N = 139	L(7) χ^2 = 20.363** CIRF = .008 FEV = .064 N = 139
20 minutes							
All news	L(11) χ^2 = 31.63** CIRF = −.022 FEV = .091 N = 408	L(12) χ^2 = 25.073* CIRF = −.619 FEV = .050 N = 407		L(5) χ^2 = 24.979*** CIRF = −1.945 FEV = .104 N = 414	L(6) χ^2 = 15.905* CIRF = −.012 FEV = .057 N = 413		
Marketwide news	L(6) χ^2 = 23.954** CIRF = −.021 FEV = .051 N = 413	L(12) χ^2 = 23.291* CIRF = −.652 FEV = .046 N = 407		L(5) χ^2 = 24.436*** CIRF = −1.825, ns FEV = .095 N = 414		L(7) χ^2 = 14.418* CIRF = −.003, ns FEV = .041 N = 412	
5 minutes							
All news	L(11) χ^2 = 23.148* CIRF = −.003 FEV = .016 N = 1,626	L(11) χ^2 = 25.501** CIRF = −.212 FEV = .013 N = 1,626	L(13) χ^2 = 29.858** CIRF = −.059 FEV = .018 N = 1,624	L(18) χ^2 = 41.761** CIRF = −.391 FEV = .024 N = 1,619		L(13) χ^2 = 34.356** CIRF = .001, ns FEV = .015 N = 1,624	L(18) χ^2 = 34.731* CIRF = .001, ns FEV = .019 N = 1,619

Note. Significances for Granger causality tests: **p* < .05. ***p* < .01. ****p* < .001; all time series were differenced; CIRF and FEV for n-lag steps. CIRF = cumulative impulse response functions; FEV = forecast error variance.

ns	CIRF < −1.000	CIRF > −1.000 and < −5.000	CIRF > −5.000
ns	CIRF < 1.000	CIRF > 1.000 and < 5.000	CIRF > 5.000

Table 2). However, neither for *favorites* on the 20-minute intervals, nor for any variable within the 1-hour intervals focusing on firm-specific news, could we evidence a relationship. Similar to the previous findings, the effects (i.e., CIRF) become stronger from 5-minute intervals over 20-minute intervals to 1-hour intervals. As an example, we find an additional increase in the fluctuations of the DJI to significantly and negatively influence *updates* in all economic Reuters and Bloomberg tweets after 18 steps (90 minutes) for 5-minute intervals, explaining 2.4% of the variance in *updates*. This effect increases within 20-minute intervals and reaches the highest value within the 1-hour intervals (see Table 2). When taking a look at the stability of the effects over several time steps (see Online Appendix G), it seems that *updates* has the most stable effect and that overall the CIRFs of the news relevance variables become more harmonic within the 1-hour intervals. Thus, it seems that an increase in the fluctuation of the DJI leads Reuters and Bloomberg to *update* news less often.

Expert Opinion

The third hypothesis proposed that the presence of *expert opinions* in economic news is related to stock market fluctuations. We find evidence for this hypothesis within the 1-hour intervals. For all economic Reuters and Bloomberg tweets as well as for marketwide economic news, *expert opinion* Granger causes the fluctuation of the DJI to increase (see Table 1). In addition, within the 5-minute intervals the DJI was found to be Granger caused by the presence of *expert opinions* in tweets. However, while we find positive CIRFs within the 1-hour intervals, the enduring effect of *expert opinions* in tweets on the DJI turns negative within the 5-minute intervals (see Table 1). Not only does the effect switch from negative to positive, the CIRFs are also more stable within the 1-hour intervals (see Online Appendix F). In fact, the CIRFs within the 5-minute intervals are never significant. In that sense, we can only confirm H4 with regard to tweets released within 1-hour intervals. In other words, an increase in *expert opinion* expressed in economic Reuters and Bloomberg tweets only seems to affect the fluctuation of the DJI when considering tweets accumulated for an hour.

In terms of reversed effects, meaning the fluctuations of the DJI affecting the presence of *expert opinion* in Reuters and Bloomberg tweets, we find the DJI to Granger cause *expert opinion* within 1-hour intervals for all economic news as well as for marketwide news (see Table 2). Furthermore, the fluctuations of the DJI Granger causes the presence of *expert opinion* in all economic news within 20-minute intervals. Similar to the previously discussed news variables, the CIRFs for *expert opinion* are more pronounced within 1-hour intervals when compared to the 20-minute intervals (see Online Appendix G). While the CIRFs within 20-minute intervals switch from positive to negative effects, not always being significant, the CIRFs for the 1-hour intervals are steadily negative and constantly significant for marketwide news. Hence, an increase in the fluctuation of the DJI seems to come along with fewer *expert opinions* expressed in Reuters and Bloomberg tweets.

Emotions

The fourth hypothesis implied that the presence of *hope* or *fear* in economic news is related to stock market fluctuations. We cannot find any evidence for this hypothesis. Emotions, such as fear or hope, neither Granger caused the fluctuations of the DJI on the 5-minute, 20-minute, nor on the 1-hour intervals. Hence, we have to reject H3. We do, however, find significant Granger causality effects for the opposite direction. Within 1-hour intervals, the fluctuations of the DJI Granger causes both *hope* and *fear* for firm-specific Reuters and Bloomberg tweets (see Table 2). Although the DJI only Granger causes *hope* within 20-minute intervals for marketwide news, again both *hope* and *fear* are Granger caused by the fluctuations of the DJI within the 5-minute intervals.

However, when inspecting the long-run effects (CIRFs; see Online Appendix G), it becomes obvious that all effects within the 5-minute, 20-minute, and 1-hour intervals are not very stable. At most, the effects of the fluctuations of the DJI on *fear* and *hope* in firm-specific economic news within 1-hour intervals indicate enduring positive CIRFs. However, in the graphs (see Online Appendix G), it is shown that an additional increase in the fluctuations of the DJI on emotions in firm-specific economic Reuters and Bloomberg tweets turns nonsignificant at least twice over the period of 7 hours. In that sense, the fluctuation of the DJI does not seem to have a stable influence on *fear* and *hope* expressed in economic tweets by Reuters and Bloomberg, or vice versa.

Contextualizing the VAR Results

We wanted to put our findings in context by comparing our results with Bloomberg influential market stories that were distributed on Bloomberg terminals in September 2015.[12]

When comparing the Bloomberg influential market coverage with the tweets by Reuters and Bloomberg, it became clear that the topics covered were quite similar. Not only were Glencore and Volkswagen present topics in both news outlets, general economic topics such as merger and acquisitions (e.g., Anheuser-Busch deal), news about the central bank (e.g., the Fed in the United States), debt crises (e.g., Puerto Rico), and financial updates on companies (e.g., Caterpillars forecast cut) were identified as the most common themes in both outlets. Hence, it seems that news dealing with these topics can be considered as market-moving news that are likely to impact stock market prices of the companies or industries involved.

When inspecting the changes of stock prices from the day the Bloomberg influential market story news were released compared with the day after, the stories seemed to be indeed influential for the share prices of the companies covered in the stories. More specifically, it became evident that the stock market prices swamped up to 9.41% (e.g., for China Electronics Corp., which was said to be in talks to acquire Atmel Corp.) or down to −41.68% (e.g., for Glencore which was said to hire banks to sell its stake in grains unit). Overall, influential market stories by Bloomberg that dealt with merger and acquisitions have moved stock market prices of the companies involved in the stories the most.

In this sense, the VAR finding that an increase in fluctuations of the DJI came along with fewer tweets, ergo fewer retweets, favorizes, updates, or expert opinions could be due to the fact that Reuters and Bloomberg tweets might not provide up-to-date market relevant information to the majority of investors anymore. Given that Reuters and Bloomberg terminals provide professional investors who subscribe to their services with firsthand information on the financial markets, the immediate effect of Reuters and Bloomberg tweets on the market becomes questionable. In fact, a manager and editor at Bloomberg with more than 20 years of experience has told us in an interview that Bloomberg only releases their news and stories online and via Twitter after they have first been released on the Bloomberg terminal. The Bloomberg expert estimated the time span between the release of information on the terminal to professionals and online to the general public at 15 minutes.

Hence, instead of releasing market-moving news, it seems that the tweets by Reuters and Bloomberg rather provide subsequent reporting on economic news for the public, which could then lead to small stock market reactions. Given that market-moving stories usually bring about broad reporting, often accompanied by news updates and expert opinions, this assumption indeed corresponds with the results of our VAR analyses. The finding that there are stronger stock market reactions on the DJI index, the more tweets there are within a time interval (i.e., 5 minutes, 20 minutes, 1 hour), the more relevant a tweet seems (e.g., retweets, favorizes, updates) and the more experts raise their voice in these tweets could indicate that Bloomberg and Reuters tweets present a follow-up reporting that triggers stock reactions among the broad public (i.e., DJI).

In fact, when taking a closer look at the topics of the Reuters and Bloomberg tweets, it becomes clear that the most occurring topics in the tweets were rather dealing with market reactions to breaking economic news (see Online Appendix D). For example, we find that while a Bloomberg market-moving story reported first on Glencore and its plan to sell a minority stake in its agricultural business, the tweets were mostly reporting on the share price by Glencore as a reaction to this news. Similarly, this was the case for news on the Volkswagen emission scandal and the subsequent market reactions of its shares as reported by Reuters and Bloomberg tweets. Hence, while Bloomberg influential market stories provide firsthand information on their terminals to professional investors, tweets by Reuters and Bloomberg can rather be considered a subsequent reporting on the stock market to the public, which also seems to impact the stock market but to a lower extent (see the CIRFs and FEVs in Table 1).

Discussion

Previous studies dealing with the interrelationship between news and the stock market have primarily focused on isolated information characteristics, foremost assessing one-way relations, and mainly on a daily level. The purpose of this study was to contribute to this research field by inspecting the various dimensions of economic news and by studying the reciprocal effects of news and the fluctuations of the DJI within a trading day and for different short-term intervals. To do so, we manually analyzed tweets by Reuters and Bloomberg for one trading month. This did not only allow us to make sense of the results of our time series analyses but it also provided us with more information on the actual content of the tweets when comparing them with influential market coverage distributed via Bloomberg terminals for the same period of analysis. The combined analysis of two news outlets to gain insights into the interrelationship between economic news and the stock market yielded interesting insights for mass communication theory and financial markets.

Answering RQ1, namely, to what extent the relations between economic news and the stock market vary with regard to different intraday time intervals, we can conclude that all effects found are stronger and more pronounced within the 1-hour intervals when compared to 20-minute or 5-minute intervals. In other words, Reuters and Bloomberg tweets have a stronger effect on the fluctuations of the DJI when aggregating the news to 1-hour intervals instead of shorter time intervals. We have previously argued from a psychological perspective that when investors are given more time and information to evaluate their investment, they are more risk-averse (Thaler et al., 1997). Although the results of the VAR analysis do not allow conclusions about directional effects, the stronger and more stable effects of Reuters and Bloomberg tweets on the fluctuations of the DJI within 1-hour intervals imply that investors react stronger when they are given more time. This is partly in line with the concept of "myopic loss aversion" (Tversky & Kahneman, 1992) which states that people are more sensitive to losses than to gains and that they tend to assess outcomes more frequently over time. Hence, the findings of the VAR analyses suggest that it takes more time for investors to assess information (i.e., 1 hour) from Reuters and Bloomberg tweets before they make a trading decision. However, whether they indeed react more risk-averse in their decisions cannot be concluded from the results of this study.

To answer RQ2, whether there are differences between Reuters and Bloomberg tweets that deal with all economic news, marketwide or firm-specific information, it can be concluded that the effects do not change, but become stronger when only considering tweets that deal with information on the market as a whole. For firm-specific information, the effects vanished or were not very stable. Given that we investigated the DJI, it is reasonable that marketwide tweets affected the fluctuations of the index instead of firm-specific tweets that, after all, might have dealt with corporations that are not even listed on the DJI. Thus, this finding might imply for investors that it is more likely to expect market reactions of indices based on economic news by Reuters and Bloomberg when the information is about the market as a whole. It yet cannot be excluded that news about companies that are listed on specific indices can also influence the share price of these firms and those indices, respectively.

RQ3 dealt with reversed effects. Hence, to what extent the stock market has an influence on the dimensions of economic news. Except for emotions, we find news volume, news relevance, and expert opinion to be negatively related to the fluctuations of the DJI. The secondary analysis of influential market coverage distributed via Bloomberg terminals brought more clarity in this finding. Although the market-moving stories by Bloomberg can lead to considerable market reactions through professional investors, particularly when reporting on mergers and acquisitions, tweets by

Reuters and Bloomberg might rather provide follow-up reports that cause public traders to react to the news. In this sense, the findings from the analyses do not only provide support for the public agenda-setting theory within the context of financial news, the results also correspond with the media agenda-setting theory and the positive feedback hypothesis by Shiller (2000).

According to Shiller (2000), the media "create the environment within which the stock market events we see are played out" (p. 105). In this sense, media do not only induce stock market reactions as seen by the influential market coverage by Bloomberg, but—in line with the media agenda-setting theory—media also respond to the market by reporting on the movements as shown in the most occurring topics in Reuters and Bloomberg tweets. By attaching importance to these stock market reactions, the media can drive further market responses as presented in our VAR analyses. In fact, the finding that the effects were more pronounced for 1-hour intervals and for marketwide news supports the assumption of Shiller's hypothesis that the reporting of stock market reactions by the public media (e.g., tweets by Reuters and Bloomberg as investigated in this study) can have a feedback effect on the stock market.

However, given that these presumed feedback loops are rather hypothetical, the limitations of this study need closer attention at this point. First, the exclusive focus on economic Reuters and Bloomberg tweets and influential market coverage by Bloomberg might have been too limited to draw general conclusion about the interrelationships between economic news and the stock market. Other major financial news outlets (e.g., *CNBC, The Wall Street Journal, Financial Times*), financial TV, and financial online communities (e.g., bloggers, *marketwatch.com*) might also provide relevant financial information and should therefore be considered in upcoming related research. Second, the rather low reliability scores of the manual analysis might imply that economic news can always be considered from two perspectives: seller and buyer. Whereas this might be difficult for manual coding, future studies could enhance automated content analysis, allowing researchers to scrutinize news from various perspectives. In so doing, the dimensions from our study could also be taken into account (e.g., updates, expert opinion). Third, although we have attempted to take a multidimensional perspective on economic news, the need of aggregating the data for the time series analyses might have vanished the actual relevance of individual news releases for moving the market (e.g., as shown in the analysis of Bloomberg influential market coverage). Future studies are therefore invited to take a case study approach in investigating the release of information for a particular event and the subsequent stock market reactions over time.

Despite these reservations, this study has contributed valuable insights to the vast literature on the interrelation between news and the stock market. First, in showing that the news dimensions of Reuters and Bloomberg tweets are negatively influenced by the fluctuations of the DJI, suggesting that Twitter might provide outdated market information for professional investors when compared to market-moving stories provided through Bloomberg terminals. Second, by revealing that news volume, news relevance, and expert opinion positively influence the fluctuations of the DJI within short-term intervals, suggesting that tweets might offer relevant information for public investors. And third, by disclosing that the news effects of tweets on the DJI were at all times stronger and more pronounced within 1-hour intervals when compared to shorter time intervals, implying that the public seems to need more time to assess news and reflect upon trading decisions.

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Notes

1. Although there are no reliable numbers on the usage of tweets for traders and investors in general, we chose Twitter to extract economic news because tweets have increasingly become acknowledged by the financial industry for making trading decisions (e.g., trading firms such as PsychSignal) and have also become incorporated in Bloomberg terminals to keep professional investors informed (Stafford, 2015).
2. The online appendix can be found at https://doi.org/10.6084/m9.figshare.4702390.v2
3. Dow Jones Industrial Average (DJI) stock market data were retrieved from http://stooq.com/db/
4. The python script can be requested from the corresponding author.
5. Reuters Top News, Reuters Business, Thomson Reuters, Reuters Insider, Reuters World, Reuters News Agency, Reuters Deals.
6. Bloomberg Business, Businessweek, Bloomberg Markets, Bloomberg Deals, Emerging Markets, and Bloomberg Tradebook.
7. The codebook can be requested from the corresponding author.
8. The steps undertaken for cleaning the data set can be requested from the corresponding author.
9. We did not distinguish between the two news wire sources to prevent dealing with too many missing values within the times series analyses.
10. Because there were too many missing values in the time series for firm-specific news and marketwide news on the 5-minute interval (more than 10% of the sample), we only conducted the Vector Auto Regression (VAR) analyses for all economic tweets. For the 20-minute interval, it was possible to distinguish between marketwide and all economic tweets.
11. The results of the Augmented Dickey–Fuller (ADF) tests, the selection-order statistics, the Lagrange-multiplier (LM) tests, the Portmanteau (Q) statistics, and the Eigenvalue stability condition tests can be requested from the corresponding author.
12. The majority of the influential market coverage dealt with mergers and acquisitions (e.g., Expedia Inc. and Orbitz Worldwide, Actelion Ltd. and ZS Pharma, or Glencore Plc.’s plan

to sell a minority stake in its agricultural business). Three stories reported on initial public offerings (e.g., Ferrari), three dealt with the refinancing of debts of companies (e.g., Amtek Auto Ltd.), two dealt with the reduction of jobs (e.g., UniCredit SpA), two with new product developments by companies (e.g., Xiaomi Corp.'s new laptop), two with Sri Lanka's central bank decision, two with the Volkswagen emission scandal, and some stories covered other isolated cases (e.g., insider trading, lawsuit fine, or bankruptcy). An overview of the Bloomberg influential market coverage in September 2015, together with the calculation of the change of stock market prices of the companies involved, can be requested from the corresponding author.

Supplemental Material

Supplemental Material is available for this article online.

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