# Manipulated markets

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# Chapter 2

# Media, Sentiment and Market Performance in the Long Run

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## 2.1 Introduction

Traditional finance leaves no room for the effect of investor sentiment on the financial markets. However, numerous empirical studies show that investor sentiment plays an important role in the development of equity prices. Baker and Wurgler (2006, 2007) define investor sentiment as a belief about future cash flows and investment risks that are not justified by the fundamentals. They demonstrate that investor sentiment affects stock markets contemporaneously and the effect reverses over the following trading days as investors realize the deviation from fundamentals. Da, Engelberg, and Gao (2014), García (2013), Goetzmann, Kim, and Shiller (2016), Tetlock (2007) confirm these findings by showing evidence for the short-term predictive activity of investor sentiment on daily DJIA returns. Lee, Jiang, and Indro

(2002) report a significant weekly contemporaneous effect of investor sentiment on the formation of conditional volatility and expected returns. They regard investor sentiment as a risk factor and show that bullish (bearish) shifts in sentiment lead to downward (upward) revisions in the volatility of returns.

Another strand of the literature suggests that the effect of investor sentiment has a long-term nature. De Long, Shleifer, Summers, and Waldmann (1990) argue that investor sentiment is associated with "noise-trader" risk, which is not arbitraged away completely and which affects prices in equilibrium. Brown and Cliff (2005) present evidence for a long-term negative relation between investor sentiment and stock market returns over two to three years. Barberis, Shleifer, and Vishny (1998) argue that investor sentiment or the way investors form beliefs is consistent with the underreaction and overreaction phenomena on financial markets. They show in their Markov-switching model that investors find themselves in one of two regimes, where they either underreact to new information, or overreact to it.

We argue that the news media not only reflect economic events, but also affect investors' sentiment. However, as a result of conservatism, investors are reluctant to adjust their sentiment to changes in media sentiment immediately (Barberis, Shleifer, and Vishny, 1998). Based on the underreaction hypothesis, we assume that investors and stock markets are slow in fully reflecting changes in news media sentiment. We hypothesize that our media pessimism indicator is associated with negative stock market returns over a period of 1 to 12 months. Similarly, we hypothesize that our media pessimism indicator is associated with positive stock market volatility over a short-run of 1 to 12 months. On the other hand, when investors are exposed to similar news media sentiment for an extended period of time, they are likely to overreact to it, extrapolate it into the future, and to revert to fundamentals once they are revealed. Hence, we hypothesize that our media pessimism indicator is positively associated with stock market returns and negatively associated with volatility over a period of two to three years.

Based on the findings by Engelberg and Parsons (2011), Fang and Peress (2009), Klibanoff, Lamont, and Wizman (1998), and Kothari, Li, and Short (2009), we expect to find a causal relation of our media pessimism indicator on stock market returns and volatility. McCombs (2004) supports our intuition by asserting that the real news media effect can be achieved only in the long-term, which is contrary to the view that media effects are immediate. Oberlechner and Hocking (2004) suggest that simply listening repeatedly to a story makes it appear credible.

We proxy for investor sentiment by constructing a media pessimism indicator. We collect our news data by searching for a predetermined set of keywords on the *LexisNexis* database. We argue that news that uses at least one of our predetermined positive (negative) words raises positive (negative) optimistic (pessimistic) thoughts in readers' minds, which subsequently affects the way readers feel about the stock markets and the economy in general. We construct our monthly media pessimism 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 the lead paragraph.

We analyze the potential impact of media pessimism on financial market returns and volatility by estimating a Vector Autoregressive (VAR) model and by performing Granger causality tests. We follow Brown and Cliff (2005) and include up to 36 lags (three years) to capture any long-term effects. We also perform a comparison analysis of our media pessimism indicator to the Baker and Wurgler (2006, 2007) investor sentiment index and the VIX. These results are available in Appendix B.

We find that our media indicator is associated with negative (positive) MSCI World and S&P 500 returns 14 to 17 (24 to 25) months in advance. Similarly, our media pessimism indicator is associated with positive MSCI and S&P 500 volatilities 1 to 24 and 12 to 24 months in advance, respectively. We find evidence for Granger causality for our media pessimism indicator on market returns and volatilities. Our results are robust after controlling for exogenous variables such as Fama and French (1993) factors for size and value, the Carhart (1997) momentum factor, the Pastor and Stambaugh (2003) liquidity factor, numerous U.S. macroeconomic variables, the

Baker and Wurgler (2006) investor sentiment index, and the VIX index.

This chapter is structure as follows: Section 2.2 presents the overview of related literature. Section 2.3 discusses data and methodology. Section 2.4 presents our findings, and Section 2.5 concludes.

## 2.2 Literature Review

The underreaction hypothesis states that stock markets incorporate and reflect new information into prices slowly, leading to positive autocorrelation of returns. Underreaction occurs as a result of *conservatism*, a psychological bias, which implies that individuals are slow to change their beliefs in the face of new evidence (Edwards, 1968). The positive long-term autocorrelation of stock returns for a time span of one to twelve months and the post-earnings announcement drift are considered to be examples of underreaction (Bernard, 1992; Bernard and Thomas, 1989, 1990; Chan, Jegadeesh, and Lakonishok, 1997; Cutler, Poterba, and Summers, 1991; Jegadeesh and Titman, 1993; Rouwenhorst, 1997).

On the other hand, the overreaction hypothesis states that after a series of announcements of good (bad) news, investors become overly optimistic (pessimistic) about future news announcements and send stock prices to unjustifiably high (low) levels (Barberis et al., 1998). Subsequent news announcements are likely to contradict this optimism (pessimism) leading to return reversals in the long run. They argue that overreaction is likely to occur as a result of *representativeness*, a psychological bias that suggests that individuals are likely to evaluate the probability of an uncertain event by the degree to which it is similar in its essential properties to the parent population and to which it reflects the salient features of the process by which it is generated (Kahneman and Tversky, 1974). The empirical evidence for overreaction is a relatively slight negative autocorrelation in stock returns over a horizon of three to five years (Cutler et al., 1991; Fama and French, 1988; Poterba and Summers, 1988). Moreover, De Bondt and Thaler (1985, 1987) show in their seminal winner–loser studies that a portfolio of stocks that has performed well in the past tends to underperform a portfolio of stocks that has performed poorly, in the course of five subsequent years.

Previous research suggests using media sentiment as a proxy for investor sentiment and investigates the immediate impact of the content of news on the performance of financial markets. Antweiler and Frank (2004) investigate the effect of the content 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 in predicting a stock's intraday volatility, but they do not find evidence of the news media content influencing market returns and trading volumes. Kim and Kim (2014) confirm this finding and show no significant effect of investor sentiment revealed on the message boards from *Yahoo! Finance* and *Raging Bull* websites on the stock returns.

Tetlock (2007) analyzes the interaction between the content of the *Wall Street Journal* column "Abreast of the Market" and the DJIA returns on a daily basis. He finds that high media pessimism puts a downward pressure on market prices followed by a reversal to fundamentals over the following couple of trading days. Additionally, 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 the 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 the proportion 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 for asymmetric predictive activity of the news content on daily DJIA 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. García (2013) shows that the effect seems to reverse over the course of next four trading days. Goetzmann et al. (2016) confirm these findings by reporting positive association of the prior day market returns and the count of positive and negative valence words in the financial press. The effect appears to be asymmetric and is more pronounced for extreme negative returns.

In contrast to Antweiler and Frank (2004), García (2013), Kim and Kim (2014), and Tetlock (2007), we investigate the effect of media pessimism on the performance of financial markets in the *long run*. Shiller (2005) argues that the news media are important players in creating market sentiment and similar thinking, as they spread ideas, can significantly contribute to herding behavior, and influence price movements on financial markets.

Numerous studies focus on the causal effect of the news media on equity returns. For instance, Engelberg and Parsons (2011) find that trading on a local platform after an earnings announcement by a S&P 500 firm is strongly related to whether the local newspaper covers the announcement. Local press coverage increases the daily trading volume of local retail investors from 8% to 50%, and this effect is significant for both buying and selling activity. Fang and Peress (2009) show that a portfolio of stocks that are not covered by news media tends to outperform a portfolio of stocks with news coverage by 8% to 12% per year after risk adjustments. They argue that the news media broaden investor recognition of stocks by disseminating information to a wide audience. Stocks with no media coverage suffer from lower investor recognition and need to offer higher returns to compensate their holders for being imperfectly diversified. Klibanoff et al. (1998) prove that country specific news reported on the front page of the *New York Times* affect the pricing of closed-end country funds. During weeks of front-page news, price movements tend to be more closely related to fundamentals. They explain their findings by arguing that events being covered in the news lead some investors to react to them more quickly. Kothari et al. (2009) investigate the effect of disclosures by management, analysts, and the business press, on the cost of capital, return volatility, and analyst forecasts. They find that positive (negative) news disclosures in business press decrease (increase) the cost of capital, return volatility, and analyst forecast dispersion.

## 2.3 Data and methodology

Following Antweiler and Frank (2004), García (2013), and Tetlock (2007), 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 WSJ'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 data gathered 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 and constructs his daily media pessimism measure by taking the difference between the proportions of negative and positive words in the total.

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 respectable newspapers, newswires, magazines, and key information providers. *LexisNexis* classifies each newspaper article into various categories based on the content. To limit our search to economic and financial markets news, we select the *LexisNexis* category Banking and Finance. This category contains news about financial institutions and services, credit and lending, financial markets and trading, investments, and banking law and policy.

Table 2.1. Keywords
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 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 headline and the lead paragraph of the newspaper article.

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

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 in the lead paragraph. We ensure that we control for an increasing trend of newspaper articles in the financial press after the emergence of the Internet in 1995 by focusing only on three news sources.

It appears that the trend is driven by the increasing number of news sources rather than an increasing number of newspaper articles per news source. We limit our search 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. The list of words is presented in Table 2.1. We assume that a newspaper article that contains one of the positive (negative) words in the headline and/or in the lead paragraph is more likely to generate positive (negative) thoughts in readers' minds and to express optimistic (pessimistic) media sentiment.

We borrow most of the negative words from the list of the thirty most frequent words occurring in 10-Ks from the so-called Fin-Neg word list, which is reported in Loughran and McDonald (2011). The list of words is available online at `http://www3.nd.edu/~mcdonald/Word_Lists.html`. 10-K forms give a summary of a company's financial performance and many words in the Loughran and McDonald's list are company specific and not relevant for financial press pessimism (e.g., "tax", "capital", "liability", and "board"). Thus, we only select those negative words from the list that clearly express negative sentiment in the financial press (e.g., "decline", "loss", "failure", and "default"). We extend our list with some additional negative words in order to broaden the scope of the newspaper articles in our database. These words are either synonyms of the words already selected or they share a similar meaning of financial pessimism. They are classified as negative in the McDonald dictionary, and we believe they are relevant for financial press reports. We add such words as "fall", "plummet", "danger", "crisis", and "pessimism". Our list of positive words contains antonyms of the negative words and some additional words, which are classified as positive in the McDonald dictionary and are often used in the financial press. For example, the antonyms of Loughran and McDonald's (2011) words are "increase", "gain", "success", "profitable", etc. Additional positive words include "growth", "optimism", "boom", "expansion", etc. Table 1 lists our defined 27 positive and 27 negative words. Our lists of positive and negative words are not exclusive; however, many of our words are used in the same context and often appear together. A potential disadvantage of including additional words is an increasing chance of including newspaper articles with irrelevant content into our database. Thus, we claim that the words we selected will suffice to extract the majority of relevant newspaper articles from the total pool of news and will minimize noise. In the Appendix A we provide examples of newspaper articles that we were able to extract using our approach.

We collected data for the period January 1, 1990 to December 31, 2012. We counted the number of newspaper articles found during a particular month in each category that includes any of the searched words in the headline and in the lead paragraph. We found 3,135 newspaper articles on average per month. When we limitted our search to predefined words, we found slightly more news articles with positive words than with negative words. We found 945 (844) articles on average per month when we searched for positive (negative) words in the headline and the lead paragraph, which is 30% (27%) of the total number of articles.

We constructed our monthly media pessimism indicator by taking the ratio of the number of newspaper articles that contained negative words to the number of newspaper articles that contained positive words. We took the log change of the resulting ratios and standardized the initial observation in January 1990 to 100. Each subsequent monthly level of our media pessimism indicator is calculated by multiplying the previous level by the exponent of the corresponding log rate of change.

In order to perform a regression analysis, we took the MSCI World and S&P 500 indices as market indices that reflect the performance of the global and the U.S. economy during our time span. We obtained market data from *Datastream* for the period between January 1990 and December 2012. We also extended the analysis to the effect of news media sentiment on market volatility. We calculated a proxy for the monthly volatility of the market index by following Tetlock (2007) approach. We de-meaned the market return variables of the MSCI World and the S&P 500 to obtain the residual values, and squared these residuals.

A potential critique of the results we obtained by using our media pessimism indicator in the statistical analysis is the issue of the omitted variables. The media pessimism indicator might capture the effect of some omitted variable that explains both: our indicator and market returns (volatility), instead of reflecting its direct effect on the financial markets. In order to mitigate this problem, we included a wide range of control variables in our analysis. We used the standard Fama and French (1993) small-minus-big ($SMB_t$) and high-minus-low ($HML_t$) factors, the Carhart (1997) momentum factor ($MOM_t$), and the Pastor and Stambaugh (2003) aggregate liquidity factor ($LIQ_t$), downloaded at a monthly frequency from *Wharton Research Data Services*. These variables were included in our regression model to control for other potential anomalies in stock market returns and volatilities that are not driven by news media sentiment. We considered monthly $SMB_t$, $HML_t$ and $MoM_t$ as state variables and included them as control variables in our model.

Following Chen et al. (1986), we extended our model with additional macroeconomic variables for the U.S. economy, such as the U.S. inflation ($CPI_t$), the U.S. consumer confidence index ($CCI_t$), the Federal fund rates ($FFR_t$), the U.S. yield spread ($Spread_t$), the U.S. industrial production ($IP_t$), and the U.S. unemployment rate ($Unemployment_t$). We measured the U.S. inflation by using the U.S. consumer price index. The U.S. yield spread is the difference between the U.S. Treasury yield adjusted to constant maturity for 20 years and the three-month U.S. Treasury bill rate. All macroeconomic variables were downloaded from *Datastream* at monthly frequency.

We also included the Baker and Wurgler (2006) investor sentiment index ($BWSent_t$) and Chicago Board Options Exchange Market Volatility Index ($VIX_t$) index as control variables in our model. $VIX_t$ is a commonly used risk measure known as a "fear gauge" for financial markets (Whaley, 2000). One reason for controlling for the investor sentiment index and the VIX is to investigate whether our media pessimism indicator demonstrates an additional predictive power over those alternative sentiment measures that are widely used. The Baker and Wurgler (2006) investor sentiment index is available on their website until December 2010. We downloaded the VIX index from *Datastream*.

To investigate the potential long-term media sentiment effect on the performance of financial markets, we designed a predictive model that allows us to determine whether changes in the level of media pessimism have an effect on subsequent changes in the level of market returns and volatilities. We followed Tetlock (2007) approach and proposed estimating two VAR models, where we specified the log return of the market index and the log change of our monthly media pessimism indicator as endogenous variables for our VAR model (1). For our VAR model (2), we specified the market volatility and the log change of our media pessimism indicator as endogenous variables. The exogenous variables are the contemporaneous values of the $SMB_t$ and $HML_t$ factors, the $MoM_t$ factor, the $LIQ_t$ factor, U.S. macroeconomic indicators such as $CPI_t$, $CCI_t$, $FFR_t$, $Spread_t$, $IP_t$, $Unemployment_t$, the log change of $BWSent_t$, and the log change of the $VIX_t$. We followed Brown and Cliff (2005) and included 36 monthly lags for each endogenous variable in order to capture any potential long-term effects. We analyzed the effect of news media sentiment by studying the following two specified VAR models:

$$\begin{aligned} Mrk_t =& \alpha_1 + \beta_{11} L36(Mrk_t) + \beta_{21} L36(Sent_t) + \beta_{31} Exog_t + \epsilon_{t1} \\ Sent_t =& \alpha_2 + \beta_{12} L36(Mrk_t) + \beta_{22} L36(Sent_t) + \beta_{32} Exog_t + \epsilon_{t2} \end{aligned} \tag{2.1}$$

and

$$\begin{aligned} Vola_t =& \alpha_1 + \beta_{11} L36(Vola_t) + \beta_{21} L36(Sent_t) + \beta_{31} Exog_t + \epsilon_{t1} \\ Sent_t =& \alpha_2 + \beta_{12} L36(Vola_t) + \beta_{22} L36(Sent_t) + \beta_{32} Exog_t + \epsilon_{t2}, \end{aligned} \tag{2.2}$$

where $Mrk_t$ is the log return of the market index; $L36(x_t)$ is a lag operator that transforms the variable $x_t$ into a row vector consisting of 36 lags of $x_t$; $Sent_t$ is the log change of our media pessimism indicator; $Vola_t$ is the squared de-meaned residuals of the market index returns; $Exog_t$ are exogenous variables such as contemporaneous $SMB_t$, $HML_t$, $MoM_t$, and $LIQ_t$ factors, U.S. macroeconomic variables, $BWSent_t$, and $VIX_t$, which are included in the model to control for other market movements that are not driven by the news media. $\alpha_j$ are estimated constants and $\beta_{ij}$ are estimated VAR coefficients. We control for the heterscedasticity of error terms by applying the Newey-West (1987) estimator for standard errors.

The results of the Augmented Dickey-Fuller Unit-Root test (not reported here) reject the null hypothesis of a unit-root in the level values of the log change of the market returns, market volatilities, and the media pessimism indicator and imply that our endogenous variables in the VAR model are stationary I(0) processes. Thus, the unrestricted VAR model is an appropriate methodology to test for the effect of media sentiment on the financial performance. A Vector Error Correction (VEC) model would be an alternative methodology only if our endogenous variables were non-stationary at the level.

McCloskey and Ziliak (1996) note that researches often focus primarily on the statistical significance of the coefficients and ignore its economic significance. The magnitude of the effect of the statistically significant variable can be so small that it does not represent any importance in economic sense. In order to account for the economic significance, we compute partial $R^2$ for each lagged media pessimism indicator in our VAR models (1) and (2) after controlling for other variables in the model. Partial $R^2$ is the squared partial correlation coefficient. This measure captures the unique contribution of an individual variable to the explanatory power of the complete model.

The VAR model allows us to establish causality by switching the dependent variables. Both Antweiler and Frank (2004)) and Tetlock (2007) draw their conclusions about news media effects by testing for the significance of the news media VAR coefficients. Given the complicated interlocking relations between the news media and the financial markets, where news influence the markets and the markets influence the news, we believe that simply testing for the significance of lagged coefficients is not sufficient to draw conclusions about causality. To disentangle these two forces, we run additional Granger causality tests. We perform Granger causality tests on each VAR model, where we test for the joint significance of the lagged coefficients for each endogenous variable in our specified VAR model. We perform Granger causality tests for all 36 lags and for the lag subsets 1–12, 12–24, and 24–36 in order to identify a narrower range in which the effect of media pessimism takes place. A joint significance of lagged media pessimism coefficients at a pre-specified subset of lags suggests the presence of a causal effect of media pessimism on market returns or volatilities. The Granger causality test does not say anything about the direction of the relation, which can be deduced by observing the signs of lagged coefficients in the estimated VAR model.

We hypothesize that markets underreact to pessimistic (optimistic) news media sentiment and demonstrate decreasing (increasing) returns and increasing (decreasing) volatilities with a lag of one to twelve months. Over a longer time horizon, market returns and volatilities tend to revert back to their fundamentals and demonstrate increasing (decreasing) returns and decreasing (increasing) volatilities with a lag of over two to three years. Our main assumption here is that investors are prone to the bias of conservatism and are reluctant to adjust their sentiment immediately in response to a change in news media sentiment (Edwards, 1968). Based on the empirical evidence for stock market underreaction, it takes from one to twelve months for stock markets to fully reflect new information (Bernard, 1992; Bernard and Thomas, 1989, 1990; Chan et al., 1997; Cutler et al., 1991; Jegadeesh and Titman, 1993; Rouwenhorst, 1997). However, once investors adhere to news media sentiment, they become prone to the bias of representativeness, and are likely to overreact to a stream of positive (negative) news and push market prices beyond their fundamentals (Barberis et al., 1998). Over a time span of from two to three years, market returns and volatilities tend to revert back to their fundamental values (Brown and Cliff, 2005; Cutler et al., 1991; De Bondt and Thaler, 1985, 1987; Fama and French, 1988; Poterba and Summers, 1988). Thus, we suggest that news media sentiment directly influences investor sentiment and the performance of financial markets not only contemporaneously, but also over a longer time horizon.

## 2.4 Discussion of the Results

### 2.4.1 The long run effect of media pessimism on financial performance

Figure 2.1 plots our media pessimism indicator against the MSCI World index. We see that the monthly media pessimism indicator follows closely the historical

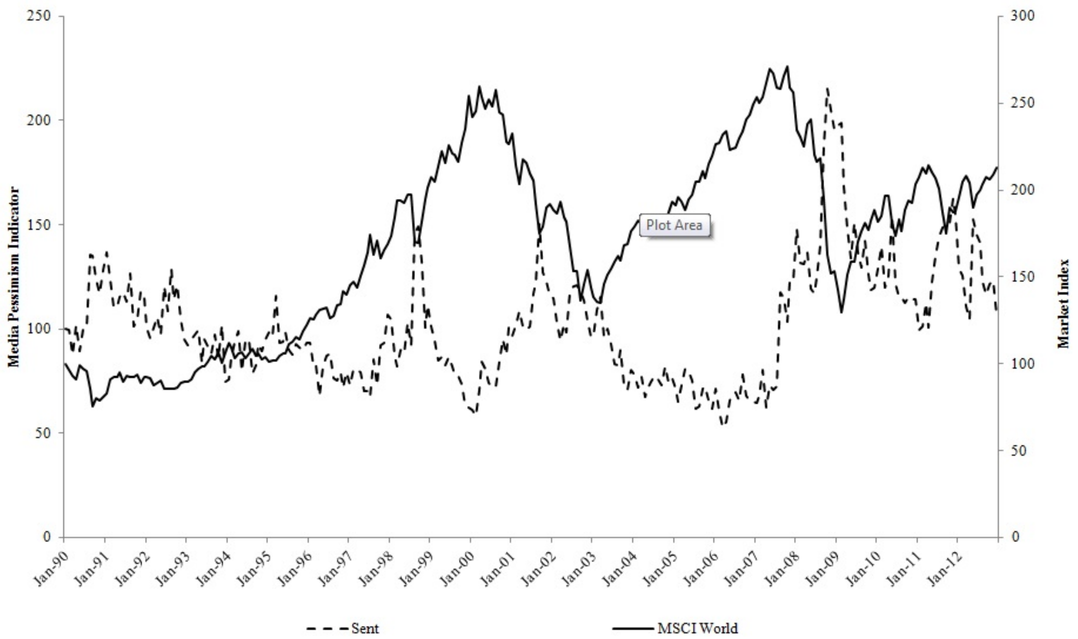


Figure 2.1. Media Pessimism and Market Returns
The graph plots at a monthly frequency our media pessimism indicator against the MSCI World index over our sample period between January 1990 and December 2012. Our media pessimism indicator (*Sent*) is constructed by taking the ratio of the negative to positive news count. *Sent* and MSCI World are standardized to 100 in January 1990.

price developments on stock markets. Our media pessimism 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 prevails as our media pessimism indicator reaches its peak in times of crises. The correlation between our media pessimism indicator and the MSCI World is -47%, which suggests a strong negative contemporaneous relation between media pessimism and market returns at monthly frequency. This observation is consistent with the findings of García (2013), Goetzmann et al. (2016), Lee et al. (2002), and Tetlock (2007). However, our findings conflict with the results in Brown and Cliff (2004) and Kim and Kim (2014), which both show no contemporaneous effect of investor sentiment on stock markets.

Figure 2.2 plots our media pessimism indicator against the MSCI World volatil-

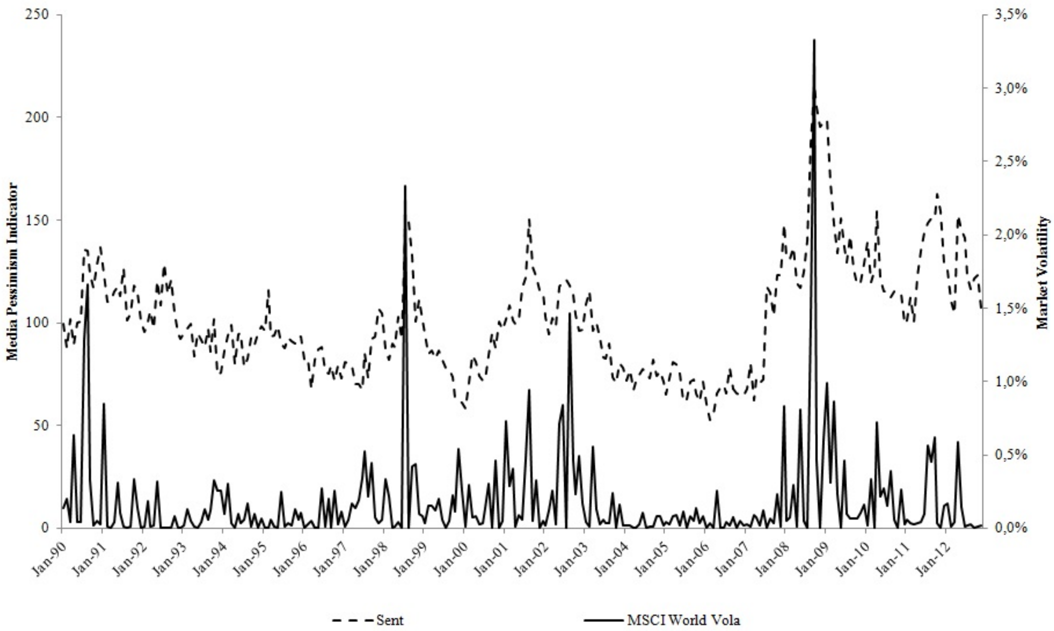


Figure 2.2. Media Pessimism and Market Volatility
The graph plots at a monthly frequency our media pessimism indicator against MSCI World volatility over our sample period between January 1990 and December 2012. MSCI World volatility is represented by squared demeaned residuals of the MSCI World log returns. Our media pessimism indicator (*Sent*) is constructed by taking the ratio of negative to positive news count. *Sent* is standardized to 100 in January 1990.

ity. Our market volatility measure indicates the level of uncertainty in the financial markets at a particular point in time. Spikes in volatility tend to occur at the outbreak of crises and coincide with the peaks of our media pessimism indicator. In contrast, periods of low market volatility coincide with periods of economic growth. Our media pessimism indicator tends to decrease and reach its bottom during this time.

Table 2.2. The Long-Term Effect of the News Media Pessimism on the Performance of Financial Markets

This table presents the estimated coefficients of our media pessimism indicator ($Sent_t$) for the VAR model (2.1) and (2.2), where the log return of the market index and demeaned squared residuals of the market index is a dependent variable, respectively. We use the MSCI World and S&P 500 as market indices. We include as control variables the contemporaneous Fama and French (1993) factors for size ($SMB_t$) and value ($HML_t$). $MoM_t$ is the Carhart (1997) momentum factor. $LIQ_t$ is the Pastor and Stambaugh (2003) liquidity factor. $Macro_t$ includes macroeconomic variables such as the U.S. inflation ($CPI_t$), the U.S. consumer confidence index ($CCI_t$), the Federal fund rates ($FFR_t$), the U.S. yield spread ($Spread_t$), the U.S. industrial production ($IP_t$), and the U.S. unemployment rate ($Unemployment_t$). $BWSent_t$ is the log change of the Baker and Wurgler (2006) investor sentiment index. $VIX_t$ is the log change of the VIX index. We control for the heteroscedasticity in error terms by applying the Newey-West (1987) estimator for standard errors. Statistical significance is reported by asterisks ** and *** at the 5% and 1% levels, respectively.

| | (1) MSCI World Return | (2) S&P Return | (3) MSCI Vola | (4) S&P Vola |
|---|---|---|---|---|
| $Sent_{t-1}$ | -0.041** | -0.060*** | 0.003 | 0.004 |
| $Sent_{t-2}$ | -0.011 | 0.005 | 0.006** | 0.004* |
| $Sent_{t-3}$ | -0.023 | -0.020 | 0.004* | 0.003* |
| $Sent_{t-4}$ | 0.008 | -0.000 | 0.001 | 0.000 |
| $Sent_{t-5}$ | -0.023 | -0.024 | -0.000 | -0.000 |
| $Sent_{t-6}$ | 0.015 | 0.006 | 0.001 | -0.000 |
| $Sent_{t-7}$ | 0.047** | 0.039 | -0.000 | -0.000 |
| $Sent_{t-8}$ | -0.014 | -0.022 | 0.003 | 0.002 |
| $Sent_{t-9}$ | 0.023 | 0.010 | 0.000 | 0.001 |
| $Sent_{t-10}$ | -0.013 | -0.014 | 0.006** | 0.008** |
| $Sent_{t-11}$ | 0.009 | 0.026 | 0.000 | 0.003 |
| $Sent_{t-12}$ | -0.018 | 0.007 | 0.004 | 0.006* |
| $Sent_{t-13}$ | -0.034 | -0.018 | 0.004 | 0.005* |
| $Sent_{t-14}$ | -0.087*** | -0.070** | 0.007 | 0.008* |
| $Sent_{t-15}$ | -0.090*** | -0.084*** | 0.002 | 0.001 |
| $Sent_{t-16}$ | -0.081*** | -0.065** | 0.003 | 0.001 |
| $Sent_{t-17}$ | -0.105*** | -0.088*** | 0.001 | 0.001 |
| $Sent_{t-18}$ | -0.032 | -0.028 | 0.000 | 0.001 |
| $Sent_{t-19}$ | -0.021 | 0.008 | 0.003 | 0.004 |
| $Sent_{t-20}$ | -0.028 | -0.026 | 0.007** | 0.007** |
| $Sent_{t-21}$ | -0.011 | -0.032 | 0.002 | 0.003 |
| $Sent_{t-22}$ | 0.026 | 0.005 | -0.000 | 0.000 |
| $Sent_{t-23}$ | 0.008 | 0.003 | 0.000 | 0.001 |
| $Sent_{t-24}$ | 0.069*** | 0.053** | 0.001 | 0.000 |
| $Sent_{t-25}$ | 0.050** | 0.012 | 0.002 | 0.002 |
| $Sent_{t-26}$ | 0.025 | 0.002 | 0.002 | 0.003 |
| $Sent_{t-27}$ | -0.021 | -0.017 | 0.003 | 0.003 |
| $Sent_{t-28}$ | 0.016 | 0.041 | 0.001 | 0.002 |
| $Sent_{t-29}$ | -0.034 | -0.036 | 0.003 | 0.005* |
| $Sent_{t-30}$ | 0.007 | 0.010 | 0.000 | 0.002 |
| $Sent_{t-31}$ | 0.007 | 0.001 | 0.001 | 0.001 |
| $Sent_{t-32}$ | -0.019 | -0.003 | 0.000 | -0.000 |
| $Sent_{t-33}$ | -0.053** | -0.044* | 0.000 | -0.000 |
| $Sent_{t-34}$ | -0.032 | -0.039* | -0.001 | -0.001 |

Table 2.2 – *Continued from previous page*

| | (1) MSCI World Return | (2) S&P Return | (3) MSCI Vola | (4) S&P Vola |
|---|---|---|---|---|
| $Sent_{t-35}$ | -0.003 | -0.003 | -0.002 | -0.001 |
| $Sent_{t-36}$ | 0.004 | 0.002 | 0.000 | 0.000 |
| Constant | 0.001 | -0.004 | 0.000 | 0.001 |
| $SMB_t$ | -0.166* | -0.261** | 0.009 | 0.005 |
| $HML_t$ | -0.198** | -0.252** | 0.014 | 0.018 |
| $LIQ_t$ | 0.098*** | 0.064 | -0.002 | -0.001 |
| $MoM_t$ | -0.131*** | -0.172*** | 0.006 | 0.006 |
| $IP_t$ | -0.620* | -0.883** | 0.073 | 0.091 |
| $Spread_t$ | -0.005 | -0.009 | -0.000 | -0.000 |
| $CPI_t$ | -0.155 | 1.006 | -0.195 | -0.250 |
| $FFR_t$ | -0.045* | -0.053 | -0.001 | -0.002 |
| $CCI_t$ | 0.043 | 0.060* | -0.009 | -0.011* |
| $Unemployment_t$ | 0.111 | 0.174 | 0.002 | -0.004 |
| $BWSent_t$ | 0.006** | 0.008** | 0.000 | 0.000 |
| $VIX_t$ | -0.159*** | -0.158*** | 0.008*** | 0.007*** |
| $Adj.R^2$ | 0.633 | 0.606 | 0.264 | 0.357 |
| $F-statistics$ | 5.298*** | 4.834*** | 1.894*** | 2.386*** |
| $OBS$ | 210 | 210 | 210 | 210 |

This observation implies that the news media seem to publish more negative (positive) news and express pessimism (optimism) during times of increasing (decreasing) riskiness and uncertainty on the market. The correlation between our media pessimism indicator and the MSCI World volatility is 22%, which suggests that there is some slight positive contemporaneous relation between media pessimism and market volatility.

This observation is consistent with the findings of Antweiler and Frank (2004) and Lee et al. (2002).

Table 2.2 Columns 1 and 2 presents the estimated VAR coefficients of $Sent_t$ for all 36 lags in the VAR models (2.1), where the MSCI World and the S&P 500 returns are the dependent variables, respectively. We find negative statistically significant coefficients for lags 1, 14, 15, 16, 17, and 33, and positive statistically significant coefficients for lags 7, 24, and 25 for the MSCI World returns as the dependent variable after including all sets of controls. We obtain similar results with the S&P 500 index as the dependent variable. We find negative and statistically significant coefficients for lags 1, 14, 15, 16, and 17, and a positive and statistically significant coefficient for lag 24 after including all sets of controls. Other coefficients are generally negative for lags between 1 and 21 and positive for lags 22 to 31, although statistically insignificant.

Our findings are generally consistent with our expectations and the previous literature. Many empirical studies document the presence of underreaction on stock markets (e.g., Bernard (1992); Bernard and Thomas (1989, 1990); Chan et al. (1997); Cutler et al. (1991); Jegadeesh and Titman (1993); Rouwenhorst (1997)). Our results show that media pessimism is associated with negative stock market returns at a lag of 1 to 21 months. We argue that our results point to the underreaction phenomenon. Investors appear to process the change in media sentiment slowly and fully incorporate it into stock prices one to one-and-a-half years later. The effect of media pessimism on stock returns appears to take place gradually.

The results also show that our media pessimism indicator is associated with positive stock market returns at lags 24 and 25. Consistent with the overreaction hypothesis of Barberis et al. (1998) and the mean-reversion phenomenon (Cutler et al., 1991; De Bondt and Thaler, 1985, 1987; Fama and French, 1988; Poterba and Summers, 1988), our results show, on average, the reversal of the negative effect of media pessimism two to two-and-a-half years later. After observing a series of positive (negative) news, investors seem to become excessively optimistic (pessimistic) about the future economy and push stock prices to unjustifiably high (low) levels. However, when the fundamentals are revealed, markets appear to correct the mispricing and stock prices return to their fundamental levels and move down (up). The reversal appears to have the strongest effect at lags 24 and 25 for the MSCI World and at lag 24 for the S&P 500.

Table 2.2 Columns 1 and 2 also present the coefficients for the control variables for VAR model (2.1), where MSCI World and S&P 500 returns are dependent variables, respectively. We find negative and statistically significant loadings on $SMB_t$, $HML_t$, and $MoM_t$ for both the MSCI World and S&P 500 indices. $LIQ_t$ is positive and statistically significant for both market indices. Concerning the U.S. macroeconomic variables, we find a statistically significant negative coefficient for $FFR_t$ for the MSCI World, negative and statistically significant coefficients for $IP_t$ and $FFR_t$ for the S&P 500, and a positive and statistically significant coefficient for $CCI_t$ for the S&P 500 index. $BWSent_t$ and $VIX_t$ exhibit positive and negative strongly statistically significant contemporaneous relation with both market indices. This means that we are able to find evidence for predictive activity of our media pessimism indicator on market returns after controlling for alternative sentiment measures such as the Baker and Wurgler (2006) investor sentiment index and the VIX.

Table 2.2 columns 3 and 4 present the estimated coefficients of $Sent_t$ for the VAR model (2.2) where MSCI World and S&P 500 volatility are the dependent variables. We obtain positive and statistically significant coefficients of $Sent_t$ for lags 2, 10, 14, and 20 for the MSCI World as the dependent variable, and for lags 2, 10, 12, 13, 14, and 20 for the S&P 500 as the dependent variable after including all sets of control variables in our model. The coefficients for other lags are predominantly positive, although statistically insignificant. The coefficients for $Sent_t$ become negative for lags 34 and 35 for the MSCI World, and for lags 32 to 35 for the S&P 500 as a dependent variable, though statistically insignificant, which might indicate the reversal effect.

Our findings in Table 2.2 columns 3 and 4 are generally consistent with our expectations and the previous literature. The results show that our media pessimism indicator is positively associated with market volatilities 2 to 20 lags in advance. This finding is consistent with the underreaction hypothesis of Barberis et al. (1998), and findings of Lee et al. (2002). Similar to the findings in Table 2.2 columns 1 and 2, we suggest that media pessimism affects stock market volatility slowly, as investors are reluctant to change their beliefs in the face of new evidence. Increasing media pessimism translates into higher volatility in the stock markets one to one-and-a-half years later. On the other hand, we do not find strong evidence for the overreaction hypothesis or the mean-reversion phenomenon for market volatility.

Table 2.3. Economic Significance of the Media Pessimism Indicator - Partial $R^2$ Analysis

This table presents the partial $R^2$ values of the individual lagged media pessimism indicator variables in our VAR models (2.1) and (2.2). Partial $R^2$ indicates the unique contribution of each variable to the explanatory power of the complete model. Our control variables are the constant, 36 lags of the market return (volatility) variables, contemporaneous Fama and French (1993) factors for size ($SMB_t$) and value ($HML_t$). $MoM_t$ is the Carhart (1997) momentum factor. $LIQ_t$ is the Pastor-Stambaugh (2003) liquidity factor. $Macro_t$ includes macroeconomic variables such as the U.S. inflation ($CPI_t$), the U.S. consumer confidence index ($CCI_t$), the Federal fund rates ($FFR_t$), the U.S. yield spread ($Spread_t$), the U.S. industrial production ($IP_t$), and the U.S. unemployment rate ($Unemployment_t$). $BWSent_t$ is the log change of the Baker and Wurgler (2006) investor sentiment index. $VIX_t$ is the log change of the VIX index. The statistical significance of the partial correlation is denoted by asterisks *, **, and *** for 10 %, 5%, and 1%, respectively.

| | (1)<br>MSCI W Ret | (2)<br>S&P 500 Ret | (3)<br>MSCI W Vola | (4)<br>S&P 500 Vola |
|---|---|---|---|---|
| $Sent_{t-1}$ | 0.019* | 0.047*** | 0.003 | 0.007 |
| $Sent_{t-2}$ | 0.000 | 0.002 | 0.035** | 0.025** |
| $Sent_{t-3}$ | 0.000 | 0.000 | 0.000 | 0.000 |
| $Sent_{t-4}$ | 0.014 | 0.011 | 0.000 | 0.000 |
| $Sent_{t-5}$ | 0.035** | 0.022* | 0.001 | 0.001 |
| $Sent_{t-6}$ | 0.001 | 0.001 | 0.000 | 0.001 |
| $Sent_{t-7}$ | 0.022* | 0.013 | 0.011 | 0.011 |
| $Sent_{t-8}$ | 0.009 | 0.003 | 0.006 | 0.000 |
| $Sent_{t-9}$ | 0.002 | 0.000 | 0.017* | 0.006 |
| $Sent_{t-10}$ | 0.008 | 0.006 | 0.063*** | 0.067*** |
| $Sent_{t-11}$ | 0.000 | 0.001 | 0.005 | 0.003 |
| $Sent_{t-12}$ | 0.006 | 0.014 | 0.007 | 0.011 |
| $Sent_{t-13}$ | 0.000 | 0.000 | 0.000 | 0.000 |
| $Sent_{t-14}$ | 0.012 | 0.009 | 0.016 | 0.033** |
| $Sent_{t-15}$ | 0.001 | 0.004 | 0.002 | 0.006 |
| $Sent_{t-16}$ | 0.004 | 0.005 | 0.000 | 0.008 |
| $Sent_{t-17}$ | 0.048*** | 0.042*** | 0.000 | 0.000 |
| $Sent_{t-18}$ | 0.005 | 0.000 | 0.000 | 0.000 |
| $Sent_{t-19}$ | 0.000 | 0.005 | 0.000 | 0.000 |
| $Sent_{t-20}$ | 0.000 | 0.000 | 0.045*** | 0.041*** |
| $Sent_{t-21}$ | 0.005 | 0.014 | 0.000 | 0.000 |
| $Sent_{t-22}$ | 0.015 | 0.013 | 0.006 | 0.001 |
| $Sent_{t-23}$ | 0.020* | 0.008 | 0.000 | 0.000 |
| $Sent_{t-24}$ | 0.017* | 0.020* | 0.001 | 0.004 |
| $Sent_{t-25}$ | 0.000 | 0.002 | 0.002 | 0.002 |
| $Sent_{t-26}$ | 0.005 | 0.002 | 0.000 | 0.000 |
| $Sent_{t-27}$ | 0.018* | 0.008 | 0.000 | 0.000 |
| $Sent_{t-28}$ | 0.007 | 0.021* | 0.000 | 0.000 |
| $Sent_{t-29}$ | 0.029** | 0.048*** | 0.013 | 0.012 |
| $Sent_{t-30}$ | 0.014 | 0.013 | 0.001 | 0.000 |
| $Sent_{t-31}$ | 0.014 | 0.003 | 0.001 | 0.005 |
| $Sent_{t-32}$ | 0.001 | 0.001 | 0.000 | 0.000 |
| $Sent_{t-33}$ | 0.025** | 0.021* | 0.000 | 0.000 |
| $Sent_{t-34}$ | 0.001 | 0.000 | 0.004 | 0.001 |
| $Sent_{t-35}$ | 0.001 | 0.002 | 0.012 | 0.006 |

Table 2.3 – *Continued from previous page*

| | (1) MSCI W Ret | (2) S&P 500 Ret | (3) MSCI W Vola | (4) S&P 500 Vola |
|---|---|---|---|---|
| $Sent_{t-36}$ | 0.002 | 0.000 | 0.003 | 0.002 |

Table 2.2 columns 3 and 4 also present the coefficients for the control variables for VAR model (2.2), where MSCI World and S&P 500 volatilities are dependent variables, respectively. There is a negative significant contemporaneous relation between $CCI_t$ and the MSCI World and S&P 500 volatilities. There is a positive and statistically significant contemporaneous relation between $VIX_t$ and the MSCI World and S&P 500 volatilities. Additionally, we find a negative and statistically significant relation between the S&P 500 volatility and $CPI_t$, and a positive and statistically significant relation between the S&P 500 volatility and $IP_t$. Similar to the results in Table 2.2 Column 1 and 2, we find that our lagged media pessimism indicator possesses additional predictive power and is able to explain variations in market volatilities that other sentiment indicators do not capture.

We are able to obtain similar results after performing the same analysis by using alternative sentiment measures instead of our pessimism measure. The media pessimism indicator appears to possess extra explanatory power and capture more stock market variations than the Baker and Wurgler (2006) investor sentiment index and the VIX. Please see Appendix B for a more detailed discussion of the results.

Our media pessimism indicator is at best the approximation of the "true" media sentiment, which remains unobservable. Thus, it consists of the actual media sentiment and an error term, which is known as a measurement error. A measurement error sometimes results in the *attenuation* bias in the OLS regression, where the estimated coefficients of the explanatory variables are inconsistent and biased towards zero. In order to ensure that the OLS coefficients are consistent and unbiased, explanatory variables must be exogenous or uncorrelated with the residuals of the model. In order to control for endogeneity, we include lagged values of our media pessimism indicator. We do not observe any correlation between our lagged media pessimism indicator variables and the residuals across different specifications of our model. Thus, we conclude that the measurement error of our media pessimism indicator does not pose a serious problem and our estimated coefficients are unbiased.

Table 2.3 reports partial $R^2$ values for each lagged media pessimism indicator in our models (2.1) and (2.2). Our statistically significant coefficients for the media pessimism indicator at lags 1, 7, 17, 24 and 33 (1, 17, 24, and 33) appear to be economically significant in VAR model (2.1), where the MSCI World (S&P 500) return is the dependent variable. Their unique contributions to the explanatory power of the complete model are 1.9%, 2.2%, 4.8%, 1.7%, and 2.5% (4.7%, 4.2%, 2.0% and 2.1%), respectively. Thus, these coefficients jointly explain roughly 13% (13%) of the variation of the MSCI World (S&P 500) returns. On the other hand, other statistically significant coefficients in Table 2.2 Column 1 (2) lack economic significance. The coefficient for the media pessimism indicator at lag 5 appears to contribute 3.5% (2.2%) to the explanatory power of the complete model, although its coefficient in Table 2.2 Column 1 (2) is statistically insignificant. For VAR model (2.2), statistically significant coefficients for our media pessimism indicator at lags 2, 10, and 20 also have statistically significant $R^2$ values and contribute 3.5%, 6.3%, and 4.5% (2.5%, 6.7%, and 4.1%) to the explanatory power of the complete model, where demeaned squared residuals of the MSCI World (S&P 500) returns is the dependent variable. In summary, we show that the effect of our media pessimism indicator on the performance of financial markets is statistically and economically significant.

### 2.4.2 The causal impact of media pessimism on financial performance

Table 2.4 presents the results of the Granger causality tests for our market indices, market volatilities, and media pessimism indicator, for various subsets of lags. Table 2.4 Panel A presents the results of the Granger causality tests of $Sent_t$ on the MSCI World (column 1) and on the S&P 500 returns (column 3), and of the MSCI World and S&P 500 returns on $Sent_t$ (columns 2 and 4).

Table 2.4. Granger Causality Test
Panel A presents the Granger causality test results of our media pessimism indicator (*Sent*) on market returns and of market returns on *Sent* for the various subset of lags. Panel B reports the Granger causality test results of *Sent* on market volatility and market volatility on *Sent* for the various subsets of lags. We report the estimated $\chi^2$ statistics that test for the joint statistical significance of all lagged coefficients in a pre-specified set of lags. We take log returns of MSCI World and S&P 500 indices as market returns. Volatility is calculated by taking the squared demeaned residuals of market returns. As exogenous variables, we include the Fama and French (1993) factors for size and value ($FF-factors_t$), the Carhart (1997) momentum factor ($MoM_t$), the Pastor and Stambaugh (2003) liquidity factor ($LIQ_t$), U.S. macroeconomic variables such as the U.S. inflation, the U.S. consumer confidence index, the Federal fund rates, the U.S. yield spread, the U.S. industrial production, and the U.S. unemployment rate ($Macro_t$), the Baker and Wurgler (2006) investor sentiment index ($BWSent_t$) and the VIX index ($VIX_t$). *p*-values are reported in brackets. Statistical significance is denoted by asterisks *, ** and *** at the 10%, 5% and 1% levels, respectively.

| *Panel A: Causality Media Pessimism and Market Return* | | | | |
|---|---|---|---|---|
| | (1) MSCI World | (2) *Sent* | (3) S&P 500 | (4) *Sent* |
| Lag 1 -12 | 11.333 | 34.811 | 14.282 | 36.224 |
| | (0.500) | (0.525) | (0.283) | (0.458) |
| Lag 12-24 | 28.449*** | 16.538 | 26.641** | 13.345 |
| | (0.007) | (0.167) | (0.013) | (0.344) |
| Lag 24-36 | 20.446* | 4.615 | 17.567 | 8.966 |
| | (0.084) | (0.982) | (0.174) | (0.775) |
| Lag 1-36 | 57.953* | 9.833 | 58.039** | 10.627 |
| | (0.011) | (0.707) | (0.011) | (0.642) |
| *Panel B: Causality Media Pessimism and Market Volatility* | | | | |
| | (1) MSCI World | (2) *Sent* | (3) S&P 500 | (4) *Sent* |
| Lag 1 -12 | 21.171** | 40.709 | 15.979 | 35.610 |
| | (0.047) | (0.270) | (0.192) | (0.486) |
| Lag 12-24 | 20.153* | 10.791 | 24.083** | 8.406 |
| | (0.091) | (0.546 | (0.030) | (0.752) |
| Lag 24-36 | 8.165 | 4.463 | 7.013 | 6.238 |
| | (0.832) | (0.985) | (0.901) | (0.937) |
| Lag 1-36 | 41.896 | 9.588 | 45.920 | 7.759 |
| | (0.230) | (0.727) | (0.124) | (0.858) |
| $FF-factors_t$ | YES | | YES | |
| $MoM_t$ | YES | | YES | |
| $LIQ_t$ | YES | | YES | |
| $Macro_t$ | YES | | YES | |
| $BWSent_t$ | YES | | YES | |
| $VIX_t$ | YES | | YES | |

We find a significant Granger causal effect of $Sent_t$ on the MSCI World returns for the lag subsets 12–24, 24–36, and 1–36, and on the S&P 500 returns for the lag subsets 12–24 and 1–36. These results imply that all lagged coefficients in each subset of lags are jointly statistically significant. Together with the results in Table 2.2 columns 1 and 2 we can deduce that the coefficients at lags 1 to 21 are predominantly negative and the coefficients at lags 22 to 32 are predominantly positive, which implies negative and positive Granger causal relation of our media pessimism indicator on market returns, respectively. On the other hand, we do not observe any evidence for jointly statistically significant lagged coefficients of market returns on $Sent_t$, which suggests that market returns do not seem to Granger cause our media pessimism indicator in the long run.

Table 2.4 Panel B presents the results of the Granger causality tests of $Sent_t$ on the MSCI World and on the S&P 500 volatilities (columns 1 and 3), and of the MSCI World and S&P 500 volatilities on $Sent_t$ (columns 2 and 4) for various subsets of lags. We find a statistically significant Granger causal effect of media pessimism on the MSCI World and for the lag subsets 1–12 and 12–24, and on the S&P 500 volatilities for the lag subset 12–24. These results imply that all lagged coefficients in each of the lag subsets considered are jointly statistically significant.

Based on the results in Table 2.2 columns 3 and 4 we deduce that the lagged coefficients of $Sent_t$ are predominantly positive, which suggests a positive Granger causal relation of our media pessimism indicator on market volatilities. On the other hand, we do not observe any evidence for jointly statistically significant lagged coefficients of market volatilities on $Sent_t$, which implies that market volatilities do not seem to exert a significant Granger causal effect on future values of $Sent_t$. The results in Table 2.4 are in line with our expectations and findings in Table 2.2. They contribute to the previous research by Brown and Cliff (2004) by showing that investor sentiment exerts a significant impact on market performance over a longer time horizon. We find that market returns and volatilities do not affect the future content of the news media, but the news media appear to influence the future performance of the stock markets. This finding is contrary to that of García (2013) and Tetlock (2007), who argue that market performance affects the content of the news on a short-term basis, and to Brown and Cliff (2004), who find no Granger causal impact of investor sentiment on market returns in the short run.

## 2.5 Conclusion

This chapter investigates a potential media pessimism effect on the performance of financial markets in the long run. The previous literature suggests that media pessimism translates into investor sentiment and is associated with negative contemporaneous market returns and positive contemporaneous market volatilities (Antweiler and Frank, 2004; García, 2013; Goetzmann et al., 2016; Tetlock, 2007). In our study, we investigate the effect of media pessimism on the financial market performance over a longer horizon: three years. We follow the intuition of the model of Barberis et al. (1998) and empirical findings of Brown and Cliff (2004) and suggest that media pessimism influences investor sentiment and is associated with market performance in the long run.

We find evidence for a Granger causal effect of media pessimism on global market returns for 12 to 24 months and volatility for 1 to 24 months in advance. We show that our media pessimism indicator is associated with negative (positive) market returns 14 to 17 (24 to 25) months and positive market volatilities 2 to 20 months in advance. Our findings appear to be both statistically and economically significant.

Our results are consistent with the underreaction and overreaction hypotheses. Investors appear to be prone to conservatism and to be reluctant to adjust their beliefs in the face of new evidence. As a result, stock markets tend to be slow in reflecting changes in investor sentiment. On the other hand, investors are also prone to representativeness, i.e., they tend to overreact to prevailing sentiment, and tend to push market prices beyond their fundamentals. Over time, the markets revert back to fundamentals as prices correct themselves.

# Appendices

# Appendix A

# News extracts

This appendix presents examples of newspaper articles found on *LexisNexis* for one of three selected sources: the *Financial Times*, the *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 headline and the lead paragraph of each newspaper article. Negative newspaper articles are found by searching for our predefined negative words in the headline and the lead paragraph of each newspaper article.

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.

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.

# Appendix B

# Comparing alternative measures of media sentiment with our media pessimism indicator

Figure B.1 plots our media pessimism indicator against the Baker and Wurgler (2006) investor sentiment index and the VIX index for our sample period. The Baker and Wurgler investor sentiment indicator is a commonly used measure for the prevailing investor sentiment, where increasing values of the index denote investor optimism and decreasing values indicate pessimism. The VIX index is known as a “fear gauge”, where increasing values of the index indicate periods of increasing riskiness and uncertainty in the financial markets (Whaley, 2000). We standardize all indices to 100 in January 1990. The average monthly change of the Baker and Wurgler investor sentiment index, the media pessimism indicator, and the VIX is -0.01%, 0.05%, and -0.14%, respectively.

Figure B.1 shows that our media pessimism indicator and the VIX index exhibit more fluctuations than the Baker and Wurgler (2006) investor sentiment index. The standard deviation of the Baker and Wurgler investor sentiment index is 1.1%, while it is 11.6% for our media pessimism indicator and 16.9% for the VIX. The correlation between our media pessimism indicator and the Baker and Wurgler sentiment index

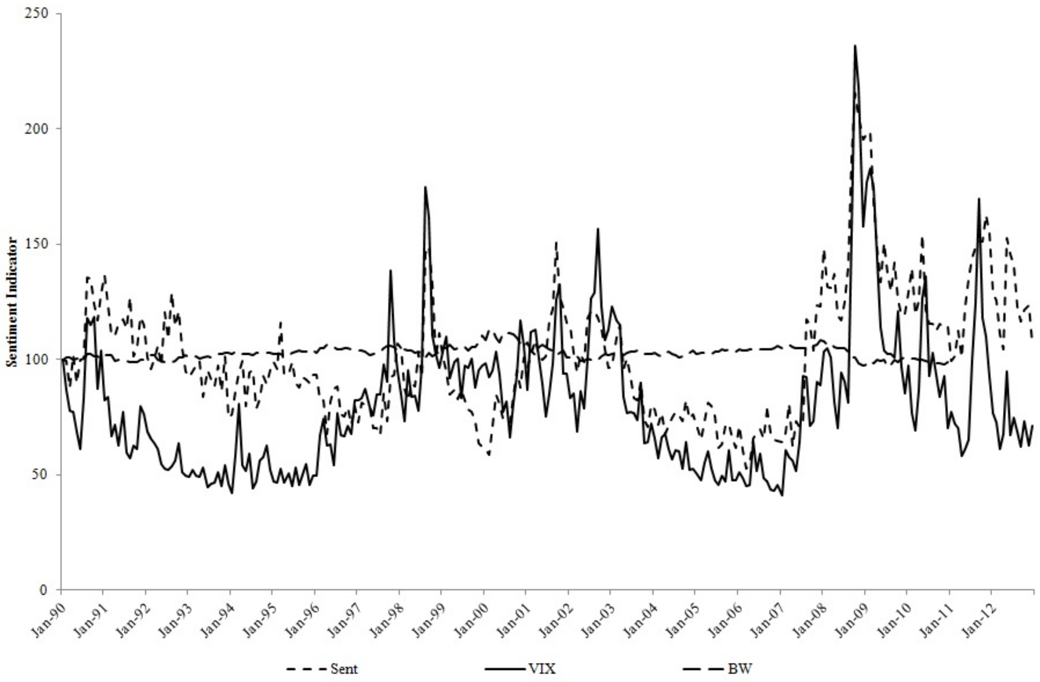


Figure B.1. Media Pessimism and Alternative Sentiment Indicators
The graph plots at a monthly frequency our media pessimism indicator against the VIX ($VIX$) and Baker and Wurgler (2006) investor sentiment index ($BWSent$) over our sample period between January 1990 and December 2012. $BWSent$ is only available until December 2010. Our media pessimism indicator ($Sent$) is constructed by taking the ratio of negative to positive news count. Increasing values of $BWSent$ indicate increasing optimism, while increasing values of $Sent$ and the VIX indicate increasing pessimism. All investor sentiment indicators are standardized to 100 in January 1990.

is only -10%, while the correlation between our media pessimism indicator and the VIX index is 41%. We also observe that while the VIX index and our media pessimism indicator tend to peak and to coincide at the outbreak of crises, the VIX seems to understate the level of pessimism during pre- and post-crisis periods. Our media pessimism indicator lies above the VIX index for the period between 1990 and 1996 in which the Southeast Asian crisis of 1997/98 began, for the period between 2004 and 2008 before the financial crisis in 2008, and for the period from 2009 to 2012 after the financial crisis.

Table B.1. VAR Model - Baker and Wurgler (2007) Investor Sentiment Index
This table presents the estimated coefficients of the Baker and Wurgler (2006) investor sentiment index ($BWSent_t$) for the VAR model (2.1) and (2.2) where the log return of the MSCI World index and the demeaned squared residuals of MSCI World log returns are dependent variables, respectively. We include as control variables the contemporaneous Fama and French (1993) factors for size ($SMB_t$) and value ($HML_t$). $MoM_t$ is the Carhart (1997) momentum factor. $LIQ_t$ is the Pastor and Stambaugh (2003) liquidity factor. $Macro_t$ includes macroeconomic variables such as the U.S. inflation ($CPI_t$), the U.S. consumer confidence index ($CCI_t$), the Federal fund rates ($FFR_t$), the U.S. yield spread ($Spread_t$), the U.S. industrial production ($IP_t$), and the U.S. unemployment rate ($Unemployment_t$). $Sent_t$ is the log change of our media pessimism indicator. $VIX_t$ is the log change of the VIX index. Statistical significance is reported by asterisks ** and *** at the 5% and 1% levels, respectively.

| | (1)<br>MSCI World Return | (2)<br>MSCI World Vola |
|---|---|---|
| $BWSent_{t-1}$ | 0.004** | -0.000 |
| $BWSent_{t-2}$ | -0.004 | -0.000 |
| $BWSent_{t-3}$ | 0.001 | -0.000 |
| $BWSent_{t-4}$ | -0.002 | -0.000 |
| $BWSent_{t-5}$ | 0.002 | -0.001* |
| $BWSent_{t-6}$ | 0.001 | -0.000 |
| $BWSent_{t-7}$ | 0.001 | -0.000 |
| $BWSent_{t-8}$ | -0.002 | -0.001*** |
| $BWSent_{t-9}$ | 0.000 | -0.000 |
| $BWSent_{t-10}$ | -0.001 | -0.000 |
| $BWSent_{t-11}$ | -0.004 | 0.000* |
| $BWSent_{t-12}$ | -0.003 | -0.000 |
| $BWSent_{t-13}$ | 0.002 | 0.000 |
| $BWSent_{t-14}$ | -0.001 | 0.001** |
| $BWSent_{t-15}$ | 0.001 | 0.000 |
| $BWSent_{t-16}$ | -0.001 | -0.000 |
| $BWSent_{t-17}$ | 0.000 | -0.000 |
| $BWSent_{t-18}$ | -0.002 | -0.000 |
| $BWSent_{t-19}$ | 0.001 | -0.000 |
| $BWSent_{t-20}$ | -0.003 | -0.001** |
| $BWSent_{t-21}$ | 0.000 | -0.001* |
| $BWSent_{t-22}$ | -0.003 | -0.000 |
| $BWSent_{t-23}$ | -0.003 | 0.000 |
| $BWSent_{t-24}$ | -0.002 | -0.000 |
| $BWSent_{t-25}$ | 0.002 | 0.000 |
| $BWSent_{t-26}$ | 0.000 | 0.000 |
| $BWSent_{t-27}$ | 0.000 | 0.000 |
| $BWSent_{t-28}$ | 0.002 | 0.000 |
| $BWSent_{t-29}$ | -0.003 | -0.000 |
| $BWSent_{t-30}$ | -0.004* | 0.000 |
| $BWSent_{t-31}$ | 0.000 | 0.000 |
| $BWSent_{t-32}$ | 0.003 | -0.000 |
| $BWSent_{t-33}$ | 0.001 | 0.000 |
| $BWSent_{t-34}$ | -0.002 | 0.000 |
| $BWSent_{t-35}$ | -0.000 | -0.000 |

Table B.1 – *Continued from previous page*

| | (1) MSCI World Return | (2) MSCI World Vola |
|---|---|---|
| $BWSent_{t-36}$ | -0.001 | 0.000 |
| $Constant$ | -0.003 | 0.001 |
| $SMB_t$ | -0.110 | 0.013 |
| $HML_t$ | 0.040 | -0.003 |
| $LIQ_t$ | -0.073 | 0.010 |
| $MoM_t$ | -0.112** | -0.001 |
| $IP_t$ | -0.474 | 0.058 |
| $Spread_t$ | -0.002 | -0.000 |
| $CPI_t$ | -0.021 | -0.007*** |
| $FFR_t$ | 1.065 | -0.188 |
| $CCI_t$ | 0.046 | -0.013*** |
| $Unemployment_t$ | 0.093 | -0.005 |
| $VIX_t$ | -0.150*** | 0.007*** |
| $Sent_t$ | -0.089*** | 0.003 |
| $Adj.R^2$ | 0.608 | 0.295 |
| $OBS$ | 210 | 210 |

In order to compare the predictive ability of our media pessimism indicator with those of the Baker and Wurgler (2006) investor sentiment index and the VIX, we propose to estimate our VAR models (2.1) and (2.2) by using these alternative sentiment measures, the MSCI World and MSCI World volatility as endogenous variables, and to control for our media pessimism indicator. Table B.1 column 1 presents the estimated coefficients for the VAR models (2.1), where the MSCI World and $BWSent_t$ are endogenous variables, and Table B.1 column 2 presents the estimated coefficients of our VAR model (2.2), where the MSCI World volatility and $BWSent_t$ are endogenous variables. As exogenous variables, we substitute $Sent_t$ for $BWSent_t$.

We find a positive statistically significant coefficient for $BWSent_t$ at lag 1 and a negative statistically significant coefficient at lag 30, suggesting that the MSCI World tends to react positively to changes in investor sentiment with a lag of one month. The effect reverses after two-and-a-half years. For the volatility of the MSCI World, we find negative and statistically significant coefficients for $BWSent_t$ at lags 5, 8, 20, and 21, and positive and statistically significant coefficients for lags 11 and 14, which suggests that positive (negative) investor sentiment is followed by low (high) levels of market volatility, and the effect seems to reverse after one to one-and-a-half years.

These results confirm the findings in Table 2.2 and are consistent with our expectations and the previous literature. Similar to the findings of Brown and Cliff (2005) and Lee et al. (2002), our results show that investor sentiment is associated with market returns and market volatilities in the long run. Consistent with Barberis et al. (1998), market prices and market volatilities tend to reflect changes in investor sentiment slowly. Investors also seem to overreact to prevailing investor sentiment and push stock prices and volatilities to unjustifiable levels. Once fundamentals are revealed, markets tend to correct the mispricing (Cutler et al., 1991; Fama and French, 1988; Poterba and Summers, 1988; De Bondt and Thaler, 1985, 1987). The coefficient for the control variable $Sent_t$ is negative and statistically significant for the MSCI World returns, indicating that there is a negative contemporaneous relation between our media pessimism measure and the MSCI World returns, which supports our findings in Figure 2.1 and the results of Tetlock (2007) and García (2013).

In contrast to our results in Table 2.2, we do not find evidence of any predictive activity of $BWSent_t$ at lags 14 to 17, or at lags 24 to 25. Table B.1 shows that the adjusted $R^2$ of the VAR (2.1) model is 61%, which is slightly lower than the adjusted $R^2$ shown in Table 2.2 for the MSCI World returns (63%). This suggests that our media pessimism measure has greater predictive power and is able to explain variations in the stock returns that are not captured by the Baker and Wurgler investor sentiment index.

Table B.2. VAR Model - VIX index

This table presents the estimated coefficients of the VIX index ($VIX_t$) for the VAR model (2.1) and (2.2) where the log return of the MSCI World index and the demeaned squared residuals of MSCI World log returns (MSCI World Vola) are dependent variables, respectively. We include as control variables the contemporaneous Fama and French (1993) factors for size ($SMB_t$) and value ($HML_t$). $MoM_t$ is the Carhart (1997) momentum factor. $LIQ_t$ is the Pastor and Stambaugh (2003) liquidity factor. $Macro_t$ includes macroeconomic variables such as the U.S. inflation ($CPI_t$), the U.S. consumer confidence index ($CCI_t$), the Federal fund rates ($FFR_t$), the U.S. yield spread ($Spread_t$), the U.S. industrial production ($IP_t$), and the U.S. unemployment rate ($Unemployment_t$). $Sent_t$ is the log change of our media pessimism indicator. $BWSent_t$ is the log change of the Baker and Wurgler (2007) investor sentiment index. Statistical significance is reported by asterisks ** and *** at the 5% and 1% levels, respectively.

| | (1) MSCI World Return | (2) MSCI World Vola |
|---|---|---|
| $VIX_{t-1}$ | 0.015 | 0.002 |
| $VIX_{t-2}$ | 0.037 | 0.001 |
| $VIX_{t-3}$ | 0.046* | 0.000 |
| $VIX_{t-4}$ | 0.057** | -0.000 |
| $VIX_{t-5}$ | 0.012 | -0.000 |
| $VIX_{t-6}$ | 0.047* | -0.004 |
| $VIX_{t-7}$ | -0.019 | -0.001 |
| $VIX_{t-8}$ | 0.013 | -0.002 |
| $VIX_{t-9}$ | 0.039 | -0.002 |
| $VIX_{t-10}$ | -0.004 | 0.002 |
| $VIX_{t-11}$ | -0.023 | 0.003 |
| $VIX_{t-12}$ | 0.037 | 0.002 |
| $VIX_{t-13}$ | -0.013 | 0.000 |
| $VIX_{t-14}$ | -0.013 | 0.005* |
| $VIX_{t-15}$ | -0.002 | 0.004 |
| $VIX_{t-16}$ | -0.005 | 0.007** |
| $VIX_{t-17}$ | 0.0117 | 0.001 |
| $VIX_{t-18}$ | 0.002 | 0.004 |
| $VIX_{t-19}$ | -0.057** | 0.005* |
| $VIX_{t-20}$ | -0.033 | 0.007*** |
| $VIX_{t-21}$ | -0.018 | 0.004 |
| $VIX_{t-22}$ | -0.029 | 0.004 |
| $VIX_{t-23}$ | -0.019 | 0.002 |
| $VIX_{t-24}$ | 0.073*** | 0.003 |
| $VIX_{t-25}$ | 0.032 | 0.002 |
| $VIX_{t-26}$ | 0.052* | 0.001 |
| $VIX_{t-27}$ | 0.033 | -0.001 |
| $VIX_{t-28}$ | 0.007 | -0.001 |
| $VIX_{t-29}$ | 0.023 | 0.001 |
| $VIX_{t-30}$ | -0.000 | 0.001 |
| $VIX_{t-31}$ | 0.029 | -0.001 |
| $VIX_{t-32}$ | 0.065*** | -0.000 |
| $VIX_{t-33}$ | -0.019 | 0.001 |
| $VIX_{t-34}$ | 0.026 | 0.000 |
| $VIX_{t-35}$ | -0.002 | -0.001 |

Table B.2 – *Continued from previous page*

| | (1) MSCI World Return | (2) MSCI World Vola |
|---|---|---|
| $VIX_{t-36}$ | -0.023 | -0.001 |
| $Constant$ | 0.019 | 0.000 |
| $SMB_t$ | -0.029 | 0.004 |
| $HML_t$ | 0.133*** | -0.007 |
| $LIQ_t$ | -0.023 | 0.013 |
| $MoM_t$ | -0.171*** | 0.002 |
| $IP_t$ | -0.534 | 0.054 |
| $Spread_t$ | -0.010 | 0.000 |
| $CPI_t$ | 0.015 | -0.003 |
| $FFR_t$ | -0.322 | -0.160 |
| $CCI_t$ | 0.060 | -0.008* |
| $Unemployment_t$ | -0.157 | 0.012 |
| $BWSent_t$ | 0.010*** | -0.000 |
| $Sent_t$ | -0.102*** | 0.005** |
| $Adj.R^2$ | 0.333 | 0.116 |
| $OBS$ | 210 | 210 |

We also compare the predictive power of our media pessimism indicator with that of the VIX index. Table B.2 column 1 presents the estimated coefficients for the VIX index in our specified VAR models (2.1), where the MSCI World return and $VIX_t$ are endogenous variables, and Table B2 column 2 presents the estimated coefficients for our VAR model (2.2), where the MSCI World volatility and $VIX_t$ are endogenous variables. We substitute $VIX_t$ for $Sent_t$ in our set of exogenous variables. We find positive and statistically significant coefficients for the $VIX_t$ at lags 3, 4, 6, 24, 26, and 32, and a negative and statistically significant coefficient at lag 19 in VAR model (2.1). Similarly, we find positive and statistically significant coefficients for the $VIX_t$ at lags 14, 16, and 20 in the VAR model (2.2). These results indicate that increasing (decreasing) levels of the VIX are associated with higher (lower) MSCI World returns in the first six months, and lower (higher) MSCI World returns after 19 months. The VIX is also positively associated with the MSCI World volatility at lags 14 to 20. These findings confirm our results in Tables 2.2 and B.2 and are consistent with the underreaction and overreaction hypotheses of Barberis et al. (1998).

Table B.2 shows that the adjusted $R^2$ for the VAR model (2.1) is 33%, which is sufficiently lower than the adjusted $R^2$ in Table 2.2 for the MSCI World return (63%). Furthermore, the adjusted $R^2$ for the VAR model (2.2) in Table B.2 is 12%, while it is 26% in Table 2.2 for the MSCI World volatility. These findings indicate a predictive power of our media pessimism indicator superior to that of the VIX index in predicting the long-term variations of the MSCI World returns and volatilities. Additionally, the VIX does not seem to predict the MSCI World returns at lags 14 to 17, and 24 to 25, as our media pessimism indicator does. Similar to the findings in Table B.2, we suggest that our media pessimism indicator is able to explain variations in stock returns that the VIX does not seem to capture.