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Lagging behind? Emotions in newspaper articles and stock market prices in the Netherlands

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ABSTRACT

This study investigates emotions in Dutch newspaper articles and their effects on, and responses to, opening prices of 21 stocks listed on the Amsterdam Exchange index for twelve years (2002–2013). With regard to the financial context, we employed a selection of the Dutch Linguistic Inquiry and Word Count dictionary to automatically content analyze emotional tone in news articles (N = 128,507). Neither positive nor negative emotions in news articles show consistent effects on the opening prices of stocks the following day. Granger causality tests suggest, however, that newspapers rather reflect movements on the stock market the following days by using more negative emotional words after an increase in the change of the opening prices.

1. Introduction

Despite the widespread and in synch provision of financial news and algorithm trading, it seems that investors do not anticipate the bursting of financial bubbles as, for example, experienced during the Global Financial Crisis 2007–2009. Rather, it appears that the market is not fully based on rationality, but subject to affective behavior by traders, such as herd-like behavior or emotional reactions (Neri, 2009). At the same time, increasing news coverage, commentaries and opinion pieces on financial topics demonstrate a tendency of the media to cover these developments on the market (e.g., Tesla's April Fool 2015), suggesting a strong relationship between media and the stock market.

However, reversed effects, the complex interaction and the mechanism between media and the stock market have hardly been investigated so far—and, above all, not from a communication science perspective (cf. Lee, 2014; see for an exception Kleinnijenhuis, Schultz, Oegema, & Atteveldt, 2013; Scheufele, Haas, & Brosius, 2011). Existing works in economics or business are primarily simulation models that investigate market indices, e.g., Dow Jones or S&P 500, but not paying attention to differences across stocks from diverse sectors or the peculiarity of news media coverage (e.g., Hayo & Neuenkirch, 2013 looking at macro-economic announcements). Therefore, the supposed reciprocal relationship between media coverage and the stock market remains to be tested.

Facing irrational exuberance on the markets (Shiller, 2000), it becomes crucial to examine to what extent emotions in news affect movements of stock market prices; or, in turn, to find out whether price movements of various stocks dictate the extent of coverage and emotions the media ascribe to these stocks the following days.

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In fact, scholars from behavioral finance have investigated the impact of emotions on trading decisions by means of experiments (Lee & Andrade, 2015); but research on the role of news media in conveying emotions, and thereby, contributing to movements on the stock market, has remained fairly unexplored so far. Taking the Netherlands as a case example, this study contributes to this field in assessing the reciprocal effects of emotional tone in Dutch leading newspaper articles on the opening prices of 21 stocks of the Amsterdam Exchange index (AEX) between 2002 and 2013.

2. Theoretical framework

While representatives of the efficient market hypothesis (EMH) have downplayed the impact of media coverage on the financial market vehemently in the past (Fama, 1965), behavioral economics and behavioral finance (Nofsinger, 2005) have put the EMH in question and showed that the stock market can indeed be predicted to a certain extent, and partly by media coverage (Tetlock, 2007).

The reason media are presumed to affect the stock market is given by investors who do not act fully rationally when making trading decisions, but are triggered by herd behavior (Oberlechner & Hocking, 2004). Herd behavior on financial markets implies that decisions taken by investors are less based on the actual value of a stock, but rather on the consensus opinion; thus, what they believe other traders might sell or buy (Prechter, 2001). Here, media are allocated a crucial role, as media sources (e.g., financial news) often report to reflect the consensus market opinion (Davis, 2006). In addition, various scholars have stressed the interdependent relationships between leading news media, financial journalists, investor relationship practices, and financial analyst. For example, by employing a Delphi methodology, Laskin (2011) found that one of the four key areas for practitioners in investor relations is to enhance analyst coverage about the company (cf. stock) they are working for.

2.1. Media attention

Building on the theory of herd behavior, it is likely that the attention media devote to specific stocks influences investors' trading decisions. According to Shiller (2000), attention created through the media increases investors' interest in those stocks, leading to a positive feedback effect. In other words, the more attention media allocate to a particular stock, the more likely investors will invest in that stock, and the more media will report on it again.

Looking at this theory from a communication science perspective, the effect of media attention on trading decisions is closely related to agenda-setting theory that assumes topics that are salient in the media are transferred to the public agenda (Carroll & McCombs, 2003). Thus, it can also be presumed that corporate information on stocks or on the financial market will be transferred from the media to the public (i.e., investors), which—in turn—might affect their judgments (i.e., trading decisions) (cf. Taylor, 1982).

Empirical studies dealing with media attention and its effects on stock market prices point in opposing directions. More recent research suggests, however, that the extent to which media devote attention to a stock might influence investors' trading decisions, either positively or negatively. The findings imply that the more media attention a stock receives, the higher the movement of the stock price (increase or decrease) the other day (Pinnuck, 2014). Given these incongruent findings, we want to put these findings under scrutiny in the Dutch context, posing the first research question:

RQ1: How does media attention for a stock affect the opening price of this stock the following days?

2.2. Emotions on the market

Emotions in news media and their effects on the financial market have recently received increasing attention in research (e.g., Bollen, Mao, & Zeng, 2011). In the field of behavioral finance, it was found that decisions made by investors are not solely based on objective information and fundamentals, but considerably biased by emotions and moods (De Long, Shleifer, Summer, & Waldmann, 1990). Arguing from a communication science perspective, it thus becomes crucial to examine to what extent news media convey such emotions and how this affects stock market movements. Appraisal theory can be used to explain the mechanism that connects an emotional charged news article to subsequent (trading) decisions (cf. Scherer, 1999).

2.2.1. Appraisal theory

Scherer (1999) claims that emotions do not exist as such, but are evoked and can be distinguished based on the subjective assessment of the situation, object or event with regard to a number of criteria. Given that this study is not investigating the micro-level of emotions on the financial market (i.e., investors as subjects), we rely on the approach of appraisals considered from the *dimension of meaning*. Representatives of this tradition are concerned with the analysis of semantic fields that are evinced by the usage of certain emotional words (Scherer, 1999). Put it differently, scholars try to define the feeling that results from specific emotional words (e.g., "loss" or "gain"). Thus, the more negative (or positive) emotion-words an article displays, the more negative (or positive) the reader will perceive the emotional tone of an article (Kahn, Tobin, Massey, & Anderson, 2007). Following Lerner and Keltner (2001), we assume a second step after the cognitive processes have taken place within the appraisal during reading an emotional word: namely a physiological action or a successive behavior based on the appraisal, i.e., trading behavior.

While the effect of sentiment on the stock market has been thoroughly studied recently (e.g., Lin, Xu, Zhang, & Lv, 2014), research dealing with emotions in news media content and their effects on the stock market is limited, and has primarily focused on social media. Given the scarcity of studies dealing with emotions in print media and the stock market, we rely more generally on findings from studies that have investigated the relationship between *sentiment* in news and stock market ratings to derive our second research question. In fact, some of the authors do not directly distinguish between sentiment or emotions in the media, measuring simply negative or positive words, but calling it "pessimism" or "optimism" (Tetlock, 2007).

Although conceptually deviating somewhat from our approach, these studies have shown diverging effects. On the one hand, media pessimism or negativity has been shown by several authors to lead to a downward pressure on the market (e.g., Carretta, Farina, Martelli, Fiordelisi, & Schwizer, 2011; Tetlock, 2007). On the other hand, positive news has rarely been found to have a positive effect on stock market ratings (e.g., Yu, Duan, & Cao, 2013). To test these findings in our study, we propose the second research question:

> RQ2: How do positive and negative emotions in news articles dealing with a certain stock affect the opening price of this stock the following days?

2.3. Availability heuristics

Based on the theory of availability heuristics (Tversky & Kahneman, 1973), it can be expected that investors will especially respond to information and emotions that are highly prevalent and easy to process. In fact, research has shown that the more information is repeated, the more it is perceived as legitimate (Hawkins & Hoch, 1992). It can thus be argued that the effect of emotionality in the newspapers on an individual stock price on the Amsterdam Exchange index (AEX) might be stronger when media attention for that particular stock increases (e.g., Akhtar, Faff, Oliver, & Subrahmanyam, 2012). Specifically, we ask in our third research question:

> RQ3: How does media attention for a stock influence the effect of emotional words in news articles on the opening price of that stock?

2.4. Reversed effects

The way news media shape investors' trading decisions, or vice versa, has been found to be part of a circular process, representing a recursive interpretation of the market and the social world participants find themselves embedded in (Warner & Molotsch, 1993). More precisely, information from news services is often based on market perceptions and assessments from traders who report directly to the financial journalists from these news services (Oberlechner & Hocking, 2004). Furthermore, practitioners of investor relations, who are in direct contact with stock analysts and financial media (Keller, Laskin, & Rosenstein, 2010), have reported that one of their main task is to ensure timely, extensive and correct analyst coverage, thereby enhancing an efficient stock market price (Laskin, 2014). News on the stock market is therefore likely to reflect, rather than predict, what is happening on the market.

This assumption is also supported by news values theory (e.g., Galtung & Ruge, 1965). Based on this theory, it can be suggested that stock market movements that provide novel, negative or exceptional information (e.g., strong jumps or crashes) are more likely to be covered in the media than regular market developments. Moreover, given the time constraints of newspaper editorials and declining readership, which have led newspapers to rely increasingly on sensational and marketable news reporting (Lewis, Williams, & Franklin, 2008), it can be assumed that financial journalists are more likely to report on stock market news in an attention-grabbing style (e.g., use of emotional words). Summing up, we also suspect reversed effects from stock market prices on media attention and emotionality in newspaper articles. The final research question reads:

> RQ4: How does the opening price of a stock influence media attention and the use of emotional words (negative/positive) in newspaper articles dealing with that stock the following days?

3. Data and method

3.1. Data

We selected 21 stocks from the Amsterdam Exchange index (AEX) that were listed for at least five years from 2002 until the end of 2013, that were sufficiently covered in the media (at least in 500 articles), and which historical data was still available. The *stock market data*, including opening price, number of shares, number of trades, and turnover, was requested from Euronext Amsterdam.

Following previous research (e.g., Scheufele et al., 2011), we focus in this paper on *articles from leading newspapers*, as these outlets are associated with veracity and quality (Lewis, Williams, & Franklin, 2008), having the highest circulation in the country, and thus, play a crucial role in forming investors' assessments of stocks. News articles from leading daily newspapers in the Netherlands (*Algemeen Dagblad, De Telegraaf, de Volkskrant, Het Financieele Dagblad, NRC Handelsblad, Trouw)* dealing with the 21 stocks were retrieved from LexisNexis for twelve years (2002–2013). All news articles in which one of the 21 stocks was mentioned at least two times, or in the headline, or in the lead were collected, which resulted in $N = 128{,}507$ articles. News items from the weekend or holidays were assigned to the previous day (e.g., Friday) and divided by the number of days the news coverage was summed up for (e.g., three for the weekend). In so doing, the decreasing impact of past news on investors' present trading decisions was taken into consideration (i.e., the limited effect of news on Friday on tradition decisions made on Monday) (cf. Kleinnijenhuis et al., 2013).

3.2. Measurements

This study examines the change in *opening prices* (difference of the opening price to the price of the previous day) as well as the change in *media attention* and *emotion index*. It is argued that today's news will not affect the closing price of tomorrow (e.g., Scheufele et al., 2011), but more likely the opening price of tomorrow (cf. Bhattacharya, Galpin, Ray, & Yu, 2009).

Media attention for a particular stock was computed for each day by counting the number of articles in which the stock was mentioned at least two times, in the headline, or in the lead.

We followed linguistic resources (Yu et al., 2013) and measured *emotions* in news articles based on a list of dichotomous (positive vs. negative) words. This approach can be adjudicated to word count strategies, which assume words to transmit psychological meanings (e.g., emotions), going beyond the literal meanings of words and the context they appear (cf. appraisal theory; Pennebaker, Mehl, & Niederhoffer, 2003). In this study, we made use of the Dutch version of the Linguistic Inquiry and Word Count (LIWC) program. Previous research has found LIWC to adequately measure emotions in language use (Tausczik & Pennebaker, 2010). More recently, the dictionary has also been applied in the financial context (Campbell, Turner, & Walker, 2012). In fact, a high reliability (correlation) between LIWC results and the human coding of online texts could be evidenced in previous research (LIWC sensitivity for overall emotional expression was 0.88) (Bantum & Owen, 2009).

In order to tailor the dictionary to the topic of this study, we selected only the categories that are closely related to the financial context, describing emotions that are likely to be associated with financial markets (negative emotions: denial, negative emotions, anxiety, anger, sadness, downwards; positive emotions: agreement, positive emotions, positive feelings, optimism, upwards). To measure the presence of positive and negative emotions in the articles dealing with the stocks (counts), computer-assisted content analyses were conducted by using the software *dtSearch*.[1]

Following previous research (e.g., Uhl, 2014), an *emotion index* was calculated that measures emotions expressed in articles dealing with a specific stock per day. More specifically, we subtracted the number of negative words from positive words, divided by the sum of the number of positive and negative words per stock and per day. This resulted in an index, ranging from −1 (very negative emotional tone) to +1 (very positive emotional tone), measuring emotions on a daily level per stock.

To draw inferences about the directional effect of negative and positive emotions, we estimated one *time series for positive* and another for *negative emotions* in the newspaper articles per stock (Soroka, 2006). To do so, we added up the number of positive (negative) emotional words per day, divided by the total number of emotional words per day, per stock.

3.3. Methods of analysis

In this study we assume media attention, emotional words in Dutch news media, and the opening prices of stocks listed on the AEX to influence each other on a daily basis (Research Question 1 and 4). All variables are thus considered endogenous and require an adequate method of time series analysis, namely *vector autoregression* (VAR) with Granger causality tests. Granger causality implies that past values of y predict z beyond and above the past values of z (Vliegenthart, 2014), thereby allowing us to make inferences whether emotions in the media predict stock market prices above and beyond the past values of the stock market prices themselves, or the other way around.

Estimating VAR models demands the researcher to take several steps (Vliegenthart, 2014). To achieve stationary of the time series, we first had to difference all the series. In the second step, we had to find a good model fit by looking at low indices of selection order criteria, such as Akaike information criterion (AIC). After estimating the model, we checked for autocorrelation,[2] heteroscedasticity,[3] and contemporaneous correlation (Vliegenthart, 2014). In total, 42 VAR models were estimated; for each stock one model with media attention and one with the emotion index and the opening prices respectively. For reasons of clarity, only the significant results will reported in this article, but all other results can be requested from the corresponding author.

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[1] The date of each article and the name of the newspaper were extracted by means of a SPSS-syntax, which can be requested from the corresponding author.

[2] We were not able to remove autocorrelation of the residuals of the media attention for Shell by transforming the series. Thus, we excluded this stock from the analyses.

[3] For most of the series we had to reject the null hypothesis of no autoregressive conditional heteroscedasticity.

Table 1
Significant Granger causality findings.

Stock Name		Opening Prices as DV		Opening Prices as IV	
		Media Attention	Emotion Index	Media Attention	Emotion Index
Reed Elsevier	CIRF				−0.032 [−0.064; −0.0004]†
	FEV				0.1% [−0.001; 0.003]†
Ahold	CIRF	−0.030 [−0.076; 0.015]†		0.079 [−0.035; 0.193]*	
	FEV	0.3% [0.001; 0.005]†		0.7% [0.001; 0.012]*	
Fugro	CIRF		−0.100 [−0.207; 0.006]*		−0.017 [−0.030; −0.004]†
	FEV		0.3% [0.00005; 0.008]*		0.4% [0.0001; 0.008]†
SBM Offshore	CIRF		−0.265 [−0.429; −0.101]†	−0.038 [−0.083; 0.007]*	
	FEV		0.4% [−0.0003; 0.008]†	0.4% [−0.001; 0.008]*	
Aegon	CIRF		−0.002 [−0.006; 0.002]**		−2.084 [−3.408; −0.760]*
	FEV		0.7% [0.002; 0.012]**		0.5% [0.001; 0.009]*
Corio	CIRF	−0.250 [−0.565; 0.065]*			
	FEV	0.1% [−0.001; 0.004]*			
Royal Boskalis	CIRF	0.002 [−0.003; 0.007]**			
Westminster	FEV	0.5% [0.001; 0.008]**			
PostNL	CIRF	−0.009 [−0.013; −0.004]**			
	FEV	0.4% [0.0009; 0.008]**			
DSM	CIRF				0.290 [−0.507; 1.087]*
	FEV				0.3% [−0.0005; 0.006]*
ASML	CIRF				−0.023 [−0.046; −0.002]†
	FEV				0.4% [0.0003; 0.008]†
TomTom	CIRF				−1.331 [−2.298; −0.365]*
	FEV				1.2% [0.004; 0.020]*
Wolters Kluwer	CIRF	−0.018 [−0.035; −0.002]†			
	FEV	0.07% [−0.0006; 0.002]†			

Notes: Cumulative impulse response function (CIRF) and forecast error variance (FEV) after eight days; 90% CI [LL, UL] in brackets; Significances for Granger causality tests: $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

For testing Research question 2 and 3 we relied on *OLS regression with Newey-West standard errors* for coefficients, as previous studies in this field of research (Akhtar et al., 2012). With this method, a heteroscedastic error structure is assumed and possible autocorrelation is taken into consideration up to a defined number of lags (Newey & West, 1987). The maximum number of lags (m) for regressions with Newey-West standard errors is estimated according to the equation: $m = 0.75 \times T^{1/3}$, where T is the number of observations (Simons, 2013). In these models, either the time series variable for media attention, the variable measuring either positive and negative words, or the interaction effect (media attention times emotion index) as independent variables and the opening prices of the stocks as dependent variables were used. It should also be noted here that we estimated the VAR and OLS models by including twelve control variables that past research has identified to affect stock market movements.[4]

4. Results

Table 1 gives an overview of the significant[5] Granger causality findings per stock. In the table, the *cumulative impulse response function* (CIRF) is reported, indicating how an additional increase by one unit in one time series (e.g., emotions in the media) causes a change in the dependent series (e.g., opening price) up to the following eight days. Furthermore, the *forecast error variance* (FEV) is reported, revealing how much of the variance in a series can be explained by shocks in its own series, or by the other variable(s) (Vliegenthart, 2014).

4.1. Media attention influencing the stock market

In the first research question we asked how media attention for a particular stock affect the opening price of that stock the following days. Results show that for five out of 21 stocks a significant effect of media attention on the opening prices could be detected (see Table 1). However, overall the effects are quite small, and primarily point into a negative direction. The strongest effect can be found for the real estate firm Corio. Here, an additional increase of an article on the stock compared to the previous day (change) leads to a −0.250 decrease of the change of the opening price eight days after. However, the effect does not stay significant in the long run. As shown in Table 1, similar but smaller effects exist for the consumer firm

[4] As such, we controlled for interest rates (deposit facility rate, the fixed rate tenders rate, the variable rate tenders rate, and the marginal lending facility rate), consumer sentiment, the gross domestic product (GDP), unemployment rate, total trading volume and turnovers of each stock per trading day, the size of the listed companies, the publication date of quarterly figures, the length of the articles, the January and Monday effect, as well as for the Global Financial Crisis (2007–2009). All tables in which the VAR and Newey West models were estimated with and without control variables can be requested from the corresponding author.

[5] Significances for Granger causality tests as shown in Table 1: $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Ahold (−0.030), the energy and construction services provider Royal Boskalis Westminster (0.002), the transportation and logistics firm PostNL (−0.009), and the technology company Wolters Kluwer (−0.018). The forecast error variance (FEV) for explaining the opening prices of the five stocks by media attention only varies between 0.07% and 0.4%. Thus, the change of media attention does not seem to explain a considerable amount of the change in the opening price of AEX stocks the following days.

4.2. Emotions influencing the stock market

Based on the second research question, we wanted to find out how positive and negative emotional words in articles dealing with a certain stock affect the opening prices of that stock the following day. We find ten significant and two marginally significant effects for *positive emotions* influencing the opening prices, out of which seven point into a negative, and five into a positive direction. Unibail-Rodamco, a financial real estate firm, evinces the strongest effect (−79.390; $p = 0.026$), followed by the energy company Fugro (36.420; $p = 0.012$) and the bank ING (−28.318; $p = 0.000$). Hence, the results indicate that positive words in articles have mixed effects on stocks, but mainly point into a negative direction. Looking at *negative emotions*, three significant and six marginally significant effects occur, mostly pointing into a negative direction. Significant effects can be identified for ING (−34.746; $p = 0.000$), the iron and steel firm ArcelorMittal (−32.752; $p = 0.041$), and the telecommunications company KPN (−4.296; $p = 0.035$). Drawing conclusions from these findings, we reason that neither positive nor negative emotions in news articles show consistent effects on the opening prices of stocks the following day.

4.3. Availability heuristics

In Research Question 3 it was questioned how the salience of a stock in the news influences the effect of emotional words in articles dealing with a stock on the opening prices of that stock. To find out about this, we estimated models with an interaction effect of media attention and emotion index for each stock. We spot only two significant effects, and three marginal significant effects. While for the technology firm ASML (−1.255; $p = 0.025$) and the consumer companies Heineken (−0.411; $p = 0.023$) and Ahold (−0.393; $p = 0.086$) we identify small (marginally) significant negative effects, the firms from the material sector ArcelorMittal (0.999; $p = 0.080$) and DSM (0.496; $p = 0.066$) evince small marginally significant positive effects. Given the mixed findings, we conclude that the salience of a stock in the news does not seem to have a moderating effect on the influence of emotional words in news articles dealing with a stock on the opening price of that stock the following day.

4.4. Reversed effects

Table 1 reveals that the opening price of stocks significantly Granger causes *media attention* for two stocks, either leading to an increase or decrease of media attention the following days. An additional increase of the change of the opening price of the oil, gas and coal company SBM Offshore lowers the change of media attention by 0.038 for this stock eight days after. On the other hand, an additional increase of the change of the opening price of the retail-consumer staples firm Ahold comes along with an increase of 0.079 articles change on Ahold in the newspapers eight days after. Hence, effects from the opening prices on media attention are small, and point in contradicting directions. Given that the forecast error variances (FEV) range between 0.4% and 0.7%, it can yet be suggested that the opening price can explain slightly more variance in media attention than the other way around. However, to answer the first part of Research Question 4, the findings do not offer convincing evidence to conclude that media is reacting to changes of stock market prices by increasing (decreasing) news coverage on these stocks.

When looking at the reversed effects found for the emotion index (see Table 1), a different story can be told. In fact, there are more effects explaining a change in the *emotion index* followed by an increase of the change in the opening prices of stocks than vice versa.

The VAR analyses reveal six significant effects. With exception of DSM (chemical firm), all Granger causality findings suggest that an additional increase in the change of the opening price of stocks leads to a decrease in the change of the emotion index the following days. The strongest effect can be spotted in the financial sector. Here, an additional one-unit increase of the change of the opening price of the insurance company Aegon causes an additional 2.084 decrease on the emotion index (change) eight days after, explaining 0.5% of the variance. In fact, the cumulative impulse response function (CIRF) is significant and negative up to eight days after a shock has occurred in the change of the opening price of Aegon. Similarly, a strong negative effect can be detected for the technology firm TomTom; smaller effects exist for the media corporation Reed Elsevier, the energy firm Fugro, and the technology company ASML. Furthermore, the opening prices explain between 0.1% and 1.2% of the variance of the usage of emotional words in articles.

Summarizing, there are more significant Granger causality effects from the change of the opening price of stocks on the change of the emotion index than the other way around. Furthermore, these effects primarily point into a negative direction, are more persistent, and are particularly present for stocks from the technology and financial sector.

5. Discussion

Reoccurring short-term fluctuations of stock market prices as a reaction to unexpected news, and newspapers reporting on these events the other day, suggest a strong interrelation between media coverage and the stock market. In trying to explain this reciprocal relationship, the results of this study give a comprehensive overview to what extent emotional words in newspaper articles affect opening prices of stocks in the Netherlands, and vice versa.

Concerning the salience of stocks in the news, we could not find media attention to explain a considerable amount of the change in the opening prices of stocks the following days. The few findings suggest media attention to have a small negative effect on the opening prices, whereas in the reversed direction no consistent effects could be identified.

Similarly, we only evidenced indications that an increase in both positive and negative emotional words in articles dealing with a stock leads to a decrease of the opening prices of the stocks. In this regard, it is also not surprising that we did not identify a moderation effect, implying the absence of a stronger effect of emotions in news articles on stock market prices when these stocks are more prevalent in the media. These findings might contradict previous research (e.g., Akhtar et al., 2012), but are in line with studies that could not detect media to affect stock market prices after all (e.g., Campbell, Turner, & Walker, 2012).

Interestingly, the VAR analyses yielded more pronounced reversed effects, showing that media appear to react with a negative change on the emotion index, after there has been an increase in the change of the opening prices, particularly for AEX stocks belonging to the technology and financial sector. As it appears, news media are prone to changes on the stock market, which corroborate the practice of financial journalists who report on today's developments on the market in tomorrow's financial section of the newspapers. Furthermore, the negative feedback in the media points to a presumably more pessimistic style of financial news reporting. According to Schuster (2006), it is especially the insecure situation on the market (fluctuations), which might lead to skepticism in the media, followed by negativism.

When looking at the differences of effects across stocks, we find most effects for internationally known stocks that receive considerable media attention (e.g., ING, Aegon, Ahold, TomTom, ASML). The reason why media might be more inclined to use more negative emotional words in the coverage on these stocks might have something to do with their association with negative issues. For example, both the bank ING and the insurance company Aegon suffered from the Global Financial Crisis (2007–2009) and had to be supported through financial injections from the Dutch government.

Despite these intriguing findings, we have to point out that the effects identified are of small size and only apply for a few of the 21 AEX stocks investigated. We thus have become more sensible to the assumption of direct daily effects of print news on stock market prices, especially in light of high frequency and algorithm trading (cf. Kleinnijenhuis et al., 2013). Consequently, and corresponding with the findings by Scheufele et al. (2011) for the German stock market, we reason the Dutch media to be more likely to follow movements of stocks listed on the AEX than vice versa. In this sense, we hope that this study will guide future studies to investigate the interrelation of media and the stock market on a lower time aggregation level (e.g., hours or minutes), also paying attention to the increasing relevance of online and social media news for stock market reactions (e.g., Bollen et al., 2011).

In this regard, our study does not come without limitations. The mere focus on Dutch leading newspapers might certainly not represent the entire media environment in which trading decisions are embedded (Shiller, 2000). In addition, the plain counting of negative and positive emotional words does not account for the complexity of language and the nuanced effect that some news has on stock market prices while others does not. Scholars might therefore consider the analysis of a variation of news media (international, online, print, social media) in the future, as well as putting a stronger focus on qualitative research (e.g., case study).

Another factor that might qualify the findings with regard to previous research in this field is the particular context in which the study was conducted: The AEX belongs to the Euronext stock exchange and has a lower market capitalization than, for example, the New York stock exchange. Furthermore, the stocks investigated differ with regard to their belongings to a sector, size, corporate reputation, coverage in the media, but also in terms of involvements in crises or scandals; thus, making generalizations of our findings limited. Upcoming studies should hence pay particular attention to characteristics of stocks, the specific stock market environment, as well as additional external factors (e.g., political or financial crises).

In spite of these limitations, we are convinced that this study makes an important contribution to public relations research, elucidating limited direct effects of media attention and emotions in newspaper articles on opening prices of stocks. Given that we have found rather reversed effects, we imply that print news may lag too much behind to reliably predict stock market movements in today's fast-moving financial markets.

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