News Media Sentiment and Investor Behavior

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Abstract

This paper investigates the impact of news media sentiment on financial market returns and volatility in the long-term. We hypothesize that the way the 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 headline and/or the lead paragraph. 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 the financial market crises and pricing bubbles over the past 20 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 whose main goal is to capture attention. They produce *anything* that aligns with the numbers from the markets. Shiller (2005) notes that news plays a crucial role in buying or selling decisions among traders, who constantly react to new incoming information. He further argues that the news media are important players 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 have 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 events and issues are packaged and presented by journalists to the public. They believe that news frames can fundamentally affect the way readers understand 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 at predictable conclusions. Price and Tewksbury (1997) explain the news media framing effect by using 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 (activation) depends on characteristics of a person's established knowledge store. When evaluating situations, people tend to use (activate) ideas and feelings that are most accessible and applicable.

Iyengar (1991) examines the impact of news framing on the way people ascribe responsibility for social, political, and economic conditions. He finds that media more often take an episodic rather than a thematic perspective towards the events they cover. Vliegenthart et al. (2008) investigate the effect of two identified news frames, risk and opportunity, on public support regarding the enlargement of the European Union. 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 may be a powerful tool in influencing public opinion and, as a consequence, the public's future actions.

Our paper uses the concept of framing effects 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 the investor's perception about future prospects as well as investor sentiment. As a result, investors may form certain expectations and update their investment decisions, behaviors 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 performances of 45 U.S. listed companies. They find weak evidence that the number of content messages posted helps to predict a stock's intraday volatility, but they do not find evidence of news media content influencing market returns and trading volumes. 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*, and finds evidence of 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 resulting monthly investor sentiment index reflects reasonably well previous U.S. financial bubbles and crises from 1961 onward until 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, which is contrary to the view that media effects are immediate. Based on this intuition, we investigate herein 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. To our best knowledge, this paper is the first that investigates the impact that the 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 about the economy and financial markets. We argue that news that uses at least one of our predetermined positive words raises positive, optimistic thoughts in readers' minds. Similarly, we assume that news that uses at least one of our negative words raises 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 compared to the number of newspaper articles that contain predetermined positive words in the headline and the lead paragraph. We limit our search for keywords to the headline and the lead paragraph as 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 Banking and Finance category in order to limit our search to only economic and financial markets news. This cateogry includes news about historical financial crises 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 in 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 performance of the global financial markets. Our results show a significant negative (positive) long-term relation between our media sentiment indicator and market returns (volatility), and we find evidence of the predictive activity of the media sentiment indicator for global market returns and volatilities 12 to 24 months in advance. The interpretation of our findings is that while the news media create pessimistic market sentiment as more newspaper articles express pessimism, this effect occurs gradually rather than immediately. We 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 those 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 the paper.

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 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 and 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. *LexisNexis* classifies each newspaper article into various categories based on the content. In order to limit our search only to economic and financial markets news, we select the *LexisNexis* category Banking and Finance. 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. We gather our data by searching *LexisNexis* for WSJ, FT, and NYT articles that are classified under the category Banking and Finance and that include one of our predetermined positive (negative) words in the headline and/or the lead paragraph. We limit our search only to the headline and the lead paragraph of a newspaper article as this paragraph summarizes the main message of the article and has the greatest impact on the reader. A list of words is presented in Table 1. We assume that a newspaper article that contains one of the positive words in the headline and/or the lead paragraph is more likely to generate positive thoughts in readers' minds and to express optimistic media sentiment. Similarly, articles that contain one of the negative words in the headline and/or the lead paragraph are more likely to generate negative thoughts in readers' minds and to express pessimism. Thus, we classify former newspaper articles as an optimistic news frame and latter articles as a pessimistic news frame.

[Please insert Table 1 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 posit are often used in the financial press. Table 1 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, results in 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 1 presents the excluded negative and positive words marked in bold. The examples of newspaper articles found using our approach are presented in Appendix.

We collect 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. We find 3,135 newspaper articles on average per month.

When we limit our search to predefined words, we find slightly more news articles with positive words than with negative words. We find 945 (844) articles when searched for positive (negative) words in the headline and/or the lead paragraph or 30% (27%) of the total number of articles. When we further limit our search query by excluding negative (positive) words from a positive (negative) word search, we find 257 (702) newspaper articles in total or 8% (22%) of the total number of newspaper articles. When negative words are excluded from the search of positive words, the number of newspaper articles decreases by almost 73% (from 945 to 257). On the contrary, when positive words are excluded from the negative word search, the number of newspaper articles declines by 17% (from 844 to 702). It seems that there are more articles that use positive words in the 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 compared to the number of newspaper articles that contain positive words. To perform regression analysis, we assign the MSCI World index as the market index. The data has been downloaded from *Datastream* for the period between January 1990 and December 2012.

We extend the analysis to the effect of news frames on market volatility. We calculate a proxy for monthly volatility of the MSCI World index by following Tetlock's

(2007) approach. We demean the MSCI World 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 as well as the Pastor-Stambaugh aggregate liquidity factor (*LIQ*) downloaded at a monthly frequency from *Wharton Research Data Services*. Furthermore, following the work of Chen, Roll and Ross (1986) we extend our model with some additional macroeconomic variables such as U.S. inflation, U.S. Consumer Confidence Index, Federal Fund Rates, U.S. Yield Spread, U.S. Industial Production, and U.S. Unemployment rate. We estimate U.S. inflation by using U.S. Consumer Price index (CPI). U.S. Yield spread is the difference between U.S. Treasury Yield adjusted to constant maturity for 20 years and three month U.S. Treasury Bill rate. All macroeconomic variables are downloaded from *Datastream* at a monthly frequency.

2.2 Methodology

To investigate a potential long-term media sentiment effect on the performance of financial markets, we estimate two VAR models, where endogenous variables are the MSCI World index and our constructed monthly media sentiment indicator for VAR model (1) and MSCI World volatility and media sentiment indicator for VAR model (2). Exogenous variables are *SMB*, *HML*, *MOM*, and *LIQ* factors and macroeconomic variables such as U.S. Inflation, U.S. Consumer Confidence Index, Federal Fund Rates, U.S. yield spread, U.S. Industrial Production, and U.S. Unemployment. 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 return and volatility. We analyze the effect of news media sentiment by performing the following regressions:

$$Mrk_t = \alpha_1 + \beta_{11} L24(Mrk_t) + \beta_{21} L24(Sent_t) + \beta_{31} Exog_t + \epsilon_{t1} \tag{1}$$

and

$$Vola_t = \alpha_2 + \beta_{12} L24(Vola_t) + \beta_{22} L24(Sent_t) + \beta_{32} Exog_t + \epsilon_{t2} \tag{2}$$

where Mrk_t is the log rate of return of the MSCI World index; $L24(x_t)$ 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 squared demeaned residuals of the MSCI World returns; $Exog_t$ are exogenous variables such as size (*SMB*), value (*HML*), momentum (*MOM*), and liquidity (*LIQ*) and other macroeconomic variables which are included in the model to control for other potential anomalies that are not driven by the news media. α_j are estimated constants and β_{ij} are estimated VAR coefficients.

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 the complicated interlinked relationship between news media and financial markets where news influences 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. To disentangle these two forces, we run additional Granger causality tests on the subsets of lagged coefficients of our media sentiment indicator. We assume that if a media sentiment effect occurs, 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 for two years before the effect becomes visible. Testing for subsets 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. To draw conclusions about market reaction, we examine 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 to control for other potential anomalies on stock market returns and volatilities that are not driven by the news media. Pastor and Stambaugh (2003) document 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 the Pastor-Stambaugh aggregate liquidity factor as state variables and include them as control variables in our model.

3 Discussion of Results

Figure 1 plots our media sentiment indicator against the MSCI World index. We see that the monthly media sentiment indicator follows closely the historical economic developments and economic crises on the global financial market. Our media sentiment indicator tends to decline when the economy is growing and to increase when the economy becomes less stable. This indicates that during global economic expansions there is a tendency to publish more optimistic than pessimistic news. On the other hand, when the global economy enters a recessionary state, media pessimism begins to prevail as our media sentiment indicator reaches its peak in times of crises. Overall, the MSCI World index tends to move upward between 1990 and 2000 with temporal downward movements during the Japanese real estate turmoil at the beginning of the 1990s and the Mexican peso crisis in late 1994, and during a wave of economic and financial crises in emerging markets in 1997-98 (Adams et al, 1998). The MSCI World was growing at an annual rate of 9.3% between 1990 and 2000. Our media sentiment indicator exhibits large swings around crisis periods ranging from 62 to 148 between 1990 and 2000 and reaching 135 in August 1990 as it reflected the 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 downward between 1990 and 2000, thus implying that media sentiment became more optimistic in the 1990s as the world economy grew.

[Please insert Figure 1 about here]

The MSCI World index reached its turning point at the beginning of the millennium when the dot-com crash in 2000-01 reversed the trend of the global economy. The MSCI World lost 66% of its value between its peak in March 2000 and its trough in September 2002. Our media sentiment indicator exhibits steady growth during this period, thus 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 13.8% and reached its historical high of 1,191.1 in October 2007. Figure 1 indicates that our media sentiment indicator falls as the economy grows. Between 2003 and October 2007, the media sentiment indicator ranged between 52 and 117, reaching its lowest level in March 2006. A significant increase in media pessimism was visible already at the beginning of 2007, while the MSCI World was still growing. Our media sentiment indicator predicts a financial downturn *ex-ante* as 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. The 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. Declining U.S. and global housing markets and a wave of bankruptcies among financial institutions set the world economy in a prolonged recession. Though our media sentiment indicator fell from its peak in September 2008, it remained at a relatively high level until the end of 2012. The average media sentiment indicator level after Lehman was 134, which was higher than the overall average of 101 for the entire time span.

[Please insert Figure 2 about here]

Figure 2 plots our media sentiment indicator against MSCI World volatility. Our MSCI World volatility measure is the squared demeaned residuals of the MSCI World return, which we use as a risk measure to indicate a level of uncertainty on the global financial markets at a particular point in time. We note that the MSCI World volatility tends to increase at times of financial crises and tends to fall during 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 3.3% (the highest) 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 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 and 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 2 presents the estimated VAR coefficients of our media sentiment indicator for MSCI World returns as a dependent variable. For the sake of convenience, we report only selected lags. The actual VAR model includes 24 lags of each endogenous variable.

[Please insert Table 2 about here]

We find negative statistically significant coefficients for lags 10 and 13 at a marginal significance of 10% and lags 14 and 17 at a 5% significance level in column 2 when we do not control for exogenous variables. Lag 10 becomes insignificant once contemporenious Fama-French factors for size and value, Carhart's factor for momentum and Pastor-Stambaugh factor for liquidity is added into the model. On the other hand, lags 14 and 17 become statistically significant at 1%. Once we extend our model with additional macroeconomic variables, a strongly statistically significant coefficient is observed only for lag 17 at 1%. Lags 13 and 14 are statistically significant at a marginal level. The negative sign of the coefficients confirms our expectations and is consistent 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 implies a negative relation between our media sentiment indicator and market returns up to 17 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.

[Please insert Table 3 about here]

Table 3 reports the estimated coefficients of our media sentiment indicator for the VAR model (2) where demeaned squared residuals of the MSCI World index is the dependent variable. The original VAR model (2) includes 24 lags for each endogenous variable. We obtain positive statistically significant coefficients for our media sentiment indicator for lags 2, 10, 12, 13, 14, and 20 in collumn 2 when we do not control for exogenous variables. All lags are statistically significant at either 5% or 1% except for lag 13, which is margnially significant. The coefficients remain negative and strongly statistically significant after controlling for Fama-French size and value factors, Carhart's momentum factor, Pastor and Stambaugh liquidity factor and macroeconomic variables. 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 monthly volatility of the MSCI World index.

Additionally to Antweiler and Frank (2004) and Tetlock (2007), who show the effect of the news media over the 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 predicts MSCI World volatility up to 20 months in advance.

The insignificance of the F statistic for both models is due to the fact that we include many lagged variables. The original VAR model (1) and VAR model (2) estimates 83 coefficients, many of which are statistically insignificant. F-statistics is improved and becomes significant once less variables are included in the model.

As already indicated in the methodology section, drawing conclusions based on only VAR coefficients may not be sufficient. Tetlock (2007) shows that not only news media influence markets, but 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 of Price and Tewksbury (1997) and McCombs (2004), we hypothesize whether news media can influence financial markets gradually over the long-term. We are interested in an approximate time span during which a significant effect of media sentiment occurs rather than an exact month. To test the hypotheses of the long-term news media effect on global financial market performance, we 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 4 reports Granger causality test results of the causal relation of our media sentiment indicator on the MSCI World returns, MSCI World returns on media sentiment, media sentiment on MSCI World volatility and MSCI World volatility on media sentiment for all 24 lags and for the subsets of lags. There is a marginally significant causal relation of our media sentiment indicator on the MSCI World return for the subset of lags 12 to 24 and 12 to 18. This means that the coefficients estimated for our VAR models (1) for lags 12 to 24 and for lags 12 to 18 are jointly statistically significant. On the other hand, there seems to be no causal relation of the MSCI World returns on our media sentiment indicator. Additionally, we find lags 1 to 24 of media sentiment indicator for MSCI World volatility jointly statistically significant at a marginal level. There are no statistically significant causality results for MSCI World volatility on our media sentiment indicator. From Table 2 and 3, we can infer that these coefficients are negative for the MSCI World returns and positive for the MSCI World 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 years in advance. The results also show that the MSCI World returns and the MSCI World volatility do not exert a causal relation on our media sentiment indicator.

[Please insert Table 4 about here]

Our results in Table 4 contribute to the previous research by showing that news media sentiment has a causal effect not only in the short-run, 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 implanted in investors' minds through the applicability effect. As pessimistic news media sentiment becomes prevalent, increasingly more investors begin to agree with this point of view, thereby forming pessimistic investor sentiment. Pessimistic investor sentiment places 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, a finding that is consistent with the hypothesis that news media can truly have an effect only over the long-term (McCombs 2004). It seems that our media sentiment indicator can send signals of a turning point in a business cycle *ex-ante* and can be used as a proxy for investor sentiment similar to the proxy constructed by Baker and Wurgler (2006).

4 Robustness Check

To check for the robustness of our results, we download a new set of news data and repeat the same statistical analysis. We collect our new dataset by performing the same search query on *LexisNexis* and by using the same positive and negative words in the headline and/or the lead 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 1. By specifying our search query in such a way, we remove, to some extent, those newspaper articles that use words that are classified as positive (negative) in the negative (positive) context. For example, words such as "risk" are classified as negative words, and words such as "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 the phrase "increasing risk" will be counted twice and classified under both optimistic and pessimistic news frames. By excluding the word "risk" from a positive word search, we remove newspaper articles that use such phrases from our optimistic news frame dataset. In total, when negative (positive) words are excluded from the positive (negative) words search, the number of newspaper articles decreases by 73% (17%). This sharp difference between the number of newspaper articles in our optimistic and pessimistic news frames before and after word exclusion may indicate that journalists tend to use more positive words in the negative context than otherwise.

The estimated coefficients for the market sentiment indicator in the VAR models (1) and (2) on the new set of news data are similar to the results obtained for the old news data set (Table 5 and Table 6). We find negative statistically significant coefficients for the MSCI World return for lags 10, 11, 13, 17 and 22 when we do not control for exogenous variables. Most of the coefficients are statistically significant only at 10% except for the coefficient for lag 10. After controlling for size, value, momentum and liquidity, we find coefficients for lags 10, 13, 14, 17, 18, and 19 statistically significant. Additionally, after controlling for macroeconomic variables, lags 10, 13, 17, 18 and 19 are strongly statistically significant except for lag 10, which is significant at 10%. (Table 5).

[Please insert Table 5 about here]

Furthermore, we observe positive statistically significant coefficients for the MSCI World volatility at lags 2, 3, 10, 12, 13, 14, 15, 16, 17, and 20 when we do not control for exogenous variables. Lags 10, 14, 15, and 20 are statistically significant at 5%. We find lags 3, 10, 12, 13, 14, 15, 17 and 20 statistically significant after controlling for size, value, momentum and liquidity factors. Additionally, lags 10, 12, 13, 14, 15 and 20 are statistically significant after including all sets of controls where the coefficients for lags 13, 14, 15, and 20 are statistically significant at 5% and 1% (Table 6).

[Please insert Table 6 about here]

Lastly, Table 6 reports Granger causality test results of the media sentiment indicator on the MSCI World returns, MSCI World returns on media sentiment indicator, media sentiment indicator on MSCI World volatility and MSCI World volatility on media sentiment indicator for our new news dataset. The causal relation of media sentiment indicator on MSCI World returns becomes insignificant for the new dataset. On the other hand, there seems to be a strong causal relation of media sentiment indicator on MSCI World volatility at lags 12 to 24 and 18 to 24. There is no causal relation of the MSCI World returns and MSCI World volatility on media sentiment indicator.

[Please insert Table 7 about here]

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 exerts 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 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 on the global economy for up to 24 months in advance.

We find evidence of the causal relation of media sentiment on the global market return and global market volatility for 12 to 24 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 a leading investment sentiment indicator similar to the investor sentiment proxy proposed by Baker and Wurgler (2006).

Our main contribution to the literature is that we show that news media can have a prolonged effect on 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, raises negative thoughts in investors' minds through the applicability effect, as 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 give rise to in their evaluation of the economic outlook. Pessimistic investors begin to anticipate the deterioration of the financial performance and start to adjust their investment decisions such that they subsequently increase the uncertainty on the markets and exert downward pressure on financial returns.

Notes

[1] the list of words is available online at `http://www3.nd.edu/~mcdonald/Word_Lists.html`

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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 and one negative news story in the *LexisNexis* category Banking and Finance. We obtain positive newspaper articles by searching for our predefined positive words in the lead paragraph of each newspaper article. Negative newspaper articles are found by searching for our predefined negative words in the lead paragraph of each newspaper article. We also present an example of a newspaper article 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: Positive

Source: The New York Times

Date of publication: 14 April 2004

Dow Jones Sales Rose in Quarter

Dow Jones & Company, publisher of The Wall Street Journal, said yesterday that its first-quarter sales rose 12 percent, the most in almost four years, on a surge in financial advertising. Profit fell 73 percent from a year earlier, when the company had a **gain** from a legal settlement.

Sales advanced to $401.6 million, from $358.2 million, the company said. Net income fell to $17.8 million, or 22 cents a share, from $66.9 million, or 82 cents, a year earlier, when the settlement produced a gain of $59.8 million, or 73 cents a share. Excluding the 2003 gain and other items, the company's profit would have almost doubled.

Advertising at The Journal rose 6.3 percent, helped by a surge in March as financial service companies increased spending from a year earlier. Financial companies like Merrill Lynch and Goldman Sachs had their most profitable first quarters ever.

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: Banking and Finance

News: Robustness check - excluded news

Source: Financial Times (London, England)

Date of publication: 15 January 1999

Interest rate cuts calm concerns

Interest rate cuts calm concerns.

UK consumers worry about keeping their jobs but show no signs of losing confidence overall, according to a survey published yesterday.

The number of people feeling ***pessimistic*** about their personal employment outnumbered those feeling ***optimistic*** to the greatest degree since 1993, said Business Strategies, the economic consultancy that conducted the survey.

But individual households are more convinced they will be better off this year, following recent reductions in interest rates by the Bank of England.

"The cutting of interest rates, the easing of criticism of the monetary policy committee, and a lack of headline financial crises have helped calm concerns about the state of the economy," Business Strategies said.

Table 1. Keywords

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**

Note: This table reports positive and negative keywords that we include in the search query on the *LexisNexis* database to extract newspaper articles from the *Financial Times* (FT), the *New York Times* (NYT), and *Wall Street Journal Abstracts* (WSJ) that express optimistic and pessimistic media sentiment about the economy and financial markets. Most of the negative words are borrowed from the list of 30 most frequent words occurring in 10-Ks from Fin-Neg Word lists in Loughran and McDonald (2011). Positive words are antonyms of negative words. The search query is limited to the headiline and the lead paragraph of the newspaper article. For the robustness check, we exclude positive (negative) words marked in bold when searching for negative (positive) words in the headline and the lead paragraph of a newspaper article.

Table 2. VAR Model - Market Return

	(1)	(2)	(3)
$Sent_{t-10}$	-0.059*	-0.042	-0.030
	(-1.781)	(-1.406)	(-0.940)
$Sent_{t-13}$	-0.064*	-0.056*	-0.059*
	(-1.930)	(-1.886)	(-1.851)
$Sent_{t-14}$	-0.068**	-0.071***	-0.065*
	(-2.064)	(-2.334)	(-1.931)
$Sent_{t-17}$	-0.071**	-0.100***	-0.104***
	(-2.151)	(-3.287)	(-3.261)
Controls			
$FFFactor$	No	Yes	Yes
MoM_t	No	Yes	Yes
LIQ_t	No	Yes	Yes
$Macro$	No	No	Yes
Adj. R-sq.	-0.019	0.176	0.176
F-stat.	0.899	2.033	1.907

Note: This table presents the estimated coefficients of our media sentiment indicator ($Sent_t$) for the VAR model (1) where the log return of the MSCI World index is the dependent variable. FF Factor are contemporaneous Fama-French factors for size (SMB_t) and value (HML_t). MoM_t is Carhart's momentum factor. LIQ_t is Pastor-Stambaugh liquidity factor. $Macro$ includes macroeconomic variables such as U.S. inflation, U.S. Consumer Confidence Index, Federal Fund Rates, U.S. Yield Spread, U.S. Industrial Production, and U.S. Unemployment rate. We report only those lags of our media sentiment indicator, which are statistically significant. Values in brackets are t-statistics. Statistical significance is reported by asterisks *, ** and *** at the 10%, 5% and 1% level respectively.

Table 3. VAR Model - Market Volatility

	(1)	(2)	(3)
$Sent_{t-2}$	0.005***	0.004**	0.004***
	(2.634)	(2.320)	(1.997)
$Sent_{t-10}$	0.006***	0.005***	0.006***
	(3.009)	(2.670)	(2.749)
$Sent_{t-12}$	0.004**	0.004**	0.005**
	(1.997)	(2.037)	(2.403)
$Sent_{t-13}$	0.004*	0.004**	0.004**
	(1.927)	(1.984)	(1.967)
$Sent_{t-14}$	0.006***	0.007***	0.005**
	(2.929)	(3.213)	(2.336)
$Sent_{t-20}$	0.004**	0.006***	0.005**
	(2.071)	(2.793)	(2.244)
Controls			
FF Factor	No	Yes	Yes
MoM_t	No	Yes	Yes
LIQ_t	No	Yes	Yes
$Macro$	No	No	Yes
Adj. R-sq.	0.081	0.142	0.176
F-stat.	1.460	1.800	1.906

Note: This table presents the estimated coefficients of our media sentiment indicator ($Sent_t$) for the VAR model (2), where the volatility of the MSCI World estimated by using demeaned squared residuals of the index, is the dependent variable. FF Factor are contemporaneous Fama-French factors for size (SMB_t) and value (HML_t). MoM_t is Carhart's momentum factor. LIQ_t is Pastor-Stambaugh liquidity factor. $Macro$ includes macroeconomic variables such as U.S. inflation, U.S. Consumer Confidence Index, Federal Fund Rates, U.S. Yield Spread, U.S. Industrial Production, and U.S. Unemployment rate. We report only those lags of our media sentiment indicator, which are statistically significant. Values in brackets are t-statistics. Statistical significance is reported by asterisks *, ** and *** at the 10%, 5% and 1% level respectively.

Table 4. Granger Causality Test

	$Sent - Mkt$	$Mrk - Sent$	$Sent - Vola$	$Vola - Sent$
Lags 1 to 24	21.636	20.193	33.781*	17.821
	(0.601)	(0.685)	(0.088)	(0.811)
Lags 1 to 12	5.974	13.226	16.905	11.927
	(0.917)	(0.352)	(0.153)	(0.451)
Lags 12 to 24	19.874*	6.405	19.425	7.535
	(0.098)	(0.930)	(0.110)	(0.872)
Lags 1 to 6	6.568	8.540	7.807	6.711
	(0.362)	(0.201)	(0.252)	(0.348)
Lags 6 to 12	2.293	2.176	10.871	5.416
	(0.941)	(0.949)	(0.144)	(0.609)
Lags 12 to 18	13.118*	3.651	5.866	7.907
	(0.069)	(0.818)	(0.555)	(0.340)
Lags 18 to 24	2.990	1.664	11.109	1.688
	(0.885)	(0.976)	(0.133)	(0.975)

Note: This table presents the Granger causality test results for the various subsets of lags. We report the estimated χ^2 statistics and its statistical significance for the causal relation of our media sentiment indicator on MSCI World returns ($Sent - Mkt$), of MSCI World on our monthly media sentiment indicator ($Mkt - Sent$), of media sentiment indicator on MSCI World Volatility ($Sent - Vola$) and of MSCI World volatility on our media sentiment indicator ($Vola - Sent$). MSCI World is the log return of the MSCI World index. MSCI World Vola is the squared demeaned residuals of the log returns of the MSCI World index. As exogenous variables, we include Fama-French factors for size and value, Carhart's momentum factor, Pastor-Stambaugh liquidity factor and macroeconomic variables such as U.S. inflation, U.S. Consumer Confidence Index, Federal Fund Rates, U.S. Yield Spread, U.S. Industrial Production, and U.S. Unemployment rate. p-values are reported in brackets. Statistical significance is denoted by asterisks ** and *** at the 10%, 5% and 1% level respectively.

Table 5. Robustness Check: VAR Model - Market Return

	(1)	(2)	(3)
$Sent_{t-10}$	-0.058**	-0.040*	-0.038*
	(-2.439)	(-1.892)	(-1.721)
$Sent_{t-11}$	-0.040*	-0.031	-0.032
	(-1.675)	(-1.432)	(-1.434)
$Sent_{t-13}$	-0.045*	-0.045**	-0.050**
	(-1.882)	(-2.105)	(-2.167)
$Sent_{t-14}$	-0.034	-0.041*	-0.035
	(-1.408)	(-1.877)	(-1.517)
$Sent_{t-17}$	-0.042*	-0.067***	-0.065***
	(-1.734)	(-2.975)	(-2.727)
$Sent_{t-18}$	-0.039	-0.052**	-0.052**
	(-1.620)	(-2.371)	(-2.297)
$Sent_{t-19}$	-0.028	-0.042*	-0.046**
	(-1.193)	(-1.953)	(-2.057)
$Sent_{t-22}$	0.040*	0.028	0.028
	(1.836)	(1.415)	(1.319)
Controls			
FF Factor	No	Yes	Yes
MoM_t	No	Yes	Yes
LIQ_t	No	Yes	Yes
$Macro$	No	No	Yes
Adj. R-sq.	-0.016	0.197	0.204
F-stat.	0.915	2.181	2.083

Note: This table presents the estimated coefficients of our media sentiment indicator ($Sent_t$) for the VAR model (1) for the robustness check, where the log return of the MSCI World index is the dependent variable. 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. FF Factor are contemporaneous Fama-French factors for size (SMB_t) and value (HML_t). MoM_t is Carhart's momentum factor. LIQ_t is Pastor-Stambaugh liquidity factor. $Macro$ includes macroeconomic variables such as U.S. inflation, U.S. Consumer Confidence Index, Federal Fund Rates, U.S. Yield Spread, U.S. Industrial Production, and U.S. Unemployment rate. We report only those lags of our media sentiment indicator, which are statistically significant. Values in brackets are t-statistics. Statistical significance is reported by asterisks *, ** and *** at the 10%, 5% and 1% level respectively.

Table 6. Robustness Check: VAR Model - Market Volatility

	(1)	(2)	(3)
$Sent_{t-2}$	0.002*	0.002	0.001
	(1.948)	(1.502)	(1.066)
$Sent_{t-3}$	0.002*	0.002*	0.002
	(1.742)	(1.779)	(1.392)
$Sent_{t-10}$	0.003**	0.003**	0.002*
	(2.507)	(2.031)	(1.853)
$Sent_{t-12}$	0.002*	0.002*	0.003*
	(1.668)	(1.759)	(1.957)
$Sent_{t-13}$	0.003*	0.003**	0.003**
	(1.923)	(2.108)	(2.152)
$Sent_{t-14}$	0.004***	0.004***	0.004**
	(2.810)	(3.035)	(2.469)
$Sent_{t-15}$	0.003**	0.003**	0.003**
	(2.187)	(2.378)	(2.169)
$Sent_{t-16}$	0.002*	0.002	0.001
	(1.795)	(1.283)	(1.114)
$Sent_{t-17}$	0.002	0.002*	0.002
	(1.384)	(1.645)	(1.257)
$Sent_{t-20}$	0.004***	0.005***	0.004***
	(2.833)	(3.351)	(2.905)
Controls			
FF Factor	No	Yes	Yes
MoM_t	No	Yes	Yes
LIQ_t	No	Yes	Yes
$Macro$	No	No	Yes
Adj. R-sq.	0.066	0.129	0.204
F-stat.	1.370	1.714	2.083

Note: This table presents the estimated coefficients of our media sentiment indicator ($Sent_t$) for the VAR model (2) for the robustness check, where the volatility of the MSCI World estimated by using demeaned squared residuals of the index, is the dependent variable. 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. FF Factor are contemporaneous Fama-French factors for size (SMB_t) and value (HML_t). MoM_t is Carhart's momentum factor. LIQ_t is Pastor-Stambaugh liquidity factor. $Macro$ includes macroeconomic variables such as U.S. inflation, U.S. Consumer Confidence Index, Federal Fund Rates, U.S. Yield Spread, U.S. Industrial Production, and U.S. Unemployment rate. We report only those lags of our media sentiment indicator, which are statistically significant. Values in brackets are t-statistics. Statistical significance is reported by asterisks *, ** and *** at the 10%, 5% and 1% level respectively.

Table 7. Robustness Check: Granger Causality Test

	$Sent - Mkt$	$Mrk - Sent$	$Sent - Vola$	$Vola - Sent$
Lags 1 to 24	28.791	26.037	28.700	21.752
	(0.228)	(0.351)	(0.231)	(0.594)
Lags 1 to 12	12.150	17.534	9.307	12.515
	(0.433)	(0.130)	(0.676)	(0.405)
Lags 12 to 24	19.342	9.769	23.708**	10.046
	(0.112)	(0.712)	(0.033)	(0.690)
Lags 1 to 6	8.040	9.292	5.188	8.780
	(0.235)	(0.157)	(0.519)	(0.186)
Lags 6 to 12	6.660	5.819	5.113	3.087
	(0.465)	(0.561)	(0.646)	(0.876)
Lags 12 to 18	11.628	7.586	4.862	6.733
	(0.113)	(0.370)	(0.676)	(0.457)
Lags 18 to 24	3.315	2.095	14.865**	7.045
	(0.854)	(0.954)	(0.037)	(0.424)

Note: This table presents the Granger causality test results for the various subsets of lags for robustness checks. 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. We report the estimated χ^2 statistics and its statistical significance for the causal relation of our media sentiment indicator on MSCI World returns ($Sent - Mkt$), of MSCI World on our monthly media sentiment indicator ($Mkt - Sent$), of media sentiment indicator on MSCI World Volatility ($Sent - Vola$) and of MSCI World volatility on our media sentiment indicator ($Vola - Sent$). MSCI World is the log return of the MSCI World index. MSCI World Vola is the squared demeaned residuals of the log returns of the MSCI World index. As exogenous variables we include Fama-French factors for size and value, Carhart's momentum factor, Pastor-Stambaugh liquidity factor and macroeconomic variables such as U.S. inflation, U.S. Consumer Confidence Index, Federal Fund Rates, U.S. Yield Spread, U.S. Industrial Production, and U.S. Unemployment rate. p-values are reported in brackets. Statistical significance is denoted by asterisks ** and *** at the 10%, 5% and 1% level respectively.

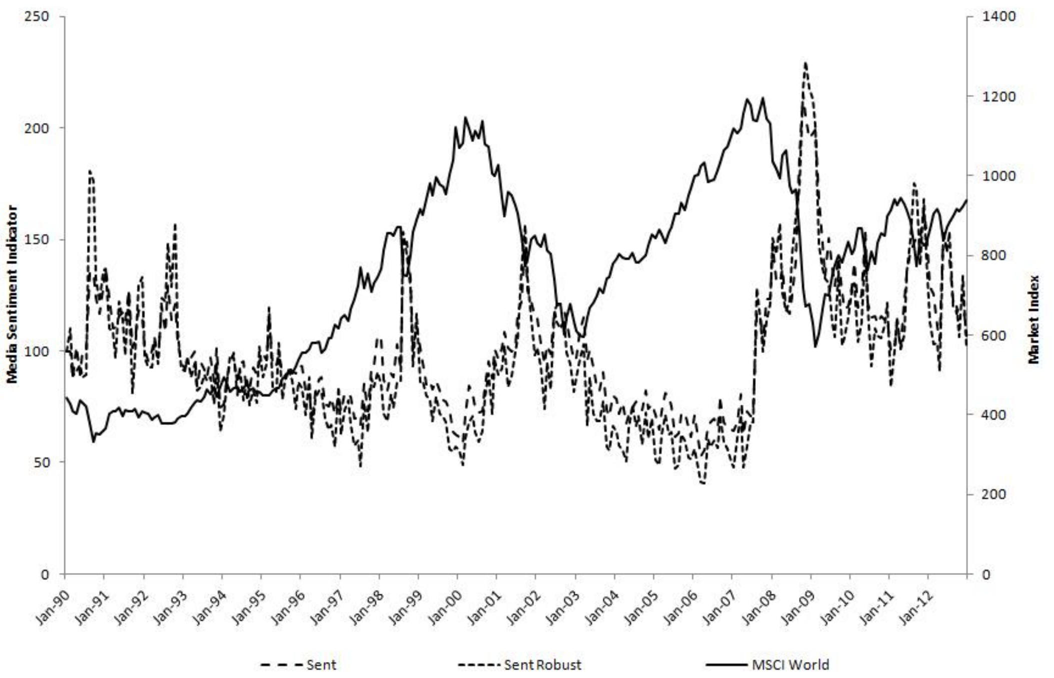

Figure 1. Media Sentiment Indicator and Market Return

Note: The graph plots at a monthly frequency our media sentiment indicator against the MSCI World index over our sample period between January 1990 and December 2012. Our media sentiment indicator (*Sent*) is constructed by taking the ratio of pessimistic news frame to optimistic news frame. *SentRobust* is the media sentiment indicator constructed for the robustness check. Both media sentiment indicators are standardized to 100 in January 1990.

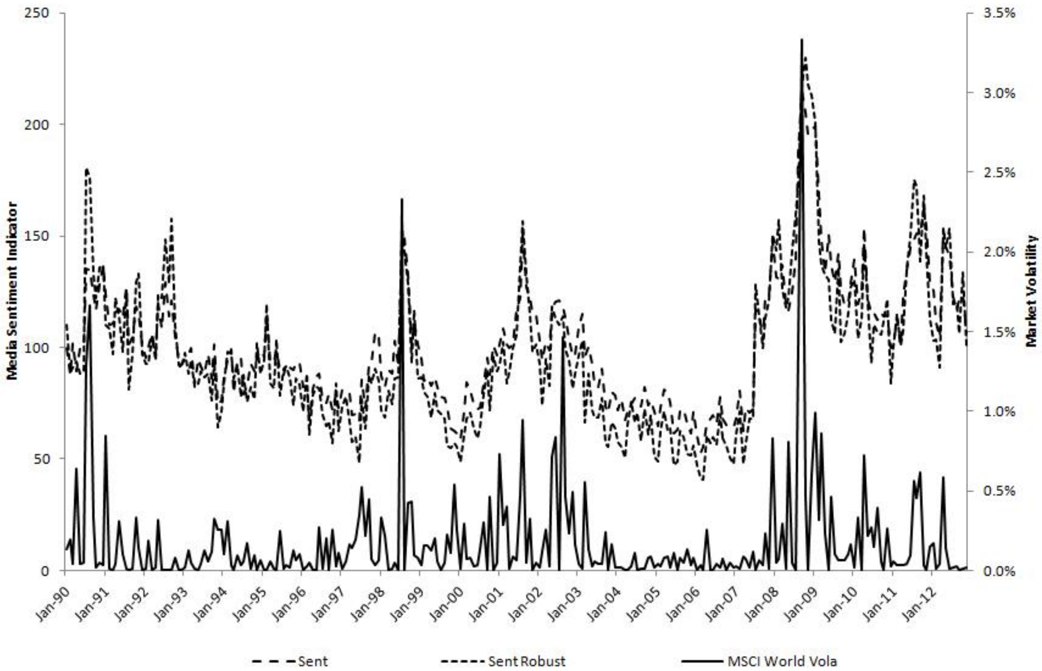

Figure 2. Media Sentiment Indicator and Market Volatility

Note: The graph plots at a monthly frequency our media sentiment indicator against MSCI World volatility over our sample period between January 1990 and December 2012. MSCI World volatility is represented by squared demeaned residuals of the MSCI World log returns. Our media sentiment indicator (*Sent*) is constructed by taking the ratio of pessimistic news frame to optimistic news frame. *SentRobust* is the media sentiment indicator constructed for the robustness check. Both media sentiment indicators are standardized to 100 in January 1990.