News media and the stock market: Assessing mutual relationships

An interdisciplinary multi-method study of financial journalism, news media, emotions, market events and the stock market

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Chapter 3

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 influences on and reactions 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). OLS regressions with Newey-West standard errors imply that for a few stocks an increase in negative emotional words leads to a decrease in the opening price, while the interaction effect of media attention and emotional words on the opening prices is mixed. 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.

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 (e.g., as experienced during the Global Financial Crisis 2007-2009). Rather, it appears that the market is not fully based on rationality but subject to affective decisions 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 (de Goede, 2005) demonstrate a tendency of the news media to cover these developments on the market, suggesting a strong relationship between news media and the stock market.

However, reversed effects, the complex interaction and the mechanism between news 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 work in economics or business is primarily aimed at constructing simulation models that investigate market indices (e.g., S&P 500), but does not pay 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 news media coverage and the stock market remains to be tested.

Yet, when facing irrational exuberance on the markets (Shiller, 2005) 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 the amount of emotions used by the news media to report on the stocks the following days. 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 relationships 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.

Theoretical Framework

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

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 (2003), 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 then, 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 assumed 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 (Campbell, Turner, & Walker, 2012; Fang & Peress, 2009; Saxton & Anker, 2013). 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 a stock the following days?*

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 here to explain the mechanism that connects an emotional charged news article to subsequent (trading) decisions (cf. Scherer, 1999).

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). In this regard, scholars try to define the feeling that results from specific emotional words (e.g., "loss" or "gain"). Thus, the more negative (or positive) emotional 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 that take place during the appraisal and when 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 media and stock market ratings. In fact, some of the authors do not directly distinguish between sentiment or emotions in the news 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?*

Availability Heuristics

Based on the theory of availability heuristics (Tversky & Kahneman, 1973), it can furthermore 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 legitimate it will be perceived (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 a stock?*

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 process 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 (Kelly, 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 the 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 news 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?*

Data and Method

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 et al., 2008), having the highest circulation in the country, and thus, playing 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 128,507 articles (see Table 3.1 for the distribution of 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).

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, Duan, & Cao, 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 et al., 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 .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).[10] 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*.[11]

Table 3.1
Amount of Articles in Dutch Leading Media per Stock

Nº	Stock Name	Articles in Dutch Leading Media
1	Aegon	6,721
2	Ahold	10,353
3	Akzo Nobel	2,960
4	ArcelorMittal	1,896
5	ASML	3,108
6	Boskalis Westminster	1,775
7	Corio	842
8	DSM	3,997
9	Fugro	1,788
10	Heineken	8,330
11	ING	20,358
12	KPN	14,747
13	Philips	15,872
14	PostNL (TNT Express, TPG Post, PTT Post)	4,591
15	Reed Elsevier	1,595
16	SBM	1,533
17	Shell	13,409
18	TomTom	3,889
19	Unibail-Rodamco[3]	638
20	Unilever	8,509
21	Wolters Kluwer	1,596
	SUM	**128,507**

Notes. Leading media are: Algemeen Dagblad, De Telegraaf, De Volkskrant, NRC Handelsblad, Het Financieele Dagblad, and Trouw; the search for articles on LexisNexis was conducted with the name of the stock as indicated in the table; [3]deviated search string: only "Unibail" due to take over by Rodamco in May, 2007.

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. Furthermore, to draw inferences about the

[10] A list of the negative/positive emotional words can be found in the Online Appendix 3.1 of this dissertation: https://doi.org/10.6084/m9.figshare.5354155.v1
[11] dtSearch produces csv-files in which each article is presented as a case and the number of negative (or positive) words as well as the first paragraph of the article as variables. 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 author of the dissertation.

directional effects of negative and positive emotions, we estimated one *time series for positive* and another for *negative emotions* in the newspaper articles per stock (cf. 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 and per stock.

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[12], heteroskedasticty[13], and contemporaneous correlation. 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 be reported here.

For testing research question 2 and 3 we relied on *OLS regression with Newey-West standard errors* for coefficients, following previous studies in this field of research (Akhtar et al. 2012). With this method, a heteroskedastic 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: $m = .75 \times T^{1/3}$, 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. To account for stationarity, all series were differenced before estimating the models.

Control variables. Before estimating the VAR and OLS models, we included control variables which past research has identified to influence stock market movements considerably. As such, we controlled for the actual figures of *interest rates*[14] (e.g., Fornari, Monticelli, Pericoli, & Tivegna, 2002), the monthly data on *consumer sentiment* (e.g., Akhtar et al., 2012); the monthly figures for the *gross domestic product* (GDP) (e.g., Birz & Lott, 2011), the monthly *unemployment rate* (e.g., Boyd, Hu, & Jagannathan, 2005), the *total trading volume* and *turnovers* of each stock per trading day (e.g., Hiemstra & Jones, 1994), the *size* of the listed companies measured by the number of shares (e.g., Chae & Yang, 2013), the *length of the articles* measured by the number of words (Antweiler & Frank, 2004), and

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

[13] For most of the series we had to reject the null hypothesis of no autoregressive conditional heteroskedasticity. Heteroskedasticity is a common problem in studies dealing with stock data, and has been dealt with GARCH models in the past (e.g., Lanne & Lütkepohl, 2010). GARCH models are however used for directional effect assumptions and thus not desirable in this study where mutual influences are investigated.

[14] The interest rates include the deposit facility rate, the fixed rate tenders rate (fixed rate), the variable rate tenders rate (minimum bid rate).

dummy variables for the *publication of quarterly figures* (e.g., Aman, 2013), the *January effect* (cf. Wachtel, 1942), *Monday effect* (cf. Lakonishok & Maberly, 1990), and the *Global Financial Crisis* (2007-2009) (e.g., Wu, Stevenson, Chen, & Güner, 2002).

Results

Table 3.1 gives an overview of the (moderately) significant Granger causality findings per stock. In the table, the *cumulative impulse response function* (CIRF) is reported, indicating to what extent an additional increase by one unit in one time series (e.g., changes in 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 one series can be explained by shocks in its own series, or by the other variable(s) (Vliegenthart, 2014).

Media Attention Influencing the Stock Market

In the first research question, we asked how media attention for a particular stock affects the opening price of that stock the following days. The VAR results show that for five out of 21 stocks a (moderately) significant effect of media attention on the opening prices could be detected (see Table 3.2). 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 (see Figure 3.1).

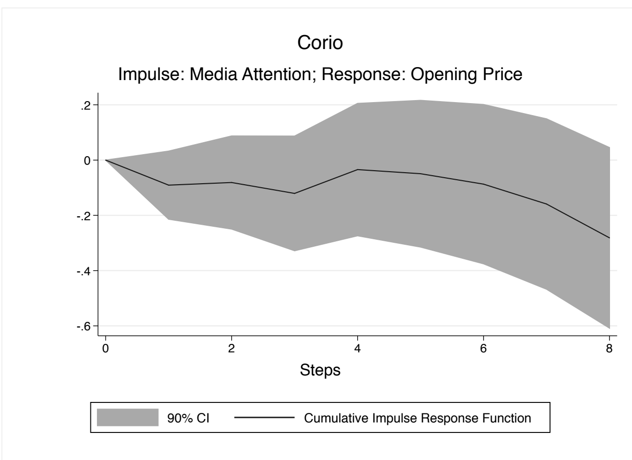

Figure 3.1 *Cumulative impulse response function for Corio.*

Table 3.2
Significant Granger Causality Findings

Stock Name	Industry		Opening Prices as DV		Opening Prices as IV	
			Media Attention	Emotion Index	Media Attention	Emotion Index
Reed Elsevier	Communication	CIRF				-0.032 [-0.064; -0.0004]†
		FEV				0.1% [-0.001; 0.003]†
Ahold	Consumer Staples	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	Energy	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	Financials	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 Westminster	Industrials	CIRF	0.002 [-0.003; 0.007]**			
		FEV	0.5% [0.001; 0.008]**			
PostNL		CIRF	-0.009 [-0.013; -0.004]**			
		FEV	0.4% [0.0009; 0.008]**			
DSM	Materials	CIRF				0.290 [-0.507; 1.087]*
		FEV				0.3% [-0.0005; 0.006]*
ASML	Technology	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: †p < .10, *p < .05, **p < .01, ***p < .001

As shown in Table 3.2, similar but smaller effects exist for the consumer firm Ahold (CIRF: -0.030), the energy and construction services provider Royal Boskalis Westminster (CIRF: 0.002), the transportation and logistics firm PostNL (CIRF: -0.009), and the technology company Wolters Kluwer (CIRF: -0.018). Except for Wolters Kluwer, the CIRFs for the other stocks are not stable over the eight following days. The forecast error variance (FEV) for explaining the opening prices of the five stocks by media attention also 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 the AEX stocks the following days.

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 price of that stock the following day. Only for three stocks moderately significant positive relationship can be identified by means of the OLS regressions with Newey-West standard errors. Here, the hardware technology firm TomTom evinces the strongest (3.061; $p = .072$) association, followed by the retail-consumer stables corporation Ahold (0.710; $p = .086$) and the chemical firm DSM (0.465; $p = .065$) (see Table 3.3). For negative emotions, five negative significant relationships can be found (see Table 3.4). The strongest association can be identified for the oil, gas and coal firm Fugro (-13.948; $p = .038$), followed by TomTom (-4.813; $p = .008$), the bank ING (-1.961; $p = .000$), the medical equipment and devices corporation Philips (-1.281; $p = .010$), and the telecom company KPN (-0.507; $p = .001$). In other words, more negative emotional words used in articles dealing with specific stocks leads to a decrease of the opening prices of those stocks. Drawing conclusions from these findings, we reason that there are overall only few (moderately) significant relationships found for positive or negative emotions in news articles affecting the opening prices of stocks, but that it is more likely that negative emotional words in news articles might lead to a downshifting effect of the opening prices of stocks the following day.

Inspecting the VAR results for the emotion index, in addition, only three significant Granger causality findings can be spotted, namely for Fugro, SBM Offshore and Aegon (see Table 3.2). Confirming the OLS regressions with Newey-West standard errors, the cumulative impulse response functions indicate that an additional increase in the change of emotional words—hence, more positive emotional words—causes the opening prices to drop after eight days. However, the sizes of the CIRFs are limited, ranging for oil, gas and coal companies between -0.100 (Fugro) to -0.265 (SBM Offshore) and evincing only -0.002 for the insurance firm Aegon. Similarly, the forecast error variances indicate that an increase in the change of the emotion index might not explain more than 0.3% (Fugro), 0.4% (SBM Offshore) or 0.7% (Aegon) of the variance of the opening prices of the stocks. Except for SBM Offshore, the CIRF are also not very stable over the course of eight days.

Availability Heuristics

In the third research question, it was queried 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 the following day. To find out about this, we estimated OLS models with Newey-West standard errors and with an interaction effect of media attention and the emotion index for each stock.

Table 3.3
Significant OLS Estimation Results for Positive Emotions

	Constant β_0	Positive Emotions (Article) β_1	F-stat.
Ahold			
Estimate	-0.008 (0.005)	$0.710^{\dagger}$ (0.414)	5.07***
t-Stat	-1.56	1.72	
Lags			13
N			3083
DSM			
Estimate	0.011 (0.009)	$0.465^{\dagger}$ (0.252)	4.05***
t-Stat	1.14	1.85	
Lags			13
N			3083
TomTom			
Estimate	-0.005 (0.013)	$3.061^{\dagger}$ (1.70)	2.72***
t-Stat	-0.40	1.80	
Lags			12
N			2210

Notes. Regression with Newey-West standard errors (in parentheses) with positive emotions time series as independent and the opening prices of stocks as dependent variable; all time series were differenced; control variables were: ECB interest rates, CPI, GDP, unemployment rate, number of shares/trades/ turnovers per stock, the amount of words per day per stock, dummy variables for quarterly earnings per stock, the financial crisis (2007-2009), and seasonal effects (January and Monday effect); non-standardized scores; $^{\dagger}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

In total, five significant and three moderately significant relationships can be detected (see Table 3.5). The direction of these effects is, however, less clear. While for the insurance firm Aegon (-0.026; $p = .064$), the semi-conductor technology company ASML (-0.078; $p = .001$) and the consumer staples corporation Heineken (-0.040; $p = .002$) we find small (moderately) significant negative relationships, the hardware technology firm TomTom (0.045; $p = .032$), the chemical company DSM (0.058; $p = .015$), the engineering and constructing service firm Boskalis Westminster (0.072; $p = .032$), the iron and steel corporation ArcelorMittal (0.069; $p = .095$) and the chemical company Akzo Nobel (0.073; $p = .090$) show small positive (moderately) significant relationships. Although the interaction effect appears to be less consistent, the few relationships can be spotted across all industries (financials, consumers, materials, technology, industrials), implying that the more a stock in those industries is visible in the media, the stronger the association (positive or negative) of emotional words in newspaper articles with the opening prices of these stocks the following day.

Table 3.4
Significant OLS Estimation Results for Negative Emotions

	Constant β_0	Negative Emotions β_1	F-stat.
Fugro			
Estimate	0.008 (0.014)	-13.948* (6.732)	4.59***
t-Stat	0.60	-2.07	
Lags			13
N			3083
ING			
Estimate	-0.004 (0.005)	-1.961*** (0.546)	3.26***
t-Stat	-0.76	-3.59	
Lags			13
N			3083
KPN			
Estimate	-0.0003 (0.001)	-0.507** (0.159)	1.44
t-Stat	-0.21	-3.19	
Lags			13
N			3083
Philips			
Estimate	-0.002 (0.007)	-1.281* (0.499)	7.34***
t-Stat	-0.29	-2.57	
Lags			13
N			3083
TomTom			
Estimate	-0.004 (0.013)	-4.813** (1.803)	2.73***
t-Stat	-0.035	-2.67	
Lags			12
N			2210

Notes. Regression with Newey-West standard errors (in parentheses) with negative emotions time series as independent and the opening prices of stocks as dependent variable; all time series were differenced; control variables were: ECB interest rates, CPI, GDP, unemployment rate, number of shares/trades/ turnovers per stock, the amount of words per day per stock, dummy variables for quarterly earnings per stock, the financial crisis (2007-2009), and seasonal effects (January and Monday effect); non-standardized scores; $^{\dagger}p < .10$, $*p < .05$, $**p < .01$, $***p < .001$.

Table 3.5
Significant OLS Estimation Results for Interaction Effect

	Constant β_0	Media Attention β_1	Emotion Index β_2	Interaction Effect β_3	F-stat.
Aegon					
Estimate	-0.008 (0.006)	0.006 (0.008)	0.0292 (0.035)	-0.026† (0.014)	1.78*
t-Stat	-1.44	0.79	0.83	-1.85	
Lags					13
N					3083
Akzo Nobel					
Estimate	0.001 (0.013)	-0.011 (0.014)	0.021 (0.073)	0.073† (0.043)	2.92***
t-Stat	0.09	-0.75	0.29	1.69	
Lags					13
N					3083
Arcelor Mittal					
Estimate	-0.006 (0.017)	-0.045 (0.04)	0.038 (0.104)	0.069† (0.042)	2.18**
t-Stat	-0.35	-1.13	0.36	1.67	
Lags					12
N					2055
ASML					
Estimate	0.018† (0.009)	-0.004 (0.021)	-0.054 (0.074)	-0.078**(0.024)	21.59***
t-Stat	1.89	-0.21	-0.73	-3.18	
Lags					13
N					3083
Boskalis Westminster					
Estimate	0.009 (0.009)	0.019 (0.027)	0.072 (0.094)	0.072* (0.034)	1.95*
t-Stat	0.92	0.71	0.77	2.14	
Lags					13
N					3078
DSM					
Estimate	0.010 (0.009)	0.011† (0.007)	0.052 (0.045)	0.058* (0.024)	3.75***
t-Stat	1.07	1.67	1.17	2.45	
Lags					13
N					3083
Heineken					
Estimate	0.005 (0.008)	-0.004 (0.007)	0.005 (0.032)	-0.040**	2.21**
t-Stat	0.61	-0.59	0.19	(0.013)	
Lags				-3.17	13
N					3083
TomTom					
Estimate	-0.007 (0.013)	0.055** (0.02)	0.172**	0.045* (0.021)	3.33***
t-Stat	-0.52	2.76	(0.056)	2.15	
Lags			3.08		12
N					2210

Notes. Regression with Newey-West standard errors (in parentheses) with media attention, emotion index and interaction effect (media attention x emotion index) as independent and the opening prices of stocks as dependent variable; all time series were differenced; control variables were: ECB interest rates, CPI, GDP, unemployment rate, number of shares/trades/ turnovers per stock, the amount of words per day per stock, dummy variables for quarterly earnings per stock, the financial crisis (2007-2009), and seasonal effects (January and Monday effect); non-standardized scores; $^{\dagger}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Reversed Effects
In posing the last research question (RQ4), we wanted to find out how the opening price of a stock influences media attention and the use of emotional words (negative/positive) in newspaper articles dealing with that stock the following days. Table 3.2 reveals that the opening price of stocks significantly Granger causes *media attention* only for two stocks, either leading to an increase or decrease of media attention the following days. For example, 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, but does not stay significant (see Figure 3.2). 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, but does not stay significant over the long-run either.

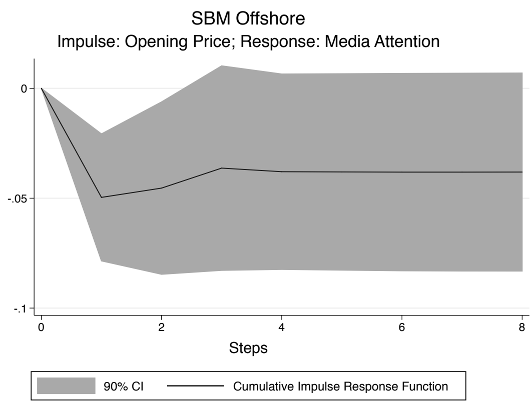

Figure 3.2 *Cumulative impulse response function for SBM Offshore.*

Hence, effects from the opening prices on media attention are small, unstable and point in contradicting directions. Yet given that the forecast error variances (FEV) range between 0.4% and 0.7%, it can be suggested that the opening price explains 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 that the news media is reacting to changes of stock market prices of stocks by increasing (decreasing) the news coverage about those stocks.

When looking at the reversed effects found for the emotion index (see Table 3.2), 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 findings. With exception of the chemical firm DSM (CIRF: 0.290), all Granger causality results 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 (see Figure 3.3).

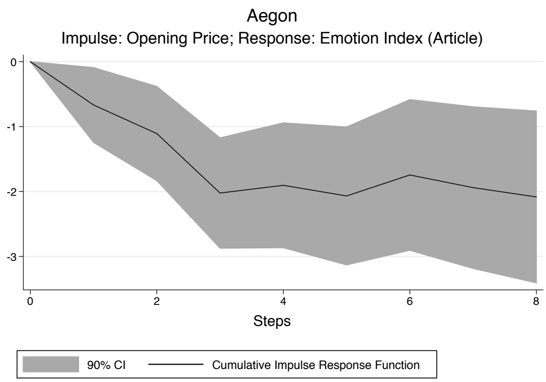

Figure 3.3 *Cumulative impulse response function for Aegon.*

Similarly, a strong negative and persistent effect can be detected for the technology firm TomTom (CIRF: -1.331); but smaller and less stable effects exist for the media corporation Reed Elsevier (CIRF: -0.032), the energy firm Fugro (CIRF: -0.017), and the technology company ASML (CIRF: -0.023). For all these stocks, a change in the opening prices explain between 0.1% and 1.2% of the variance of the change of emotional words in articles eight days after. Summarizing, there are more significant Granger causality effects from the opening price of stocks on 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.

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 news media coverage and the stock market. In trying to explain these reciprocal relationships, the results of this study give a comprehensive overview to what extent media attention and 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, the interaction effect of media attention and emotional words on the opening prices of AEX stock words did not yield coherent conclusions.

Furthermore, while we only evidenced few moderately significant relationships for an increase in positive emotional words in articles on the opening prices of stocks, the findings from the OLS regressions imply that more negative emotional words in articles might lead to a downward shifting effect on the opening prices for particular stocks listed on the AEX (e.g., Fugro, ING, KPN, Philips, TomTom). Yet when inspecting the VAR results for the emotion index, the effect of emotional words on the opening prices did not seem to be very stable. In this vein, and although previous findings have evidenced a relationship between sentiment and the stock market (e.g., Carretta et al., 2011; Tetlock, 2007), we are cautious in drawing definite conclusions about the directional effects of emotional words in newspaper articles on stock market prices the following days.

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. This corroborates with 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 the fact that these companies have been associated with negative issues in the past. For example, both the bank ING and the insurance company Aegon suffered from the Global Financial Crisis 2007-2009 (GFC) and had to be supported through financial injections from the Dutch government. Not only the governmental and state interferences with the financial sector, but also the GFC and its aftermaths have received rather critical and negative coverage in the Netherlands over the past years.

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. In addition, when considering that we have aggregated news media coverage per stock for one day, disregarding intraday movements and initial price reactions toward unexpected news, the results need be seen with caution. Overall, we 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 research to have a more nuanced look into the interactions between emotions and the stock market. Upcoming studies might consider to investigating the interrelations of news 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.

Following up on this, 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, 2005). In addition, the plain counting of negative and positive emotional words does not account for the complexity of language and the nuanced effects 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) or accounting for the influence of specific market-relevant events (e.g., MacKinlay. 1997).

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, their size, corporate reputation, coverage in the media, but also in terms of involvements in crises or scandals; thus, generalizations of our findings are 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 the field of financial communication, elucidating limited direct effects of media attention and emotions in newspaper articles on opening prices of stocks on a daily level. Instead, our findings regarding reversed effects imply that print news might lag too much behind to reliably predict stock market movements in today's fast-moving information and trading environment.

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