News Media Sentiment and Investor Behavior

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November 2013

Abstract

This paper investigates the impact of news media sentiment on financial market returns and volatilities in the long run. We hypothesize that the way media formulate and present news to the public produces different perceptions and, thus, incurs different investor behavior. To analyze such framing effects we distinguish between optimistic and pessimistic news frames. We construct a monthly media sentiment indicator by taking the ratio of the number of newspaper articles that contain predetermined negative words to the number of newspaper articles that contain predetermined positive words in the leading paragraph. We investigate four different financial market segments to study sentiment and pricing bubbles in isolation. Our results indicate that pessimistic news media sentiment is positively related to global market volatility and negatively related to global market returns 12 to 24 months in advance. We show that our media sentiment indicator reflects very well financial market crises and pricing bubbles over the past twenty years.

JEL Classification: G01, G10, E32

Keywords: Investor behavior; News media sentiment; Financial market crises; Pricing bubbles; Framing effects

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1 Introduction

News media are a very competitive industry and its main goal is to capture attention. They produce *anything* that goes along with the numbers from the markets. Shiller (2005) notes that news plays a crucial role in buying or selling decisions among traders as they constantly react on newly incoming information. He argues that news media are an important player in creating market sentiment and similar thinking as it spreads ideas and, thus, can significantly contribute to herding behavior and influence price movement on financial markets.

Framing effects within the news media has been an important research topic among journalism, political science and mass communication scholars. Price, Tewksbury, and Powers (1997) argue that the news framing effect has to do with the way how events and issues are packaged and presented by journalists to the public. They believe that news frames can fundamentally affect the way readers understand these events and issues. Authors suggest that news frames can activate certain ideas, feelings, and values, encourage particular "trains of thoughts" and lead audience members to arrive to predictable conclusions. Price and Tewksbury (1997) explain the news media framing effect by the applicability effect in their knowledge activation process model. A framing effect of a news story renders particular thoughts applicable through salient attributes of a message such as its organization, selection of content or thematic structure. The knowledge activation model assumes that at any particular point in time, a mix of particular items of knowledge that are subject to processing (activating) depends on characteristics of a person's established knowledge store. When making evaluations of situations, people tend to use (to activate) ideas and feelings that are most accessible and applicable.

Iyengar (1991) examines the impact of news framing on the ways people ascribe responsibility for social, political, and economic conditions. He finds that news takes more often an episodic rather than thematic perspective towards events they cover. Schuck and Vreese (2006) investigate the effect of two identified news frames, risk and opportunity, on the public support for the European Union enlargement. They find that participants in the opportunity frame condition show significantly higher support compared to participants in the risk condition. These studies show that framing influences the perception of new information and might be a powerful tool in influencing public opinion and possibly public's future actions.

Our paper uses the concept of framing effects in order to explain the way news media influence investors' decisions. We hypothesize that the way in which a newspaper article describes a current financial market state or presents new financial information influences investor's perception about future prospects and investor sentiment. As a result, investors might form certain expectations and update their investment decisions that can have a direct influence on the performance of the financial markets.

Previous research investigates the immediate impact news media might have on the performance of financial markets. For instance, Antweiler and Frank (2004) investigate the effect of Internet stock message boards posted on the websites of *Yahoo! Finance* and *Raging Bull* on the short-term market performance of 45 U.S. listed companies. They find weak evidence that the number of content messages posted helps to predict stock's intraday volatility but do not find evidence of news media content influencing market returns and trading volume. Tetlock (2007) analyzes the interaction between the content of the *Wall Street Journal* column *Abreast of the Market* and the stock market on a daily basis. He finds that unusually high or low values of media pessimism predict high trading volume, while low market returns lead to high media pessimism, and concludes that news media content can serve as a proxy for investor sentiment. In a more recent study, García (2013) constructs a daily proxy for investor sentiment by taking a fraction of positive and negative words in two columns of financial news, *Financial Markets* and *Topics in Wall Street* from the *New York Times.* He finds evidence of an asymmetric predictive activity of news content on stock returns, especially during recessions. The effect is particularly strong on Mondays and on trading days after holidays, which persists into the afternoon of the trading day.

Another strand of the financial market sentiment literature analyzes how investor sentiment affects the cross-section of stock returns. For instance, Baker and Wurgler (2006) construct an investor sentiment indicator by considering a number of proxies suggested in previous research and by forming a composite sentiment index based on their first principle component. The proxies for investor sentiment are the closed-end-fund discount, the New York Stock Exchange (NYSE) share turnover, the number and average first-day returns on initial public offerings (IPOs), the equity share in new issues, and the dividend premium. They show that their resulted monthly investor sentiment index reflects reasonably well previous U.S. financial bubbles and crises from 1961 onwards till the Internet bubble of 2000-01.

Our paper combines these two strands of the literature. However, in sharp contrast to Antweiler and Frank (2004), Tetlock (2007), and García (2013), we investigate the effect of media sentiment on the performance of financial markets in the *long-run.* García (2013) argues that the effect of news media sentiment partially reverses over the following four trading days. On the other hand, McCombs (2004) asserts that the real news media effect can be achieved only in the long-run, on the contrary to the view that media effects are immediate. Based on this intuition, we investigate here whether news media sentiment can significantly influence investor decisions over a longer horizon. Thus, we hypothesize that pessimistic news media sentiment exerts a downward (upward) pressure on financial market returns (volatility) in the long-run. As far as we know, this paper is the first that investigates the impact news media have over a longer horizon on financial markets.

We collect our news data by searching a predetermined set of keywords on the *LexisNexis* database. As news sources, we select the *New York Times*, the *Wall Street Journal Abstracts*, and the *Financial Times*. We distinguish between two news frames: optimism and pessimism. The former expresses optimistic news media sentiment, whereas the latter expresses pessimistic news media sentiment. We argue that news that uses at least one of our predetermined positive words raise positive, optimistic thoughts in readers' minds. Similarly, we assume that news that uses at least one of our negative words raise negative, pessimistic thoughts in readers' minds. We borrow negative words from the list of the thirty most frequent words occurring in 10-Ks from the Fin-Neg Word lists presented in Loughran and McDonald (2011). We determine positive words by searching for antonyms of those negative words.

We construct our monthly media sentiment indicator by taking the ratio of the number of newspaper articles that contain predetermined negative words to the number of newspaper articles that contain predetermined positive words in the leading paragraph. We limit our search for keywords to the leading paragraph only since we believe that this paragraph summarizes the main message of the article and has the greatest impact on the reader. *LexisNexis* classifies news into categories based on the information discussed in the article. We select four such categories: (1) Banking and Finance; (2) Computing and Information Technology; (3) Property; (4) Asia. These specific categories allow us to investigate particular crises in isolation, such, as but not limited to, the Asian crisis in 1997/98, the dot-com crash in 2000-01, and the most recent financial downturn caused by declining prices on the U.S. housing market and by the bankruptcy of the global U.S. investment bank Lehman Brothers in September 2008. We analyze the potential media sentiment impact on financial market returns and volatility by estimating a vector autoregressive (VAR) model and by performing Granger causality tests. We specify in our monthly model the market index, the media sentiment indicator, and the market volatility as endogenous variables up to two years (lag 24) to capture any long-term effects.

We find a significant long-term causal relation of our monthly media sentiment indicator on the global financial markets performance. Our results show a significant negative (positive) long-term relation between our media sentiment indicator and market returns (volatility). We find strong evidence of the predictive activity of the media sentiment indicator for global market returns and volatilities 12 to 24 months in advance. Additionally, we find evidence of the predictive activity of the media sentiment indicator for Asian market returns and volatilities 1 to 6 months in advance. The interpretation of our findings is that news media create pessimistic market sentiment as more newspaper articles express pessimism. This effect takes place gradually rather than immediately. We also show that our constructed monthly media sentiment indicator reflects reasonably well historical crises that have occurred between 1990 and 2013. As such, we argue that it can be used as a leading investor sentiment indicator similar to the ones proposed by Baker and Wurgler (2006).

The remainder of this paper is organized as follows: Section 2 presents our sample and discusses the methodology. Section 3 presents our findings. Section 4 performs the robustness check and Section 5 concludes.

2 Data and Methodology

2.1 Sample

Following Antweiler and Frank (2004), Tetlock (2007), and García (2013), we focus our analysis on the three most relevant daily financial newspapers: *Wall Street Journal Abstracts* (WSJ), the *Financial Times* (FT), and the *New York Times* (NYT). Both Tetlock (2007) and García (2013) employ a computer algorithm with built-in dictionaries in order to construct their news indices. Tetlock (2007) uses a well-known quantitative content analysis program called *General Inquirer* to analyze daily variations in the *Wall Street Journal's Abreast of the Market* column. He gathers newspaper data by counting the number of words on a daily basis that fall into one of the 77 predetermined *General Inquirer* categories from Harvard's psychosocial *IV-4* dictionary. These 77 categories are strongly related to pessimistic words in the newspaper column so that a single media factor constructed from the gathered data is referred to as a pessimism factor. Similarly, García (2013) constructs his news media indicator by analyzing the content of the two NYT columns *Financial Markets* and *Topics of Wall Street* by employing a dictionary approach. He counts the number of positive and negative words in each newspaper article by using the word dictionaries provided by McDonald[1] and constructs his daily sentiment indicator by taking the difference between the fractions of the number of negative and positive words with respect to the total number of words.

We obtain our news data from the *LexisNexis* database, which provides newspaper articles, market research, and company information. The news section contains online articles from the world's most accredited newspapers, newswires, magazines, and key information providers. We gather our data by searching *LexisNexis* for WSJ, FT, and NYT articles that include one of our predetermined positive (negative) words in the leading paragraph. A list of words is presented in Table I. We assume that a newspaper

[1] The list of words is available online at $http://www3.nd.edu/\sim mcdonald/Word\_Lists.html$.

article that contains one of the positive words in the leading paragraph is more likely to raise positive thoughts on readers' minds and to express optimistic media sentiment. Similarly, articles that contain one of the negative words in the leading paragraph are more likely to raise negative thoughts on readers' minds and to express pessimism. Thus, we classify former newspaper articles as an optimistic news frame and latter as a pessimistic news frame. We limit our search only to the leading paragraph of a newspaper article since this paragraph summarizes the main message of the article and has the greatest impact on the reader.

[Please insert Table I about here]

We borrow some negative words from the list of the thirty most frequent words occurring in 10-Ks from the so-called Fin-Neg word list, which are reported in Loughran and McDonald (2011). We extend the list with some additional negative words, which are classified as negative in the McDonald dictionary and which we believe are relevant for financial press reports. Our list of positive words contains antonyms of negative words and some additional words, which are classified as positive in the McDonald dictionary and which we believe are often used in the financial press. Table I lists our defined 27 positive and 27 negative words.

For robustness checks we prepare a different set of news data by limiting our search query to only those newspaper articles that contain positive (negative) words and do not contain certain negative (positive) words. Such a search specification allows preventing to some extent the inclusion of news with negative (positive) content in the optimistic (pessimistic) news frame data set, and thus, making data more void of noise. *LexisNexis* allows excluding only up to 15 words. Therefore, we create a subset of excluded words from the original list of negative and positive words. Table I presents the excluded negative and positive words marked in bold.

We distinguish four *LexisNexis* categories: (1) Banking and Finance, (2) Computing and Information Technology, (3) Property, and (4) Asia. *LexisNexis* describes each category as following: the category Banking and Finance contains news about financial institutions and services, credit and lending, financial markets and trading, investments, and banking law and policy. The category Computing and Information Technology covers news about the computing industry, including the design, production and sale of electronic components, computer hardware and software. The category Property targets news about the commercial and residential property markets, including property development, management and sales. Asia is the fourth and final category and contains news about countries and regions located in the Asian region.

By specifying our news search to these particular categories we are able to extract news with the relevant content and to study the effect of these newspaper articles on the financial markets. In particular, we are interested to see the effect of news around the time of major economic downturns such as the Japanese real estate bubble in 1990/91, the Asian crisis of 1997-98, the dot-com crash in 2000-01, the U.S. housing market that reached its peak in 2006, started to decline in 2007 and reached a new low in 2012, and the bankruptcy of Lehman Brothers in September 2008 that was followed by a wave of bankruptcies of other financial institutions across the world (Adams, C., et al, 1998; Matieson, D., et al., 2001).

We collect the data for the time span between January 1, 1990 and December 31, 2012. We count the number of newspaper articles found during a particular month in each category that includes any of the searched words. Table II presents descriptive statistics of the average number of newspaper articles that are found on *LexisNexis* for all four categories and for each category separately on a monthly frequency: (i) the average number of all newspaper articles; (ii) the average number of newspaper articles, that contain one of our predetermined positive (negative) words in the leading paragraph; and (iii) the average number of newspaper articles that exclude positive (negative) words from negative (positive) word search on a monthly frequency. There are 7,355 newspaper articles found on average per month that are published in one of the selected sources and are classified at least to one of the selected category. Most of these newspaper articles are classified into the categories Banking and Finance (3,135 articles) and Asia (2,061 articles). On average per month, 705 articles are classified to Computing and Information Technology, and 587 articles are classified to Property. Newspaper articles are mostly published in the *Financial Times* (3,563 articles) and the *New York Times* (2,644 articles).

[Please insert Table II about here]

When we limit our search to predefined words, Table II shows that we find slightly more news with positive words than with negative words: 1,862 (1,538) articles or 25% (21%) of the total number of articles is found when searched for positive (negative) words in the leading paragraph. When we further limit our search query by excluding negative (positive) words from positive (negative) word search, we find 555 (1,266) newspaper articles in total or 8% (17%) of the total number of newspaper articles. When negative words are excluded from the search of positive words, the number of newspaper articles drops by 70% (from 1,862 to 555). On the contrary, when positive words are excluded from the negative word search, the number of newspaper articles drops by 17% (from 1,538 to 1,266). It seems that there are more articles that use positive words in a negative context than the other way around.

We construct our monthly media sentiment indicator by taking the ratio of the number of newspaper articles that contain negative words to the number of newspaper articles that contain positive words. In order to perform regression analysis, each of the five categories is assigned with a market index: the MSCI World for the category Banking and Finance, the NASDAQ for Computing and Information Technology, the MSCI Real Estate (RE) for the category Property. For the category Asia we build our own index by taking a weighted average of the MSCI EM Asia excluding Japan and the MSCI Japan based on the average monthly market capitalization of each index. Average monthly market capitalization data is available from May 2004 for both indices. We set the weights for the MSCI EM Asia and the MSCI Japan constant between January 1990 and May 2004 and equal to the weights calculated for May 2004 using the available average market capitalization data. From May 2004 on, weights are calculated by using the existing data for each month. On average, market capitalization is 78% for the MSCI Japan index and 23% for the MSCI EM Asia excl. Japan. The time series have been downloaded from *Datastream* for the period between January 1990 and December 2012 for all indices except for the MSCI RE, which is available only from January 1995 onwards.

We extend the analysis to the effect of news frames on market volatility. We calculate a proxy for monthly volatility of each market index by following Tetlock's (2007) approach. We demean market return variables to obtain residual values and square these residuals. As control variables, we use the standard Fama-French small-minus-big (SMB), high-minus-low (HML), and momentum (MOM) factors, and the Pastor-Stambaugh aggregate liquidity factor (LIQ), downloaded at a monthly frequency from *Wharton Research Data Services.*

2.2 Methodology

In order to investigate a potential long-term media sentiment effect on the performance of financial markets, we propose to estimate a VAR model for each category, where endogenous variables are the market index, our proxy for market volatility, and our constructed monthly media sentiment indicator. Exogenous variables are *SMB*, *HML*, *MOM*, and *LIQ* factors. We include 24 lags for each endogenous variable. Similar to Antweiler and Frank (2004), Tetlock (2007), and García (2013), we analyze the potential news media sentiment effect on market's return and on its volatility. We analyze the effect of news media sentiment by performing the following regressions:

$$Mrk_t = \alpha_1 + \beta_1 L24(Mrk_t) + \beta_2 L24(Sent_t) + \beta_3 L24(Vola_t) + \beta_4 Exog_t + \epsilon_{1t} \quad (1)$$

and

$$Vola_t = \alpha_2 + \beta_1 L24(Mrk_t) + \beta_2 L24(Sent_t) + \beta_3 L24(Vola_t) + \beta_4 Exog_t + \epsilon_{2t}, \qquad (2)$$

where Mrk_t is the log rate of return of the market index for each category; $L24(x_t)$ is a lag operator that transforms the variable x_t into a row vector consisting of 24 lags of x_t; $Sent_t$ is the log change of our media sentiment indicator; $Vola_t$ is the estimated volatility of its corresponding market index; $Exog_t$ are exogenous variables such as size (*SMB*), value (*HML*), momentum (*MOM*), and liquidity (*LIQ*), which are included in the model to control for other potential anomalies that are not driven by the news media.

Antweiler and Frank (2004), Tetlock (2007), and García (2013) draw their conclusions about news media effects by testing for the significance of news media VAR coefficients. Given complicated interlinked relationship between news media and financial markets, where news influence markets and markets influence news (Tetlock, 2007), we believe that simply testing for the significance of lagged coefficients is not sufficient to make conclusions about the causality. In order to disentangle these two forces, we propose to run additional Granger causality tests on the subsets of lagged coefficients of our media sentiment indicator. We assume that if media sentiment effect takes place, it affects investor sentiment gradually over a long period of time. We perform Granger causality tests for all 24 lags, and for subgroups of lags 1 to 6, 1 to 12, 6 to 12, 12 to 24, 12 to 18, and 18 to 24. Statistical significance of coefficients for all 24 lags would imply that media sentiment impacts market returns and volatilities every month for two years before the effect becomes visible. Testing for subgroups of lags allows us to identify a more narrow time span when the effect of news media takes place. We hypothesize that markets react to pessimistic (optimistic) news media sentiment with decreasing (increasing) returns and increasing (decreasing) volatilities. However, Granger causality tests do not show the signs of the coefficients. In order to draw conclusions about the market reaction, we suggest looking at the signs of the media sentiment indicator VAR coefficients for the lags that are statistically significant.

Additionally, exogenous variables for the size (SMB), value (HML), momentum (MOM), and liquidity (LIQ) are included in the model in order to control for other potential anomalies on the stock market returns and volatilities that are not driven by the news media. Pastor and Stambaugh (2003) documents the presence of a time-series relation between market liquidity and expected market returns and consider marketwide liquidity as a state variable that affects expected stock returns because its innovations have effects that are pervasive across common stocks. Following the same logic, we consider monthly Fama-French factors for size, value, momentum and Pastor-Stambaugh aggregate liquidity factor as state variables and include them as control variables in our model.

3 Discussion of Results

In this section we present and discuss the results of our VAR models (1) and (2) and Granger causality test results for the category Banking and Finance that represents global markets and for the subcategories Computing and Information Technology, Property, and Asia.

3.1 Banking and Finance

Banking and Finance is a *LexisNexis* category that targets news about financial institutions and services, credit and lending, financial markets and trading, investments and banking law and policy. Figure I plots our media sentiment indicator against the MSCI World index (left-side) and its corresponding volatility (right-side). We see that our monthly media sentiment indicator seems to follow closely historical economic developments and economic crises on the global financial market. Our media sentiment indicator tends to go down when the economy is growing and to go up when the economy becomes less stable. This indicates that during global economic expansions there seem to be more optimistic than pessimistic news published. On the other hand, when the global economy enters a recessionary state, media pessimism starts to prevail: our media sentiment indicator reaches its peak at the times of crises. The figure on the left plots the media sentiment indicator against the MSCI World index. Overall, the MSCI World index tends to move upwards between 1991 and 2000 with temporal downward movements at the times of the Japanese real estate turmoil at the beginning of the 1990s, the Mexican peso crisis in late 1994, and during a wave of economic and financial crises in emerging markets in 1997-98 (Adams, C., et al., 1998). MSCI World was growing at the annual rate of 9.3% between 1990 and 2000. Our media sentiment indicator exhibits large swings around crisis periods. It ranged between 62 and 148 levels during 1990-2000 reaching 135 in August 1990 as it reflected Japanese real estate pricing bubble, 115 in March 1995 as a result of Mexican peso crisis, and 148 in September 1998 after the Asian Crisis. However, the general time trend of the media sentiment indicator seems to move downwards between 1990 and 2000 implying that media sentiment became more optimistic in the 90s as the world economy grew.

[Please insert Figure I about here]

The MSCI World index reached its turning point at the beginning of the Millennium. The dot-com crash in 2000-01 seems to reverse the trend of the global economy. The MSCI World lost 66% of its value between its peak in March 2000 and the trough in September 2002. Our media sentiment indicator exhibits steady growth during this period implying that media pessimism prevailed over optimism. In September 2001 the media sentiment indicator reached its new high of 150. A period of recession was followed by a state of economic growth and expansion when the MSCI World recovered from its heavy losses and started growing again. Between January 2003 and October 2007 the MSCI World index grew at an annual rate of 13.89% and reached its historical high of 1,191.1 in October 2007. Figure I indicates that our media sentiment indicator falls as the economy grows. During 2003-October 2007 the media sentiment indicator ranged between 52 and 117 levels reaching its lowest in March 2006. A significant increase in media pessimism is visible already at the beginning of 2007, while the MSCI World was still growing. Our media sentiment indicator seems to predict a financial downturn *ex-ante*. A peak in our media sentiment indicator coincides with the trough of the MSCI World in September 2008, precisely when the global U.S. investment bank Lehman Brothers filed for bankruptcy. MSCI World fell to 717.2 from its peak in October 2008 and lost 51% of its value. At the same time, the media sentiment indicator spiked to 215 level. Declining U.S. and global housing markets and a wave of bankruptcies of financial institutions set the world economy in a prolonged recession. Our media sentiment indicator fell from its peak in September 2008, but remained on a relatively high level until the end of 2012. The average media sentiment indicator level after Lehman is 134, which is higher than the overall average of 101 for the entire time span.

The chart on the right of Figure I plots our media sentiment indicator against the monthly MSCI World volatility measure. Our MSCI World volatility measure is squared demeaned residuals of the MSCI World return and is uses as a risk measure indicating a level of uncertainty on the global financial markets at a particular point in time. We see that the MSCI World volatility tends to increase at times of financial crises and tends to fall during the times of economic growth. An average level of volatility for the MSCI World is 0.2% for our sample time span. The spikes in volatility such as 1.6% in September 1990, 2.3% in August 1998, 1.4% in September 2002, and the highest 3.3% in October 2008, coincide with the spikes in our media sentiment indicator. The corresponding media sentiment indicator levels for these spikes in volatility are 134, 146, 118, and 215 respectively. Media pessimism seems to grow with the global market uncertainty. When the market volatility falls indicating that the market becomes more stable, media sentiment becomes more optimistic. Average monthly volatility of the MSCI World between 1993-1997 and between 2003 and October 2007 is only 0.1%. The media sentiment indicator reaches its lowest value of 52 in March 2006.

Table III presents the estimated VAR coefficients of our media sentiment indicator. For the sake of convenience we report only selected lags. The actual VAR model (1) includes 24 lags of each endogenous variable. Column 2 presents the coefficients for the category Banking and Finance.

[Please insert Table III about here]

We find negative statistically significant coefficients for lags 13, 14, 16, 17, 18, and 19. The sign of coefficients confirms our expectations and is in line with the findings by Tetlock (2007) and García (2013), but not with Antweiler and Frank (2004), who do not find significant media effect on market returns. Our VAR regression results imply that our media sentiment indicator tends to grow when the return on the MSCI World tends to fall. The significance of lags 13, 14, and 16 to 19 shows that our media sentiment indicator tends to predict MSCI World returns up to 19 months in advance. This confirms our expectations of the long-term relation between media sentiment and market returns and suggests that our proposed media sentiment indicator can be useful as an *ex-ante* predictor of the global market performance.

Table IV reports the estimated coefficients of our VAR model (2). Column 2 reports only those VAR coefficients of our media sentiment indicator variables that are statistically significant. The original VAR model (2) includes 24 lags of each endogenous variable. We obtain positive statistically significant coefficients for our media sentiment indicator for lags 10, 12, 13, and 14. However, we find a negative statistically significant coefficient for lag 22. These results support our expectations. Antweiler and Frank (2004) and Tetlock (2007) investigate the impact of news content on market volatility and find similar results. A positive statistically significant coefficient implies that there is a positive relation between our media sentiment indicator and the monthly volatility of the MSCI World index. Additionally to Antweiler and Frank (2004) and Tetlock (2007), who show the effect of the news media on a short-term, our results prove that there is a long-term relation between market volatility and news sentiment. We find that an increasing level of media pessimism tends to predict the MSCI World volatility 10 to 14 months in advance. A negative coefficient for lag 22 is a conflicting result, since it goes against our expectations and the results from the previous literature. The coefficients for lags 20, 21, 23, and 24 are positive and statistically insignificant implying that there seem to be no significant effect of media sentiment on global market volatility more than 14 months in advance.

[Please insert Table IV about here]

As we already indicated in the methodology section, drawing conclusions based on only VAR coefficients might not be sufficient. Tetlock (2007) shows that not only news media influence markets, but also markets influence what is published in newspapers. This means that we cannot claim the causality of news media on market returns and volatility after observing VAR coefficients. Furthermore, statistically significant coefficients for certain lags do not necessarily mean that news media sentiment has an effect on market returns and volatility *exactly* on that month in advance. Following the works by Price and Tewksbury (1997) and McCombs (2004), we hypothesize whether news media can influence financial markets gradually over a long time. We are rather interested in an approximate time span during which a significant effect of media sentiment takes place rather than an exact month. In order to test the hypotheses of the long-term news media effect on global financial market performance, we propose to run Granger causality tests on our VAR models (1) and (2) for all 24 lags, and for the subset of lags 1 to 6, 1 to 12, 6 to 12, 12 to 24, 12 to 18, and 18 to 24 of the media sentiment indicator coefficients.

Table V reports Granger causality test results of our media sentiment indicator on the global market returns (Panel A) and global market volatilities (Panel B) for all 24 lags and for the subsets of lags. Column 2 shows results for the category Banking and Finance where the market index is the MSCI World. From both Panel A and Panel B we see that our media sentiment indicator exerts a significant causal relation on the MSCI World return and its volatility for the subset of lags 12 to 24 and 12 to 18. This means that the coefficients estimated for our VAR models (1) and (2) for the lags 12 to 24 and for the lags 12 to 18 are jointly statistically significant. From Table III we can infer that these coefficients are negative for market returns and positive for market volatility. Consistent with Antweiler and Frank (2004), Tetlock (2007) and García (2013), this implies that media sentiment tends to have a significant negative (positive) causal effect on global market returns (volatility) roughly one-year to one-and-a-half-year in advance.

[Please insert Table V about here]

Our results in Table V contribute to the previous research by showing that news media sentiment has a causal effect not only in the short, but also in the long-run. Following the intuition of Price and Tewksbury (1997), as news media starts to use negative words more frequently than positive words, negative thoughts and pessimistic feelings about the economy are more likely to be activated on investors' minds through the applicability effect. As pessimistic news media sentiment becomes prevalent, more and more investors start to agree with this point of view, forming pessimistic investor sentiment. Pessimistic investor sentiment puts a downward pressure on the returns and increases volatility on the global financial markets as investors adjust their investment decisions. The effect of media sentiment becomes apparent after one to two years consistent with the hypothesis that news media can truly have an effect only over a long-term (McCombs, 2004). It seems that our media sentiment indicator can send signals of a turning point of a business cycle *ex-ante* and can be used as a proxy for investor sentiment similar to the proxies constructed by Baker and Wurgler (2006).

3.2 Computing and Information Technology

The category Computing and Information Technology (IT) is a *LexisNexis* category that targets news about the computing industry, including the design production and sale of electronic components, computer hardware and software. We assign the NASDAQ index to this category as a market index, since it tracks the performance of stocks of IT companies. This category allows us to investigate a particular market segment, namely the IT sector, in isolation. Figure II plots our media sentiment indicator against the NASDAQ index (left-side) and its volatility (right-side) over January 1990 to December 2012.

Figure II shows that our media sentiment indicator moves in a wave-like fashion exhibiting an increase during crises and a decline during economic growth. For the first ten years of our sample, the NASDAQ index exhibits an upward sloping trend. At the same time, our media sentiment indicator tends to slope downward, showing that news media sentiment becomes more optimistic over time. Our media sentiment indicator reflects the financial crises that occurred between 1990 and 2000 with an increasing level of pessimism before and during each crisis such as the Japanese real estate turmoil in 1990-91, the Mexican peso crisis in December 1994, the Asian crisis in 1997-98, the Russian debt crisis in August 1998, the LTCM bailout in September 1998, and the Brazilian crisis in January 1999. We observe that our media sentiment indicator spikes at the outbreak of each crisis as media pessimism reaches its highest level at that time.

The major downturn on the IT market during the past 20 years has been the dot-com crash of 2000-01. Figure II indicates that a pricing bubble in the IT sectors evolved during 1998-2000. Our media sentiment indicator gradually declines as the NASDAQ index reached new highs. Dot-com companies' rising stock prices were accompanied by an increasing level of media optimism. In March 2000, the NASDAQ reached its historical high at 4,696.6 followed by a price decline, during which the index lost over 72% of its value by August 2002. Our media sentiment indicator sloped upwards as the NASDAQ fell pushing the prices further down; it spiked in the second half of 2001 and started to decline as media sentiment became more optimistic again. The media sentiment indicator rose from its lowest of 43 in November 1999 to 127 in August 2001 when the NASDAQ plummeted to 1,805.4 from its earlier peak of 4,696.6 in March 2000. We see that our media sentiment indicator started to increase again in January 2006 and spiked in September 2008 when Lehman Brothers filed for bankruptcy. The media sentiment indicator grew from 44 in December 2005 to 150 in November 2008. The NASDAQ reacted to this financial market shock with a sharp decline. It fell from 2,859.1 in November 2007 to 1,377.8 in March 2009 losing 73% of its value.

[Please insert Figure II about here]

The graph on the right of Figure II plots our monthly media sentiment indicator against the NASDAQ volatility. We see that the IT market became more volatile in the second half of the 1990s as a wave of crises on emerging markets and the dot-com crash occurred. Between 1997 and 2003 the NASDAQ volatility level averaged to 1.1% comparing to the average of 0.5% for the entire time span with some periods reaching up to 7.1% as in November 2000. We also observe higher volatility in the aftermath of the Lehman Brothers bankruptcy in 2008-09. Average NASDAQ volatility for the period between September 2008 and January 2011 was 0.6%, slightly above the overall average volatility, with peaks in volatility reaching 4.1% as in October 2008. Figure II shows that spikes in volatility were accompanied by high levels of news media pessimism. Media sentiment seems to be more pessimistic during increasing uncertainty on the IT market. The media sentiment indicator ranged between 43 and 127 during 1997-2003 reaching its maximum in August 2001 and between 54 and 150 in September 2008-2011. The volatility of the NASDAQ index was relatively low between 1993 and 1996 and between 2004 and 2007. During these periods the volatility of the NASDAQ did not surpass a 1% level. These periods are also characterized by relatively low levels of our media sentiment indicator and prevailing media optimism. The media sentiment indicator levels ranged between 51 and 111 in 1993-1996 and between 45 and 73 in 2004-2007.

Column 4 of Table III reports the estimated coefficients of the media sentiment indicator for the VAR model (1). Negative statistically significant coefficients are observed for the subsets of lags 1 to 5 and a positive statistically significant coefficient is observed for the lag 23. The results show that our media sentiment indicator predicts NASDAQ returns half a year in advance. We see that the increasing pessimism within news media tends to put a downward pressure on NASDAQ returns as investors become more pessimistic. These results confirm our hypothesis of a negative relation between media sentiment and market returns and are in line with the results reported in the previous literature. The results show that there is a long-term relation between media sentiment and NASDAQ returns consistent with McCombs (2004). For the Computing and IT category, it takes only up to 6 months before the NASDAQ index reacts to news media sentiment. Comparing these findings to the ones for the category Banking and Finance, we conclude that the effect of the news media on the IT market is quicker.

Column 4 of Table IV reports the estimated coefficients of our media sentiment indicator for the VAR model (2). In contrast to the results obtained in Table IV for the category Banking and Finance, no statistically significant coefficients are desplayed for the IT market. The majority of coefficients is positive, which is in line with our expectations of a positive relation between media pessimism and market volatility, though insignificant. It appears that media sentiment predicts NASDAQ returns, but does not have any significant effect on the NASDAQ volatility for the selected time span.

Panel A and Panel B in Table V report the Granger causality test results that test for the joint statistical significance of the media sentiment coefficients in VAR models (1) and (2). Column 3 in Panel A reports statistically significant results for all 24 lags and for lags 1 to 12 and 1 to 6. The results for lags 1 to 6 are strongly statistically significant at 1%. On the contrary, column 3 in Panel B does not report any statistically significant causal relation of media sentiment on NASDAQ volatility. The results from Panel A in both Table III and Table V present evidence of the causal negative long-term relation of media sentiment on NASDAQ returns six to twelve months in advance. These results confirm our expectation and are consistent with the results by Tetlock (2007), and García (2013) that show a short-term negative relation between media sentiment and market returns. However, our results are not in line with Antweiler and Frank (2004), who do not find a significant media effect on market returns but on market volatility.

Our findings contribute to the existing literature by showing that the effect of news media on market returns also takes place in the long run, which is consistent with assertions made by McCombs (2004). The results for the category Computing and IT are also in line with the results for the category Banking and Finance implying that our media sentiment indicator can be used not only for predictions of the global financial performance, but also for particular markets such as IT market. In contrast to our findings for the category Banking and Finance, the news media effect seems to take place sooner for the IT market.

3.3 Property

The category Property is a *LexisNexis* category that contains news about the commercial and residential property markets, including property development, management and sales. This category allows us studying the effect of media sentiment on the development of housing prices in isolation. The market index for this category is chosen to be the MSCI Real Esate (RE) index since it tracks an aggregate level of housing prices worldwide. Figure III plots our monthly media sentiment indicator against the MSCI RE index (left-side) and against the demeaned squared residuals of the MSCI RE, which we use as a proxy for volatility, (right-side) over the period January 1995 to December 2012.

[Please insert Figure III about here]

Figure III indicates that the MSCI RE index exhibits two major crashes: during the Asian crisis 1997-98, and in 2007 when U.S. housing prices started to decline, which became one of the major causes of the outbreak of the financial crisis in September 2008 when Lehman Brothers filed for bankruptcy. MSCI RE index lost 65.9% of its value between July 1997 and September 1998 and 97.8% between May 2007 and January 2009. Our media sentiment indicator tends to decline when the MSCI RE index grows and tends to increase when the MSCI RE index falls. Moreover, our media sentiment indicator tends to spike and reaches its highest levels at the time when the MSCI RE reaches troughs. The average level of media sentiment indicator for the sample time span is 84. In October 1998 the media sentiment indicator reached a 87 level from 44 when MSCI RE fell to 97 from its peak of 158 in July 1997. Similarly, the media sentiment indicator increased to 171 in February 2009 from 66 level in May 2007 when the MSCI RE fell to 71.3 level from its historical high of 224.3 in May 2007. We observe that the media sentiment indicator started to increase in 2006 while the MSCI RE index continued to grow as fears about the U.S. housing market started to circulate on the news media. At the time of an increasing uncertainty of the housing market, which corresponds to periods 1997-1999 when average monthly volatility of the MSCI RE was 0.6%, slightly higher than the overall average of 0.3%, and to periods 2007-2010 when the average volatility was 0.7%, our media sentiment tends to be more pessimistic. During 1997-1999 media sentiment indicator started to increase from 47 in December 1995 to 79 in April 1999. Similarly, during 2007-2010 media sentiment indicator grew from 58 in January 2007 to 188 in September 2008. On the other hand, we can infer from Figure III that optimistic media sentiment prevails when the housing market is calm and market volatility is relatively low. Thus, for the period between 2002 and 2006 average monthly volatility of the MSCI RE was 0.1%, significantly lower than the overall average of 0.3%. At the same time, our media sentiment indicator stayed within a range of 40 and 92, mostly below the overall average of 84.

Column 6 of Table III reports the estimated coefficients of the media sentiment indicator for our VAR model (1). We observe negative statistically significant coefficients for lags 10, 12, and 15. This result suggests a negative long-term relation between our media sentiment indicator and the MSCI RE index. It confirms our expectation about the existence of a negative long-term relation between media sentiment and market returns. Our findings are in line with the results by Tetlock (2007) and García (2013) and consistent with the intuition in Price and Tewksbury (1997) and McCombs (2004).

Column 6 of Table IV displays the estimated coefficients of the media sentiment indicator for our VAR model (2). The results for the volatility of the MSCI RE index are mixed. We observe a positive statistically significant coefficient for the media sentiment indicator at lag 12 and a negative statistically significant coefficient at lag 4. A positive statistically significant coefficient is in line with our expectations of the long-term media sentiment relation with market volatility on the housing market and with previous works by Antweiler and Frank (2004) and Tetlock (2007). However, the negative statistically significant coefficient at lag 4 conflicts our predictions. We cannot make definite conclusions about the existence of a media sentiment effect on MSCI RE volatility based on the results in Table IV.

Column 4 in both Panel A and Panel B of Table V presents the Granger causality test results for the joint significance of the media sentiment coefficients in our VAR models (1) and (2). In contrast to our findings for the categories Banking and Finance and Computing and IT and despite the results in Table III for the category Property, we do not find any statistically significant causal relation of our media sentiment indicator on neither the MSCI RE returns nor on the MSCI RE volatility. These results do not support our expectations of the negative (positive) causal long-term relation of media sentiment on market returns (volatility). It seems that our media sentiment indicator does not predict the performance of the housing market and puts limits on the usage of our indicator for specific markets.

3.4 Asia

Asia is a *LexisNexis* category that targets news about countries and regions located on the Asian continent. As the market index, we build a MSCI EM Asia incl. Japan index by taking a weighted average of MSCI EM Asia index and MSCI Japan index based on the average market capitalization. Figure IV plots our media sentiment indicator against the MSCI EM Asia incl. Japan index on the left and against the volatility of the MSCI EM Asia incl. Japan index on the right.

[Please insert Figure V about here]

Figure IV shows that Asian markets have suffered several major downturns over our selected time span. Firstly, the MSCI EM Asia incl. Japan index was strongly hit by the Japanese real estate turmoil in the early 1990s. From January 1990 until July 1992, the MSCI EM Asia incl. Japan index lost 65% of its value and fell from 3,242.6 to 1,692.4. This period is also characterized by an increase in the media sentiment indicator from 100 to 121 between January 1990 and July 1992. The media sentiment indicator jumped to 232 in August 1990 when the MSCI EM Asia incl. Japan index fell to a 2,306.3 level from 3,242.6, a 34% drop. The monthly volatility of the MSCI EM

Asia incl. Japan index on average between 1990 and 1992 was 0.8%, higher than the overall average monthly volatility of 0.4% for the entire time span. The volatility hit its maximum in October 1990 when it reached 4.7%. A volatile period between 1990 and 1992 was followed by the growth in the MSCI EM Asia incl. Japan index and by relative stability on the market. From July 1992 until April 1996 the index gained almost 57%. The monthly volatility stayed at a 0.4% level on average for the same period. The media sentiment indicator fell from its peak of 121 in July 1992 and reached a 85 level on April 1996. Thus, it seems that economic growth and relative stability on Asian markets between 1993 and 1997 due to strong capital inflows to Tiger countries from developed economies was accompanied by prevailing media optimism. From April 1996 the MSCI EM Asia incl. Japan index experienced another shock, which subsequently was followed by the Asian crisis in July 1997. The MSCI EM Asia inc. Japan index dropped by 27% from 2,981.1 to 2,271.7 at the outbreak of the Asian crisis in July 1997. The monthly volatility of the MSCI EM Asia incl. Japan index reached 1.4% and our monthly media sentiment indicator increased to 201 level in August 1998. Figure IV clearly indicates that our media sentiment indicator experienced a sharp rise in July 1997 when it jumped from 81 to 101 level. The MSCI EM Asia incl. Japan index returned to the growth in October 1998 after hitting its trough of 1,464.4 in September 1998. From the end of 1998 until March 2000 the MSCI EM Asia incl. Japan index was growing at the annual rate of 45.4% and reached its new high of 3,004.1 in March 2000. The media sentiment indicator fell from its peak of 201 in September 1998 to 100 in March 2000 while the MSCI EM Asia incl. Japan rallied. The crash of dot-com companies reversed this trend and set the MSCI EM Asia incl. Japan index at a downward trend. The MSCI EM Asia incl. Japan index continued to fall until April 2003 and reached another trough of 1,214.9 in March 2000, a 91% decline from its previous high of 3,004.1. During 2000-2003 the media sentiment indicator was growing and staying at a relatively high level indicating that news media expressed more pessimism than optimism. However, in April 2003 media sentiment seems to become more optimistic. It declined from 142 in April 2003 to 76 in October 2005. At the same time, the MSCI EM Asia incl. Japan index exhibited a visible growth of a slightly more than 19% annually and monthly volatility of the index was 0.2% on average between April 2003 and 2007. The next downturn followed after the U.S. and worldwide housing prices fell and Lehman Brothers filed for bankruptcy in September 2008. The MSCI EM Asia incl. Japan index fell from 2,655.1 in January 2007 to 1,280.6 in February 2009 while monthly volatility of the MSCI EM Asia incl. Japan index grew from 0.03% to 2.0% for the same time. The media sentiment indicator jumped from 77 in January 2007 to 160 in February 2009. For the following four years between 2009 and 2012 the media sentiment indicator remained at a relatively high level while the MSCI EM Asia incl. Japan stayed on a constant close to its earlier trough level. The monthly volatility of the MSCI EM Asia incl. Japan was also relatively high between 2009 and 2012. From Figure IV it seems that media sentiment becomes more pessimistic before and at the time of economic downturns and increasing market uncertainty. During economic growth media pessimism remains on a low level while media optimism prevails.

Column 10 of Table III reports estimated coefficients for the media sentiment indicator for VAR model (1). The table reports a negative statistically significant coefficient for the media sentiment indicator at lag 3. This result goes in line with our expectations about a negative relation between media sentiment and market returns and the results reported by Tetlock (2007) and García (2013). On the other hand, this result conflicts with the results by Antweiler and Frank (2004), who do not find evidence of the negative effect of media sentiment on the market returns.

Column 10 of Table IV reports the coefficients for the media sentiment indicator for VAR model (2). The coefficients for most of the lags are positive, but statistically insignificant. On the other hand, coefficients for lags 22 and 23 are negative and statistically significant. These are conflicting results that go against our expectations of a positive relation between media sentiment and market volatility over the long-run and the results reported in previous literature.

Panel A and Panel B of Table V column 5 report Granger causality test results for the joint statistical significance of the media sentiment indicator coefficients on the MSCI EM Asia incl. Japan returns and the MSCI EM Asia incl. Japan volatilities for all 24 lags and for the subsets of lags. On the contrary to the results in Table III, Panel A reports no statistically significant results for the causal relation of the media sentiment indicator on the MSCI EM Asia incl. Japan returns. On the other hand, Panel B shows statistically significant coefficients for lags 1 to 6 and 1 to 24. These results imply that the market sentiment indicator coefficients for lags 1 to 6 and for all 24 lags are jointly statistically significant. Similar to our results for categories Banking and Finance and Computing and IT, the results in Tables IV Panel B and Table V suggest that there is a positive causal long-term relation of media sentiment on the MSCI EM Asia incl. Japan volatility and that our media sentiment indicator seems to predict increasing volatility on Asian markets half a year in advance.

4 Robustness Check

In order to check for the robustness of our results, we download a new set of news data and perform the same statistical analysis again. We collect our new dataset by performing the same search query on *LexisNexis* by using the same positive and negative words in the leading paragraph. However, now we exclude a number of negative (positive) words while searching for positive (negative) words. Excluded positive and negative words are marked in bold in Table I. By specifying our search query in such a way we remove to some extent those newspaper articles that use words, which are classified as positive or negative, in the negative or positive context. For example, words like “risk” are classified as negative words and worlds like “increase” are classified as positive words; however, a phrase like “increasing risk” has a negative meaning. With the current data collection method, the article that uses a phrase like “increasing risk” will be counted twice and classified under optimistic and pessimistic news frame. By excluding the word “risk” from a positive word search, but not excluding the word “increase” from the negative word search, we remove newspaper articles that use such phrases from our optimistic news, but not from pessimistic news dataset. Similarly, a phrase like “positive stock performance despite crisis” will be removed from the pessimistic news dataset, but not from optimistic one. Newspapers with phrases like “prevailing optimism despite declining stock prices” will be removed from both optimistic and pessimistic news datasets. Table II reports an average number of newspaper articles per month with and without excluded words for each category. In total, when negative (positive) words are excluded from the positive (negative) words search, the number of newspaper articles drops by 70% (18%). This sharp difference between the number of newspaper articles in our optimistic and pessimistic news frames before and after word exclusion might indicate that journalists tend to use more positive words in the negative context than otherwise.

Table VI reports the estimated coefficients for the market sentiment indicator in the VAR model (1) on the new set of news data. The results for categories Banking and Finance, Computing and IT, and Property are similar to the results obtained for the old news data set (Table III). We find negative statistically significant coefficients for the category Banking and Finance for lags 10, 13, 14, 17, 18, and 19. For this category, the coefficient for lag 10 becomes significant, the coefficient for lag 16 becomes insignificant, and overall the statistical significance of coefficients becomes stronger for the new set of data. We find negative statistically significant coefficients for lags 1, 3, and 4 for the category Computing and IT. The coefficients for lags 2 and 5 become insignificant for the new set of data. Furthermore, the conflicting result for the lag 23 in the category Computing and IT disappears after performing the analysis on the new data set. For the category Property we find one negative statistically significant coefficient for lag 18. On the other hand, coefficients for lags 10, 12, and 15 become insignificant. For the category Asia, we find a negative statistically significant coefficient for lag 3 and a positive statistically significant coefficient for lag 13.

[Please insert Table VI about here]

Table VII reports the estimated coefficients for the market sentiment indicator in VAR model (2) on the new set of news data. We observe positive statistically significant coefficients for the category Banking and Finance at lags 13, 14, 15, 17, and 20 and a negative statistically significant coefficient for the lag 22. Comparing to the results in Table IV, lags 10 and 12 become insignificant and lags 15, 17, and 20 become significant for the new dataset. The conflicting negative coefficient for lag 22 remains. Similar to the results in Table IV, there are no statistically significant coefficients for the category Computing and IT. For Property we find one negative statistically significant coefficient for lag 4, which we also observe for the old dataset. This result conflicts with our expectations of the positive relation between media sentiment and market volatility. The coefficient for lag 12 becomes insignificant after the robustness check. For category Asia we do not find any statistically significant coefficients.

[Please insert Table VII about here]

Lastly, Table VIII reports Granger causality test results of the media sentiment indicator on market returns (Panel A) and market volatilities (Panel B) for our new dataset. The results for the category Banking and Finance are consistent with the results in Table V. We find statistically significant coefficients for lags 12 to 24 and lags 12 to 18. This result shows the robustness of our previous results reported in Tables III and V for the category Banking and Finance. On the other hand, we find statistically significant Granger causality test result for the category Asia at lags 1 to 6. This result conflicts with the results from Table V for Asia category of no significant causal relation of media sentiment on market returns. There seem to be no statistically significant causal relation of the media sentiment indicator on market returns for other categories. The causal relation reported for the category Computing and IT disappears. For the market volatility we find statistically significant causal relation of the media sentiment indicator for the categories Banking and Finance at lags 12 to 24 and 18 to 24 and for Asia at lags 1 to 6. These results show the robustness of our previous results obtained in Tables IV and V for these categories. For other categories, we do not find evidence of the causal relation between the market sentiment indicator and market volatilities.

[Please insert Table VIII about here]

Overall, it seems that our monthly media sentiment indicator is able to predict the returns and volatilities on the global financial markets one to two years in advance and on Asian markets 1 to 6 month in advance. On the other hand, the ability of our monthly media sentiment indicator to predict returns and volatilities for specific markets such as IT and Real Estate is limited. One explanation for the lack of significant results for these categories might be the fact that there are relatively few newspaper articles that are written in these categories comparing to categories such as Banking and Finance and Asia. There are only 705 newspaper articles on average per month for Computing and IT and 587 for Property category. On the other hand, Banking and Finance category has 3,135 newspaper articles per month and Asia has 2,061 (Table II). A low number of newspaper articles makes our monthly media sentiment indicator index very volatile. An average rate of change (standard deviation) of the media sentiment indicator for categories Banking and Finance and Asia are 0.02% (11.60%) and -0.01% (13.99%) respectively, whereas an average rate of change (standard deviation) for the categories Computing and IT and Property are -0.10% (20.57%) and -0.08% (17.52%) respectively. Thus, high volatility of the market sentiment indicator for the categories Computing and IT and Property due to relatively few newspaper articles found might explain a lack of significant results for these categories. Furthermore, the number of newspaper articles significantly drops when we search for specific words. Adding additional sources or expanding the list of keywords might result in a better predictive ability of the media sentiment indicator for specific markets. Another explanation of a lack of statistically significant results for Computing and IT and Property categories might lie in the fact that NASDAQ and MSCI RE prices respond to the performance of other financial markets, different from IT and real estate. For example, we see that NASDAQ declined during the Asian crisis, as the performance of Asian emerging markets indirectly influenced technology prices. However, our media sentiment indicator for categories Computing and IT and Property does not contain news about other markets that might indirectly influence NASDAQ and MSCI RE indices.

5 Conclusion

This paper investigates a potential media sentiment effect on the performance of financial markets in the long-run. Previous literature suggests that negative media sentiment creates pessimistic investor sentiment and puts a downward pressure on market prices and an upward pressure on market volatilities in the short-run (Antweiler and Frank, 2004; Tetlock, 2007; García, 2013). In our study, we propose to investigate the long-term effect of media sentiment on financial market performance. We follow Price and Tewksbury (1997) and McCombs (2004), who argue that news media can influence people's opinions over time. We investigate news media effects for up to 24 months on the global economy and on specific markets such as IT, Property, and Asian markets.

We find robust evidence of the causal relation of media sentiment on the global market return and global market volatility for 12 to 24 months in advance and on Asian returns and Asian volatility for 1 to 6 months in advance. We show that pessimistic media sentiment tends to exert a downward pressure on global market returns and an upward pressure on global market volatilities 12 to 24 months in advance. We suggest using our media sentiment indicator as leading investment sentiment indicator similar to proxies proposed by Baker and Wurgler (2006). Our media sentiment indicator can also be used to analyze the outlook of particular market segments, such as Asian markets.

Our main contribution to the literature is that we show that news media can have a prolonged effect on the market sentiment and on long-term financial performance. Increasing media pessimism expressed by salient attributes of the newspaper, such as language used, selection of content, and organization, raise negative thoughts in investors' minds through the applicability effect defined by Price and Tewksbury (1997). As media pessimism becomes dominant over time, investors are more likely to adhere to the point of view that generally circulates on news media and to use negative thoughts that news media arise in their evaluation of the economic outlook. Pessimistic investors start to anticipate deterioration of the financial performance and start to adjust their investment decisions that subsequently increase the uncertainty on the markets and put a downward pressure on financial returns.

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Appendix

This appendix presents examples of newspaper articles found on *LexisNexis* for one of three selected sources: *Financial Times*, *New York Times*, and *Wall Street Journal Abstracts*. We present one positive news story for the category Asia and one negative news story for the category Banking and Finance. We obtain positive newspaper articles by searching for our predefined positive words in the leading paragraph of each newspaper article. Negative newspaper articles are found by searching for our predefined negative words in the leading paragraph of each newspaper article. We also present an example of a newspaper article from the category Banking and Finance that is excluded from our database for robustness checks. Positive and negative keywords are marked in bold, whereas excluded words are marked in *italics*.

Category: Banking and Finance
News: Negative
Source: Financial Times (London, England)
Date of publication: 15 December 2012

Triple A Berating

The British sometimes **drop** their HHHs, and even their RRRs. Now their AAAs are in peril. Standard & Poor's has become the third of the three big rating agencies to put the UK's credit rating on its **danger** list. The UK's creditworthiness outlook is "**negative**", and a downgrade of its credit rating cannot be far away.

With a non-existent economic recovery and wayward public finances, it is not a surprise. Still, it will be a blow. A triple A credit rating is not to be discarded lightly, if only because, once lost, it is very hard to get it back. Having one not only offers lower borrowing costs. It enables a country to say: "I have a triple A rating, and you don't! " In fact, the bragging rights attached to it are probably as valuable to the owner as the cheaper borrowing, and, let's face it, a lot more fun.

Category: Asia
News: Positive
Source: Financial Times (London, England)
Date of publication: 28 January 2005

Philippines set for further growth

The Philippine economy has been growing at its fastest in more than a decade and is expecting further **growth**. Romulo Neri, economic planning secretary, said gross domestic product was forecast to grow by as much as 6.3 per cent this year, largely due to expected foreign investment in mining projects and plans to spend more on large civil works projects.

Category: Banking and Finance
News: Robustness check - excluded news
Source: Financial Times (London, England)
Date of publication:

Euro hits highest since May on signs of easing *recession*

The euro surged to its highest point since early May against the US dollar yesterday as unexpectedly **positive** economic data suggested the eurozone *recession* was easing amid continuing fears of **easy** monetary policy in the US.

The "flash" estimate of Markit's composite eurozone Purchasing Managers' Index rose to 47.3, its highest level in nine months, but still below the 50 mark denoting expansion.

BNP Paribas' FX team said the single currency was also benefiting from a positioning perspective as year-end window dressing dragged in positive flows.

The euro gained 0.7 per cent against the dollar to a high of $1.3173 to finish the week up 1.8 per cent.

The dollar index fell 0.5 per cent to 79.5 points as a US report on inflation showed prices fell in November for the first time in six months .

Sterling retrenched following Standard & Poor's decision on Thursday to downgrade the outlook on Britain's triple A rating to negative, implying a one-third chance of a downgrade in the next two years. All three large credit rating agencies now have Britain's triple A status on negative outlook. A downgrade might hit sterling if it deters haven flows, which have supported the pound during the financial crisis.

The pound gained 0.2 per cent against the dollar to $1.6141 to finish the week up 0.6 per cent.

The Japanese yen steadied ahead of elections on Sunday when the opposition Liberal Democratic party and its overtly dovish leader Shinzo Abe are expected to return to power. The yen fell as far as Y83.96 to near a nine-month low earlier in the session after the Bank of Japan's quar-terly Tankan report , released yesterday, showed the key measure of business confidence among big manu-facturers fell sharply. Credit Suisse said the data probably reinforced expectations the BOJ might increase easing measures.

Despite the yen fighting back, to trade up 0.2 per cent against the dollar on Friday to Y83.49, analysts be-lieve it will resume its fall throughout 2013.

The yen has lost 8 per cent against the dollar since the middle of September when it sat at Y77.11 and ana-lysts are targeting levels of between Y85 and Y90 in 2013.

Derek Halpenny of Bank of Tokyo-Mitsubishi argued that since markets have priced in a sizeable majority being formed by an LDP-led government, any failure to reach this might encourage yen buying in the short term to square short positions, which sit at multiyear highs.

Table I: Keywords

This table reports the positive and negative keywords that we searched for on the *LexisNexis* database in *Financial Times* (FT), *New York Times* (NYT), and *Wall Street Journal Abstracts* (WSJ) in order to extract newspaper articles that express optimistic and pessimistic media sentiment. The search query is limited to the leading paragraph of the newspaper article. For our robustness check, the bold positive (negative) words got excluded when searched for negative (positive) words in the leading paragraph of a newspaper article.

Positive Words	Negative Words
rise	**fall**
improve	**decline**
increase	**decrease**
climb	**plummet**
ascend	**drop**
expansion	**recession**
benefit	**reduction**
gain	**loss**
success	failure
improvement	impairment
favorable	adverse
advantageous	**disadvantage**
positive	negative
safe	**critical**
secure	**uncertain**
easy	difficult
profitable	default
strong	**weak**
high	**low**
attractive	**risk**
calm	hazard
boom	danger
certainty	crisis
growth	crash
optimistic	downturn
lucrative	impasse
prosperity	**pessimism**

Table II: Descriptive Statistics

This table presents descriptive statistics of the newspaper articles collected for each category. BF, CI, RE, and Asia refer to the *LexisNexis* categories Banking and Finance, Computing and IT, Property, and Asia respectively. FT, NYT, and WSJ refer to the *Financial Times*, *New York Times*, and *Wall Street Journal Abstracts* sources. Panel A presents the average number of newspaper articles on a monthly frequency for all news published in one of our selected categories. Panel B (C) reports descriptive statistics for news that only contains predetermined positive (negative) words in the leading paragraph of a newspaper article. Panel D (E) reports descriptive statistics of newspaper articles that contain predetermined positive (negative) words excluding predetermined negative (positive) words in the leading paragraph of an article.

	Total	BF	CI	RE	Asia	FT	NYT	WSJ
				Panel A: All Data				
Average	7,355	3,135	705	587	2,061	3,563	2,644	1,146
				Panel B: Positive Words				
Average	1,862	945	163	160	461	1,101	547	235
% all data	25%	30%	23%	27%	22%	31%	15%	7%
Min	1,102	526	29	89	247	572	394	92
Max	2,488	1,392	500	411	960	1,578	5,524	416
				Panel C: Negative Words				
Average	1,538	844	98	138	385	898	434	205
% of all data	21%	27%	14%	24%	19%	25%	12%	6%
Min	961	460	26	50	167	484	263	89
Max	3,636	2,544	284	625	988	2,287	826	664
				Panel D: Positive excl. Negative Words				
Average	555	257	51	47	141	347	155	54
% of all data	8%	8%	7%	8%	7%	10%	4%	2%
% Drop	70%	73%	69%	71%	69%	69%	72%	77%
Min	287	124	7	17	66	156	97	18
Max	805	408	159	110	319	538	260	102
				Panel E: Negative excl. Positive Words				
Average	1,266	702	79	114	326	718	363	185
% of all data	17%	22%	11%	19%	16%	20%	10%	5%
% Drop	18%	17%	20%	18%	15%	20%	16%	10%
Min	818	368	21	40	141	381	240	81
Max	3,215	2,272	229	547	910	2,033	677	522

Table III: VAR Model - Market Proxy

This table presents the estimated coefficients for the VAR model (1):

$$Mrk_t = \alpha_1 + \beta_1 L24(Mrk_t) + \beta_2 L24(Sent_t) + \beta_3 L24(Vola_t) + \beta_4 Exog_t + \epsilon_{1t}$$

where Mrk_t is the log rate of return of the market index for each of the 4 categories; $L24(x_t)$ is a lag operator that transforms the variable x_t into a row vector consisting of 24 lags of x_t; $Sent_t$ is the log change of our media sentiment indicator; $Vola_t$ is the estimated volatility of the corresponding market index; $Exog_t$ are exogenous variables such as *SMB*, *HML*, *MOM*, and *LIQ*. We report only those lags of our media sentiment indicator, which are statistically significant for at least one category. The original VAR model includes 24 lags for each endogenous variable. Statistical significance is reported by asterisks *, **, and *** at the 10, 5, and 1% level, respectively.

	MSCI World	*t*-stat.	NASDAQ	*t*-stat.	MSCI RE	*t*-stat.	MSCI EM Asia incl. Japan	*t*-stat.
$Sent_{t-1}$	-0.023	-0.763	-0.074***	-3.222	-0.026	-0.786	0.014	-0.040
$Sent_{t-2}$	-0.016	-0.509	-0.065**	-2.117	0.001	0.040	-0.051	-0.048
$Sent_{t-3}$	0.008	0.259	-0.122***	-3.533	-0.014	-0.376	-0.086*	-0.049
$Sent_{t-4}$	0.018	0.557	-0.093***	-2.556	0.002	0.060	-0.064	-0.049
$Sent_{t-5}$	-0.001	-0.057	-0.072**	-1.988	0.026	0.708	-0.069	-0.050
$Sent_{t-10}$	-0.036	-1.121	-0.023	-0.639	-0.062*	-1.709	-0.021	-0.049
$Sent_{t-12}$	-0.028	-0.861	0.002	0.058	-0.062*	-1.711	0.041	-0.051
$Sent_{t-13}$	-0.057*	-1.767	0.024	0.707	-0.031	-0.816	0.038	-0.049
$Sent_{t-14}$	-0.071**	-2.146	0.037	1.089	-0.011	-0.286	0.004	-0.049
$Sent_{t-15}$	-0.030	-0.907	0.042	1.270	-0.069*	-1.785	0.031	-0.049
$Sent_{t-16}$	-0.056*	-1.658	0.039	1.252	0.012	0.327	0.034	-0.049
$Sent_{t-17}$	-0.104***	-3.056	0.048	1.544	-0.020	-0.547	0.018	-0.048
$Sent_{t-18}$	-0.060*	-1.721	0.024	0.793	-0.013	-0.345	0.001	-0.044
$Sent_{t-19}$	-0.061*	-1.829	-0.001	-0.059	-0.040	-1.031	-0.047	-0.043
$Sent_{t-23}$	0.006	0.209	0.051**	1.975	0.004	0.125	0.049	-0.041
SMB_t	0.056	0.566	0.584***	4.803	0.281	1.802	0.178	-0.137
HML_t	-0.323***	-3.203	-0.934***	-7.412	0.080	0.494	-0.100	-0.146
MOM_t	-0.202***	-3.023	-0.373***	-4.439	-0.421***	-4.669	-0.143*	-0.080
LIQ_t	0.1511***	3.468	0.118**	2.181	0.169***	2.591	0.127**	-0.057
Adj.R.sq.	0.142		0.502		0.193		0.058	
$F-Stat.$	1.546		4.326		1.602		1.204	
Number of obs.	251		251		192		251	

Table IV: VAR Model - Market Volatility

This table presents the estimated coefficients for our VAR model (2):

$$Vola_t = \alpha_1 + \beta_1 L24(Mrk_t) + \beta_2 L24(Sent_t) + \beta_3 L24(Vola_t) + \beta_4 Exog_t + \epsilon_{1t}$$

where Mrk_t is the log rate of return of the market index for each of the 4 categories; $L24(x_t)$ is a lag operator that transforms the variable x_t into a row vector consisting of 24 lags of x_t; $Sent_t$ is the log change of our media sentiment indicator; $Vola_t$ is the estimated volatility of the corresponding market index; $Exog_t$ are exogenous variables such as *SMB*, *HML*, *MOM*, and *LIQ*. We report only those lags of our media sentiment indicator, which are statistically significant for at least one category. The original VAR model includes 24 lags for each endogenous variable. Statistical significance is reported by asterisks *, **, and *** at the 10, 5, and 1% level, respectively.

	Vola MSCI World	*t*-stat.	Vola NAS-DAQ	*t*-stat.	Vola MSCI RE	*t*-stat.	Vola MSCI EM Asia incl. Japan	*t*-stat.
$Sent_{t-2}$	0.002	1.006	0.004	1.049	0.002	0.444	0.004	-0.003
$Sent_{t-4}$	-0.001	-0.456	0.002	0.505	-0.012**	-2.308	0.003	-0.004
$Sent_{t-8}$	0.000	0.273	-0.000	-0.077	-0.006	-1.121	-0.001	-0.004
$Sent_{t-9}$	-0.000	-0.308	0.000	0.073	0.001	0.186	0.003	-0.004
$Sent_{t-10}$	0.005**	2.051	0.004	0.815	0.007	1.342	0.003	-0.004
$Sent_{t-12}$	0.005*	1.959	0.003	0.591	0.013***	2.437	-0.003	-0.004
$Sent_{t-13}$	0.007***	2.767	0.000	0.006	0.003	0.562	0.004	-0.004
$Sent_{t-14}$	0.008***	3.207	-0.002	-0.434	0.001	0.303	0.005	-0.004
$Sent_{t-20}$	0.003	1.396	0.004	0.876	0.003	0.579	-0.003	-0.003
$Sent_{t-22}$	-0.005**	-2.054	-0.001	-0.234	0.002	0.424	-0.009***	-0.003
$Sent_{t-23}$	-0.001	-0.002	-0.001	-0.003	-0.002	-0.005	-0.005*	-0.003
SMB_t	-0.003	-0.428	0.004	0.242	0.012	0.552	-0.020*	-0.011
HML_t	0.004	0.532	0.019	1.025	-0.012	-0.542	-0.006	-0.011
MOM_t	0.007	1.418	0.016	1.291	0.012	0.965	0.000	-0.006
LIQ_t	-0.011***	-3.342	-0.030***	-3.707	-0.017*	-1.794	0.000	-0.004
Adj.R.sq.	0.160		0.354		0.093		0.146	
$F - Stat.$	1.630		2.803		1.260		1.566	
Number of obs.	251		251		192		251	

Table V: Granger Causality Test

This table presents the χ^2 statistics that tests for the joint significance of coefficients of our monthly media sentiment indicator for various lags. Panel A reports the results for the VAR model (1) where we specify the market index returns as a dependent variable, while Panel B reports the results for the VAR model (2) in which the market volatility is the dependent variable. Market indices are the MSCI World index for the category Banking and Finance, the NASDAQ index for the category Computing and Information Technology, the MSCI RE index for the category Property, and our built-in MSCI EM Asia incl. Japan index for the category Asia. The market volatility is given as demeaned squared residuals of each market index. p-values are reported in brackets. Statistical significance is denoted by asterisks *, **, and *** at the 10, 5, and 1% level, respectively.

	MSCI World	NASDAQ	MSCI RE	MSCI EM Asia incl. Japan
Panel A: Market Return				
Sentiment (Lags 1 to 24)	24.456	40.338**	23.024	16.708
	(0.435)	(0.019)	(0.518)	(0.860)
Sentiment (Lags 1 to 12)	5.438	21.166**	11.422	10.585
	(0.941)	(0.048)	(0.493)	(0.564)
Sentiment (Lags 12 to 24)	24.200**	9.479	13.680	9.734
	(0.029)	(0.735)	(0.396)	(0.715)
Sentiment (Lags 1 to 6)	4.530	17.383***	3.463	7.832
	(0.605)	(0.008)	(0.748)	(0.250)
Sentiment (Lags 6 to 12)	2.650	6.486	8.562	5.251
	(0.915)	(0.484)	(0.285)	(0.629)
Sentiment (Lags 12 to 18)	14.199**	3.108	5.538	3.638
	(0.047)	(0.874)	(0.594)	(0.820)
Sentiment (Lags 18 to 24)	5.765	7.224	6.013	5.573
	(0.567)	(0.405)	(0.538)	(0.590)
Panel B: Market Volatility				
Sentiment (Lags 1 to 24)	32.869	12.464	24.018	35.894*
	(0.106)	(0.974)	(0.460)	(0.056)
Sentiment (Lags 1 to 12)	10.588	8.864	15.966	13.153
	(0.564)	(0.714)	(0.192)	(0.358)
Sentiment (Lags 12 to 24)	34.504***	5.132	16.969	16.026
	(0.001)	(0.972)	(0.200)	(0.247)
Sentiment (Lags 1 to 6)	6.457	5.558	8.402	22.113***
	(0.373)	(0.474)	(0.210)	(0.001)
Sentiment (Lags 6 to 12)	5.383	4.780	5.479	9.021
	(0.613)	(0.686)	(0.601)	(0.251)
Sentiment (Lags 12 to 18)	16.264**	1.570	10.575	11.363
	(0.022)	(0.979)	(0.158)	(0.123)
Sentiment (Lags 18 to 24)	13.338*	2.821	11.626	10.829
	(0.064)	(0.901)	(0.113)	(0.146)

Table VI: Robustness Check: VAR Model - Market Proxy

This table presents the estimated coefficients for the VAR model (1):

$$Mrk_t = \alpha_1 + \beta_1 L24(Mrk_t) + \beta_2 L24(Sent_t) + \beta_3 L24(Vola_t) + \beta_4 Exog_t + \epsilon_{1t}$$

where Mrk_t is the log rate of return of the market index for each of the 4 categories; $L24(x_t)$ is a lag operator that transforms the variable x_t into a row vector consisting of 24 lags of x_t; $Sent_t$ is the log change of our media sentiment indicator; $Vola_t$ is the estimated volatility of the corresponding market index; $Exog_t$ are exogenous variables such as *SMB*, *HML*, *MOM*, and *LIQ*. For the robustness check we construct our monthly media sentiment indicator with a new set of news data, for which we exclude positive (negative) words from our predetermined list of negative (positive) words. We report only those lags of our media sentiment indicator, which are statistically significant for at least one category. The original VAR model includes 24 lags for each endogenous variable. Statistical significance is reported by asterisks *, **, and *** at the 10, 5, and 1% level, respectively.

	MSCI World	t-stat.	NASDAQ	t-stat.	MSCI RE	t-stat.	MSCI EM Asia incl. Japan	t-stat.
$Sent_{t-1}$	-0.018	-0.890	-0.027*	-1.870	-0.023	-1.105	0.005	-0.027
$Sent_{t-3}$	0.010	0.434	-0.049**	-2.134	-0.021	-0.730	-0.074**	-0.034
$Sent_{t-4}$	0.033	1.403	-0.042*	-1.716	-0.002	-0.083	-0.044	-0.034
$Sent_{t-10}$	-0.046**	-2.064	0.020	0.770	-0.019	-0.698	-0.006	-0.036
$Sent_{t-12}$	-0.016	-0.710	0.016	0.629	-0.008	-0.309	0.042	-0.036
$Sent_{t-13}$	-0.044**	-1.954	0.017	0.683	0.003	0.128	0.061*	-0.035
$Sent_{t-14}$	-0.040*	-1.740	0.021	0.867	0.018	0.641	0.021	-0.036
$Sent_{t-17}$	-0.078***	-3.190	0.024	1.028	-0.026	-0.989	0.026	-0.036
$Sent_{t-18}$	-0.061***	-2.564	0.000	0.016	-0.048*	-1.774	0.006	-0.033
$Sent_{t-19}$	-0.051**	-2.178	-0.010	-0.475	-0.040	-1.490	-0.030	-0.032
$Sent_{t-22}$	0.020	0.956	0.014	0.752	-0.028	-1.132	0.013	-0.030
SMB_t	0.081	0.841	0.587***	4.698	0.372***	2.408	0.152	-0.133
HML_t	-0.342***	-3.401	-0.950***	-7.180	0.156	0.961	-0.104	-0.139
MOM_t	-0.233***	-3.654	-0.360***	-4.121	-0.449***	-4.800	-0.173**	-0.080
LIQ_t	0.149***	3.440	0.115**	1.998	0.155***	2.326	0.115**	-0.056
Adj.R.sq.	0.170		0.461		0.499		0.082	
$F-Stat.$	1.674		3.823		1.511		1.297	
Number of obs.	251		251		192		251	

Table VII: Robustness Check: VAR - Market Volatility

This table presents the estimated coefficients for our VAR model (2) :

$$Vola_t = \alpha_1 + \beta_1 L24(Mrk_t) + \beta_2 L24(Sent_t) + \beta_3 L24(Vola_t) + \beta_4 Exog_t + \epsilon_{1t}$$

where Mrk_t is the log rate of return of the market index for each of the 4 categories; $L24(x_t)$ is a lag operator that transforms the variable x_t into a row vector consisting of 24 lags of x_t; $Sent_t$ is the log change of our media sentiment indicator; $Vola_t$ is the estimated volatility of the corresponding market index; $Exog_t$ are exogenous variables such as *SMB*, *HML*, *MOM*, and *LIQ*. For the robustness check we construct our monthly media sentiment indicator with a new set of news data, for which we exclude positive (negative) words from our predetermined list of negative (positive) words. We report only those lags of our media sentiment indicator, which are statistically significant for at least one category. The original VAR model includes 24 lags for each endogenous variable. Statistical significance is reported by asterisks *, **, and *** at the 10, 5, and 1% level, respectively.

	Vola MSCI World	*t*-stat.	Vola NAS-DAQ	*t*-stat.	Vola MSCI RE	*t*-stat.	Vola MSCI EM Asia incl. Japan	*t*-stat.
$Sent_{t-4}$	-0.002	-1.150	0.002	0.731	-0.008*	-1.954	0.000	-0.002
$Sent_{t-13}$	0.005***	2.863	0.001	0.406	0.001	0.241	0.004	-0.002
$Sent_{t-14}$	0.006***	3.375	0.001	0.398	-0.001	-0.295	0.004	-0.003
$Sent_{t-15}$	0.004**	2.124	0.000	0.170	-0.001	-0.258	0.003	-0.003
$Sent_{t-17}$	0.003*	1.876	-0.001	-0.323	-0.000	-0.139	0.000	-0.003
$Sent_{t-20}$	0.003***	2.071	0.001	0.567	0.003	0.825	-0.001	-0.002
$Sent_{t-21}$	0.000	0.123	0.000	0.048	0.002	0.608	0.001	-0.002
$Sent_{t-22}$	-0.003*	-1.914	-0.000	-0.225	0.001	0.416	-0.003	-0.002
SMB_t	-0.006	-0.795	0.015	0.835	0.006	0.267	-0.020	-0.011
HML_t	0.004	0.547	0.023	1.209	-0.016	-0.696	-0.009	-0.011
MOM_t	0.008	1.598	0.017	1.336	0.016	1.213	0.000	-0.006
LIQ_t	-0.012***	-3.466	-0.030***	-3.539	-0.017*	-1.779	0.000	-0.004
$Adj.R.sq.$	0.157		0.341		0.050		0.120	
$F-Stat.$	1.614		2.704		1.132		1.452	
Number of obs.	251		251		192		251	

Table VIII: Robustness Check: Granger Causality Test

This table presents the χ^2 statistics that tests for the joint significance of coefficients of our monthly media sentiment indicator for various lags. Panel A reports the results for the VAR model (1) where we specify the market index returns as a dependent variable, while Panel B reports the results for the VAR model (2) in which the market volatility is the dependent variable. Market indices are the MSCI World index for the category Banking and Finance, the NASDAQ index for the category Computing and Information Technology, the MSCI RE index for the category Property, and our built-in MSCI EM Asia incl. Japan index for the category Asia. For robustness checks we download a new set of news data by excluding prespecified positive (negative) words from the original list of negative (positive) words. The market volatility is given as demeaned squared residuals of each market index. p-values are reported in brackets. Statistical significance is denoted by asterisks *, **, and *** at the 10, 5, and 1% level, respectively.

	MSCI World	NASDAQ	MSCI RE	MSCI EM Asia incl. Japan
Panel A: Market Return				
Sentiment (Lags 1 to 24)	31.055	24.03	19.024	21.753
	(0.152)	(0.459)	(0.750)	(0.594)
Sentiment (Lags 1 to 12)	12.512	12.983	6.457	12.336
	(0.405)	(0.370)	(0.891)	(0.419)
Sentiment (Lags 12 to 24)	23.576**	7.021	15.805	14.849
	(0.035)	(0.901)	(0.259)	(0.316)
Sentiment (Lags 1 to 6)	6.978	9.285	3.903	13.581**
	(0.322)	(0.158)	(0.689)	(0.034)
Sentiment (Lags 6 to 12)	6.202	6.236	3.402	5.784
	(0.516)	(0.512)	(0.845)	(0.565)
Sentiment (Lags 12 to 18)	13.608*	3.879	7.701	4.715
	(0.058)	(0.793)	(0.359)	(0.694)
Sentiment (Lags 18 to 24)	4.900	3.511	7.088	6.687
	(0.672)	(0.834)	(0.419)	(0.462)
Panel B: Market Volatility				
Sentiment (Lags 1 to 24)	32.241	9.078	17.618	29.677
	(0.121)	(0.997)	(0.821)	(0.195)
Sentiment (Lags 1 to 12)	5.555	7.087	8.064	10.734
	(0.936)	(0.851)	(0.780)	(0.551)
Sentiment (Lags 12 to 24)	40.528***	4.973	12.598	12.573
	(0.000)	(0.975)	(0.479)	(0.481)
Sentiment (Lags 1 to 6)	4.580	2.408	5.743	15.634**
	(0.598)	(0.878)	(0.452)	(0.015)
Sentiment (Lags 6 to 12)	1.589	3.550	4.734	5.618
	(0.979)	(0.829)	(0.692)	(0.585)
Sentiment (Lags 12 to 18)	13.680*	3.048	3.789	6.869
	(0.057)	(0.880)	(0.803)	(0.442)
Sentiment (Lags 18 to 24)	16.709**	5.036	9.862	8.313
	(0.019)	(0.655)	(0.196)	(0.305)

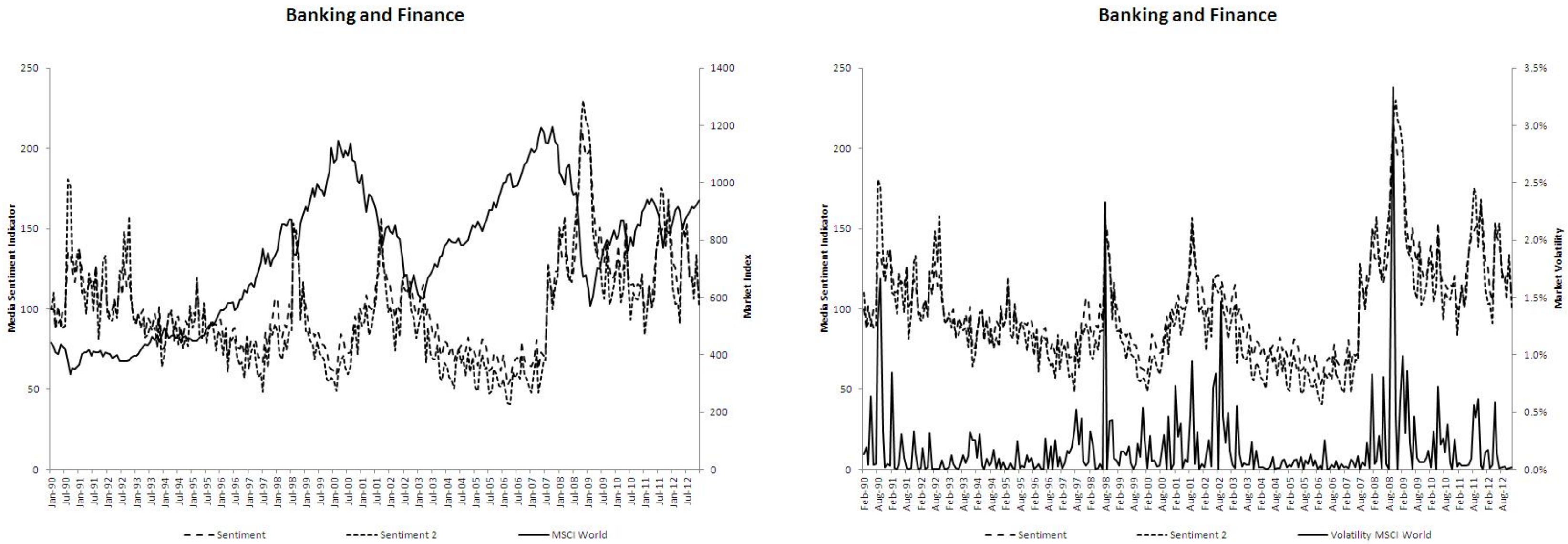


Figure I: Banking and Finance

The graph on the left plots at a monthly frequency media sentiment indicator for the category Banking and Finance and its corresponding market index, MSCI World, over our sample period between January 1990 and December 2012. The graph on the right shows our media sentiment indicator against the demeaned squared residuals of the MSCI World index as a proxy for market volatility. Our media sentiment indicator is constructed by taking the ratio of pessimistic news frame to optimistic news frame. Sentiment 2 is media sentiment indicator constructed for the robustness check. Both media sentiment indicators are standardized to 100 in January 1990.

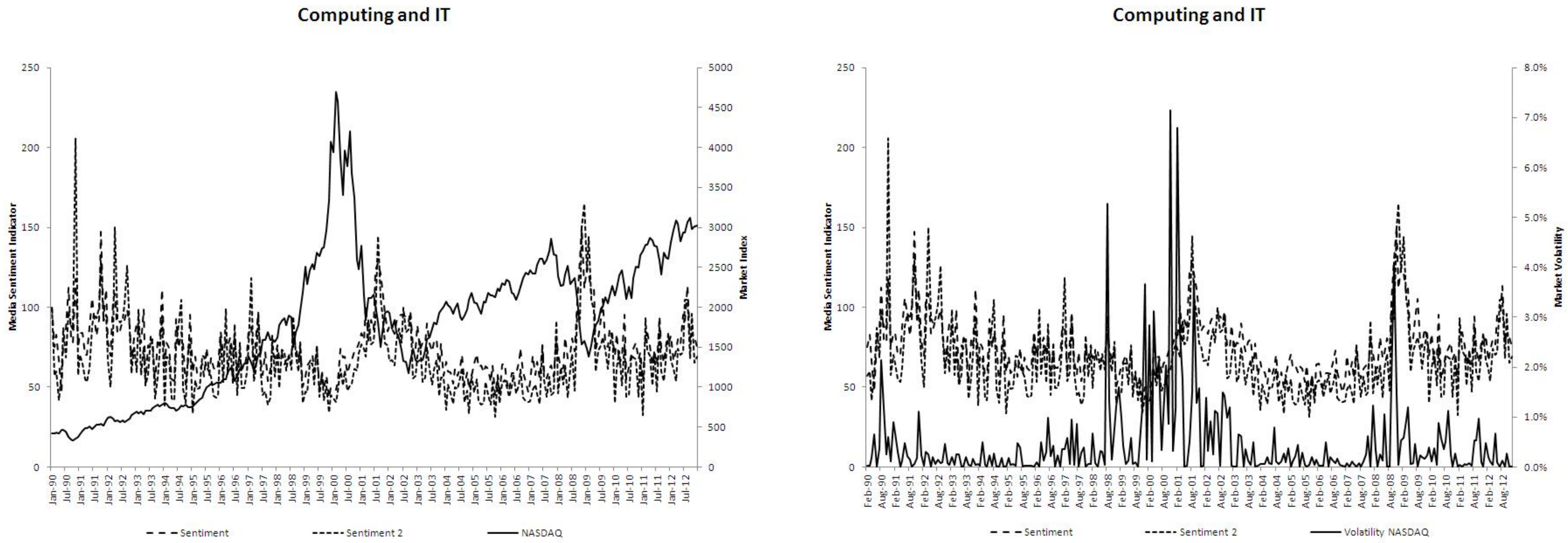


Figure II: Computing and IT

The graph on the left plots our monthly media sentiment indicator for the category Computing and IT and its corresponding market index, NASDAQ, over the sample period between January 1990 and December 2012. The graph on the right shows the media sentiment indicator against the demeaned squared residuals of the NASDAQ as a proxy for market volatility. The media sentiment indicator is constructed by taking the ratio of pessimistic news frame to optimistic news frame. Sentiment 2 is the media sentiment indicator constructed for robustness checks. Both media sentiment indicators are standardized to 100 in January 1990.

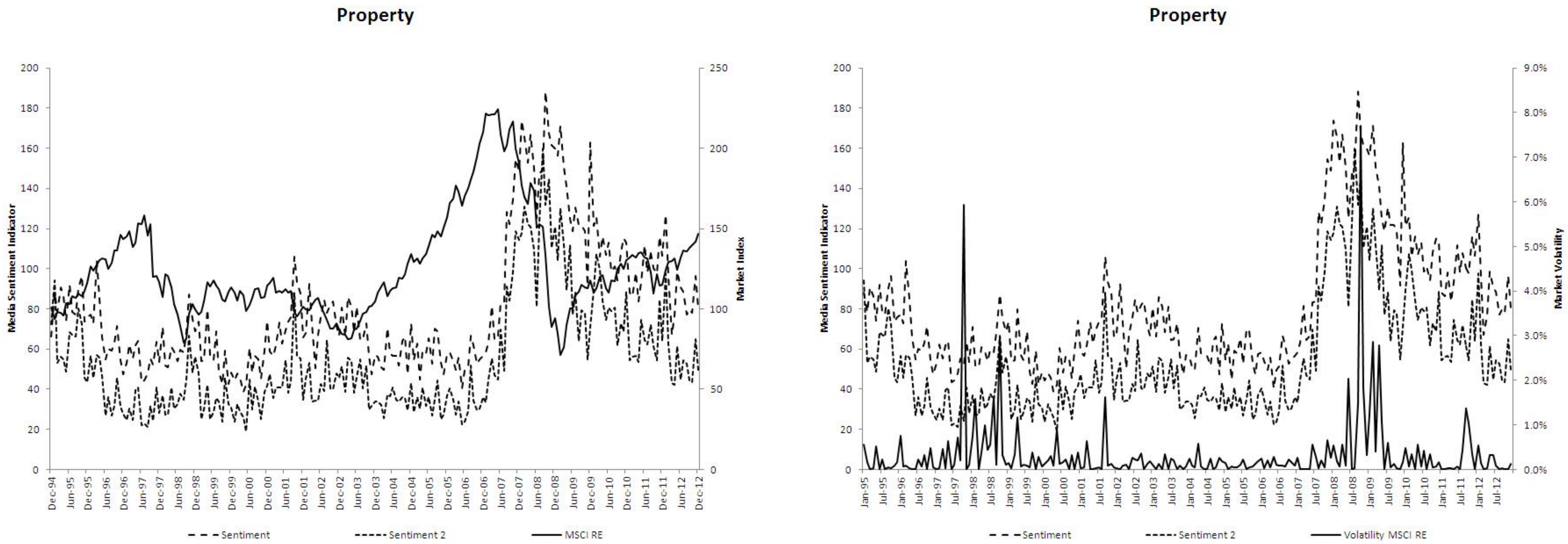
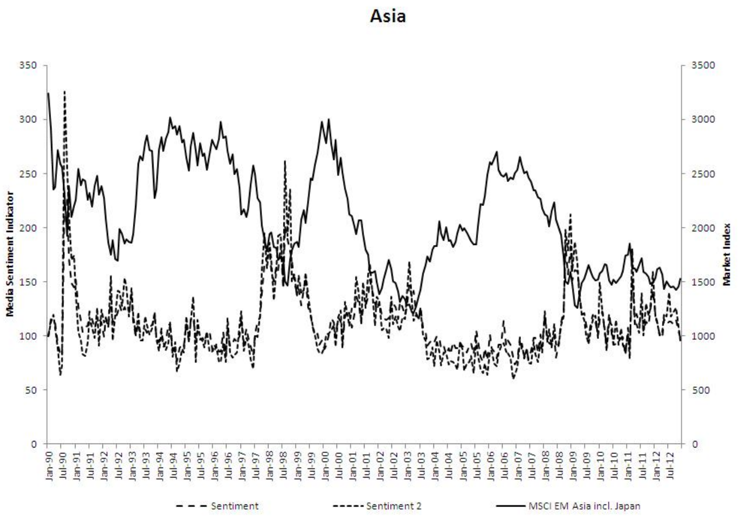


Figure III: Property

The graph on the left shows our media sentiment indicator at a monthly frequency for the category Property and its corresponding market index, MSCI RE, over the sample period between January 1990 and December 2012. The graph on the right shows our media sentiment indicator against the demeaned squared residuals of the MSCI RE as a proxy for market volatility. The media sentiment indicator is constructed by taking the ratio of pessimistic news frame to optimistic news frame. Sentiment 2 is the media sentiment indicator constructed for robustness checks. Both media sentiment indicators are standardized to 100 in January 1990.



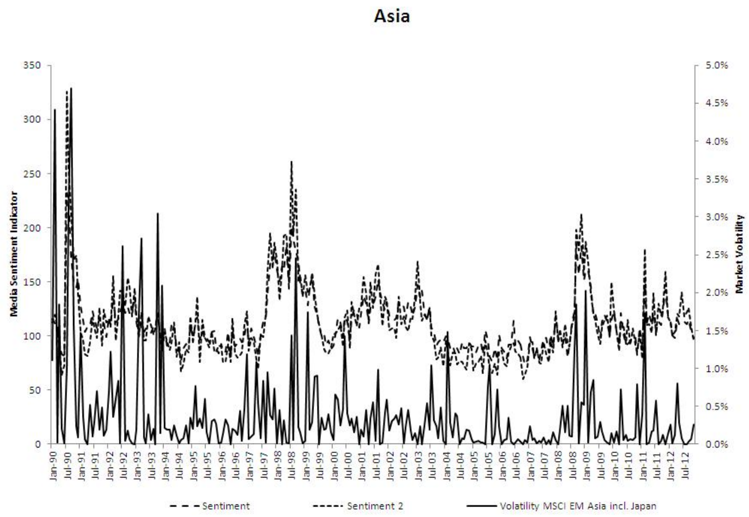


Figure IV: Asia

The graph on the left plots our monthly media sentiment indicator for the category Asia and its corresponding market index, MSCI EM Asia incl. Japan, over the sample period between January 1990 and December 2012. The MSCI EM Asia incl. Japan index is a built-in index that we construct by taking a weighted average of the MSCI EM Asia and the MSCI Japan indices by market capitalization. The graph on the right shows the media sentiment indicator against the demeaned squared residuals of the MSCI EM Asia incl. Japan as a proxy for market volatility. The media sentiment indicator is constructed by taking the ratio of pessimistic news frame to optimistic news frame. Sentiment 2 is the media sentiment indicator constructed for robustness checks. Both media sentiment indicators are standardized to 100 in January 1990.