Giving Content to Investor Sentiment: The Role of Media in the Stock Market

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ABSTRACT

I quantitatively measure the nature of the media's interactions with the stock market using daily content from a popular *Wall Street Journal* column. I find that high media pessimism predicts downward pressure on market prices followed by a reversion to fundamentals, and unusually high or low pessimism predicts high market trading volume. These results and others are consistent with theoretical models of noise and liquidity traders. However, the evidence is inconsistent with theories of media content as a proxy for new information about fundamental asset values, as a proxy for market volatility, or as a sideshow with no relationship to asset markets.

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> One of the more fascinating sections of the *WSJ* is on the inside of the back page under the standing headline "Abreast of the Market." There you can read each day what the market did yesterday, whether it went up, down or sideways as measured by indexes like the Dow Jones Industrial Average .... In that column, you can also read selected post-mortems from brokerage houses, stock analysts and other professional track watchers explaining why the market yesterday did whatever it did, sometimes with predictive nuggets about what it will do today or tomorrow. This is where the fascination lies. For no matter what the market did—up, down or sideways—somebody will have a ready explanation. ... - Vermont Royster (January 15, 1986)

Casual observation suggests the content of financial news about the stock market could be linked to investor psychology and sociology. However, it is unclear whether the financial news media induces, amplifies or simply reflects investors' interpretations of stock market performance. This paper attempts to characterize the relationship between the content of media reports and daily stock market activity, focusing on the immediate influence of the *Wall Street Journal*'s (*WSJ*'s) "Abreast of the Market" column on U.S. stock market returns.

To my knowledge, this paper is the first to find evidence that news media content can predict movements in broad indicators of stock market activity. Using principal components analysis, I construct a simple measure of media pessimism from the content of the *WSJ* column. Then I estimate the intertemporal links between this measure of media pessimism and the stock market in basic vector auto-regressions (VARs). First and foremost, I find that high levels of media pessimism robustly predict downward pressure on market prices, followed by a reversion to fundamentals. Second, unusually high or low values of media pessimism forecast high market trading volume. Third, low market returns lead to high media pessimism. These findings suggest that measures of media content serve as a proxy for investor sentiment or non-informational trading. By contrast, statistical tests reject the hypothesis that media content contains new information about fundamental asset values and the hypothesis that media content is a sideshow with no relation to asset markets.

I use the General Inquirer (GI), a well-known quantitative content analysis program, to analyze daily variation in the *WSJ* "Abreast of the Market" column over the 16-year period 1984 to 1999 inclusive. This column is a natural choice for a data source that reflects and influences investor sentiment for three reasons. First, the *WSJ* has by far the largest circulation—over 2 million readers—of any daily financial publication in the U.S. and Dow Jones Newswires, the preferred medium for electronic *WSJ* distribution, reaches over 325,000 finance and investment professionals.[1] Second, the *WSJ* and Dow Jones Newswires, founded in 1889 and 1897 respectively, are extremely well-established and have strong reputations with investors. Third, electronic texts of the *WSJ* "Abreast of the Market" column are accessible over a longer time horizon than texts of any other column about the stock market.[2]

For each day in my sample, I gather newspaper data by counting the words in all 77 *predetermined* GI categories from the Harvard psychosocial dictionary. To mitigate measurement error and enhance construct validity, I perform a principal components factor analysis of these categories. This process collapses the 77 categories into a single media factor that captures the maximum variance in the GI categories. Because this single media factor is strongly related to pessimistic words in the newspaper column, I refer to it as a pessimism factor hereafter.

In standard return predictability regressions, changes in this pessimism factor predict statistically significant and economically meaningful changes in the distribution of daily U.S. stock returns and volume. I confirm the robustness of this relationship by looking at the sensitivity of the results to the timing of information and to the use of different measures of pessimism. The results remain the same when I allow for a significant time gap between the release of media pessimism and the event return window. I also replicate the results using alternative measures of media pessimism based on the original GI categories. Using the GI category for either Negative words or Weak words (the two GI categories most highly correlated with pessimism), I find similar relationships between the media and the market. This approach to modeling behavioral phenomena yields factors and corresponding regression coefficients that can be readily interpreted in terms of well-established psychological variables.

Section I provides some context and motivation for studying the impact of the media on the stock market. Section II describes the factor analysis of the content of the daily "Abreast of the Market" column in the *Wall Street Journal*. Section III reports myriad tests of whether the pessimism media factor correlates with future stock market activity. In Section IV, I interpret the pessimism factor in terms of investor sentiment and show that the risk premium explanation does not explain the results. I conclude in Section V with a brief discussion of the results and suggestions for future research on the influence of media in asset markets. Finally, because this study relies heavily on a technique unfamiliar to many economists, the Appendix introduces the method of quantitative content analysis as it is employed in this study—for more detailed information, see Riffe, Lacy, and Fico (1998).

I. Theory and Background

Since John Maynard Keynes coined the term animal spirits 70 years ago, economists have devoted substantial attention to trying to understand the determinants of wild movements in stock market prices that are seemingly unjustified by fundamentals (see Keynes (1936)). Cutler, Poterba, and Summers (1989) is one of the first empirical studies to question the link between news coverage and stock prices. Surprisingly, the authors find that important qualitative news stories do not seem to help explain large market returns unaccompanied by quantitative macroeconomic events.

Two recent studies identify interesting relationships between trading volume and measures of communication activity. Antweiler and Frank (2004) study messages in Internet chat rooms focused on stocks, characterizing the content of the messages as "buy," "sell" or "hold" recommendations. Although they do not find a statistically or economically significant effect of "bullish" messages on returns, Antweiler and Frank (2004) do find evidence of relationships between message activity and trading volume and message activity and return volatility. Similarly, Coval and Shumway (2001) establish that the ambient noise level in a futures pit is linked to volume, volatility and depth—but not returns.

Most theoretical models of the effect of investor sentiment on stock market pricing make two important assumptions—see, for example, DeLong et al. (1990a). First, these models posit two types of traders: noise traders who hold random beliefs about future dividends and rational arbitrageurs who hold Bayesian beliefs. In this paper, I will refer to the level of noise traders' beliefs relative to Bayesian beliefs as investor sentiment. For example, when noise traders have expectations of future dividends that are below the expectations of rational arbitrageurs, I will call their beliefs pessimistic. Further, I will assume that these misperceptions of dividends are stationary, implying that beliefs do not stray arbitrarily far from Bayesian expectations over time.

Second, both types of traders have downward-sloping demands for risky assets because they are risk-averse, capital-constrained, or otherwise impaired from freely buying and selling risky assets. These assumptions lead to an equilibrium in which noise traders' random beliefs about future dividends influence prices. When noise traders experience a negative belief shock, they sell stocks to arbitrageurs, increasing volume and temporarily depressing returns. On average, returns rebound next period when there is a new belief shock because these shocks are stationary. Thus, models of investor sentiment such as DeLong et al. (1990a) predict low sentiment will produce downward price pressure and unusually high or low values of sentiment will generate high volume.

More generally, models of trade for any non-informational reason, such as liquidity needs or sudden changes in risk aversion, make these same predictions. For example, Campbell, Grossman, and Wang (1993) model how changes in the level of risk aversion for a large subset of investors can affect short-term returns. The only way to distinguish noise trader and liquidity trader theories is to interpret the media pessimism variable as a proxy for either investor sentiment or risk aversion. Because this debate is more philosophical than economic, I defer to the reader to draw her own conclusions.

The timing of media pessimism is important in each theory. This paper will test the specific hypothesis that high media pessimism is associated with low investor sentiment, resulting in downward pressure on prices. It is unclear whether media pessimism forecasts investor sentiment or reflects past investor sentiment. If the former hypothesis is correct, then one would expect high media pessimism to predict low returns at short horizons and a reversion to fundamentals at longer horizons. If the latter theory is correct, then one would expect high media pessimism to follow low returns and predict high returns in the future.

The most likely scenario, however, is that both theories have an element of truth. If media pessimism serves as a proxy for periods of low past and future investor sentiment, one would expect to find that high pessimism follows periods of low past returns, forecasts low future returns at short horizons, and predicts high future returns at longer horizons. Insofar as pessimism reflects past investor sentiment, the high long-horizon returns will exceed the low short-horizon returns. These predictions concerning returns are summarized in Figure 1.

[Insert Figure 1 around here]

One alternative hypothesis is that the media pessimism measure is a proxy for negative information about the fundamental values of equities that is not currently incorporated into prices. If pessimism reflects negative news about past and future cash flows rather than sentiment, then one would still observe a negative relationship between media pessimism and short-horizon returns. However, the sentiment and information theories make different predictions about long-horizon returns and volume. Whereas the sentiment theory predicts short-horizon returns will be reversed in the long run, the information theory predicts they will persist indefinitely.

Although this discussion focuses on extreme views of the newspaper column as either pure noise or pure information, it is also possible that the column contains some information but traders over- or underreact to this information. I will explore these possibilities further in the empirical tests in Section III.

Another theory of media pessimism is that it is a proxy for negative information about dividends that is already incorporated into prices. This theory predicts media pessimism should have no effect on future market activity. Similarly, if one believes that the media pessimism measure contains no information about past, present, and future dividends, then one would not expect to observe any impact of pessimism on market activity. Many economists who have read the "Abreast of the Market" column in the *WSJ* support some variant of this theory, believing the column's goal is to entertain readers.

Trading volume provides another measure of market behavior for assessing theories of media pessimism. If media pessimism either reflects past or predicts future investor sentiment, unusually high or low levels of pessimism should be associated with increases in trading volume. More precisely, if pessimism has a mean of zero, then the absolute value of pessimism is high in times when irrational investors trade with rational investors.[3] Whereas the sentiment theory makes a clear prediction about the relationship between volume and pessimism, the information theory makes no obvious prediction.[4] Finally, the stale or no information theory predicts no effect of media pessimism on trading volume.

II. Generating the Pessimism Media Factor

As a completely automated program, the General Inquirer (GI) produces a systematic and easily replicable analysis of the *WSJ* column. The GI employs an extremely rudimentary measurement rule for converting the column into numeric values: it counts the number of words in each day's column that fall within various word categories. The word categories are neither mutually exclusive nor exhaustive—one word may fall into multiple categories and some words are not categorized at all. To reduce redundancy in categorization, I use only the most recent versions of categories in the General Inquirer's Harvard IV-4 psychosocial dictionary.

To minimize semantic and stylistic noise in the column, I re-center all GI categories so that their conditional means are equal across different days of the week. This ensures that I do not select media factors that capture the systematic variation in the *WSJ* column on different days of the week. I use day-of-the-week dummy variables in the regressions in the next section to control for the possibility that market behavior differs across different days of the week.

I employ a principal components factor analysis to extract the most important semantic component from the (77x77) variance-covariance matrix of the categories in the Harvard dictionary. This process is designed to detect complex structure in the *WSJ* column and to eliminate the redundant categories in the dictionary. Factor analysis assumes the existence of an underlying media factor—a linear combination of GI categories that is not directly observable.[5] Variation in this factor over time generates the observed daily correlations between the various GI categories.

Operationally, factor analysis chooses the vector in the 77-dimensional GI category space with the greatest variance, where each GI category is given equal weight in the total variance calculation. I have explored other factor analysis techniques, such as principal factors analysis and maximum-likelihood factor analysis. The qualitative empirical conclusions are not sensitive to the methodology chosen, and the quantitative conclusions change only minimally. For the remainder of this paper, I will present the results using the single factor identified by principal components analysis that captures the maximum variation in GI categories. Principal components analysis effectively performs a singular value decomposition of the correlation matrix of GI categories measured over time. The single factor selected in this study is the eigenvector in the decomposition with the highest eigenvalue.

Because this singular value decomposition uses only the GI category variables in the correlation matrix, *completely disregarding all stock market variables*, the resulting media factor will not necessarily correspond to any traditional measurements of past market performance. Also, because I did not subjectively eliminate any categories, the factor analysis generates a media factor that equally considers all sources of variation in the *WSJ* column, even though it is likely that some categories are more relevant for measuring investor sentiment.[6] Theoretical imprecision is the cost of avoiding data mining. To facilitate the interpretation of the single factor chosen, I will adopt a complementary approach to creating a summary media variable later in the paper.

The principal components analysis exploits time variation in GI category word counts to identify the media factor. To avoid data mining and any look-ahead bias in the regressions that follow, I construct the media factor using only information available to traders. I estimate the factor loadings in year $t-1$ using principal components analysis. Then I use these loadings, along with the daily word counts in year t, to calculate the values of the factor throughout year t. Because this procedure does not guarantee any consistency in factor loadings across years, it is possible that changes in the structure of media content over time will cause this procedure to generate a meaningless factor. For example, if the column writer focuses on different issues in different years, then this procedure will generate a single factor that covaries with different issues in different years.

To examine whether time variation in the GI categories is stable and whether the above procedure is reasonable, I analyze the relationship between the loadings used in each yearly factor. For each year in the data sample, I use the loadings estimated from that year to calculate the value of the hypothetical value of the yearly factor in all years. Then I compare the correlations for these hypothetical yearly factors across the entire sample.

Fortunately, the media factor estimated using the loadings from any given year looks very similar to the media factor estimated using another year's loadings. In Table I, I report the correlation matrix of yearly factors. The average pairwise correlation between the yearly media factors is 0.96 and the average squared correlation is 0.91. The minimum pairwise correlation is 0.80, suggesting all pairs of media factors are very highly correlated. I conclude from this analysis that the loadings on the individual GI categories are quite stable over time.

[Insert Table I around here]

Each yearly factor analysis can be interpreted in terms of the underlying GI categories. The average of the first eigenvalue in each yearly factor analysis is 6.72, implying that the first factor contributes as much variance in media content as more than six of the original GI category variables. This first factor is approximately equal to a linear combination with positive weights on just four of the 77 GI categories: Negative, words of negative outlook; Weak, words implying weakness; Fail, words indicating goals have not been achieved; and Fall, words associated with falling movement. In fact, the Negative and Weak GI categories *each* can explain over 57% of the variance in the first factor. This factor also negatively weights categories such as Positive, words of positive outlook.[7] But the negative relationship between the factor and Positive words is not as strong as the positive relationship between the factor and Negative words.

On days in which the *WSJ* column loads highly on this first factor, it probably contains negative interpretations of market events. These interpretations may or may not correspond to objectively negative news about corporate earnings and other relevant economic indicators.

Hereafter, I use the term "pessimism" factor to refer to this first media factor.

In thinking about the pessimism factor, it is important to remember that the typical "Abreast of the Market" column reads like a post-mortem of the market's life on the prior day.[8] The *Wall Street Journal*'s "Abreast of the Market" column is written immediately after the closing bell on Wall Street on the most recent day of market activity. In fact, the writing process usually begins even before the closing bell at 2:30 to 3:00 p.m. EST. It is unlikely that the column contains any information unknown to the specialists on the floor of the exchange at the conclusion of trading. Nevertheless, in robustness tests shown below, I introduce a significant time gap between the release of the column in the afternoon and the beginning of the event return window. The same column produced and released by Dow Jones Newswires each afternoon is re-published in the *Wall Street Journal* on the morning of the next day of market activity.

III. Market Activity and Pessimism

The market returns regressions presented below control for many known sources of predictability found in daily return data. In a frictionless complete market where traders have rational expectations, financial theory predicts daily prices will follow a random walk with drift (Samuelson (1965)). More generally, classic arbitrage arguments suggest prices should approximate a random walk with drift. But market microstructure phenomena—*i.e.*, bid-ask bounce, non-synchronous trading, and transactions costs—sully the purity of the theoretical prediction. Some of these mechanisms induce statistical artifacts that make observed returns appear autocorrelated, whereas other mechanisms lead to genuine return autocorrelation.[9]

With these caveats in mind, this study attempts to control for the influence of the lagged returns of indices and the lagged returns of any leading, larger indices. Regressions also include lagged volume to try to capture liquidity effects. Finally, lagged return volatility acts as a proxy for the influence of several other market frictions. The return and volatility predictability regressions control for all lags up to five trading days—*i.e.*, at least one week of calendar time.

This study runs two main sets of regressions to test whether the pessimism factor predicts returns and volume beyond known sources of predictability. In the first set of tests, I adopt a vector auto-regressive (VAR) framework in which I simultaneously estimate the relationships between returns, volume, and the pessimism factor. In the second set of tests, I examine the robustness of these results. Finally, I assess the economic importance of the return predictability and whether it implies there are profitable sentiment-based trading strategies.

A. VAR Estimates

Because Dow Jones and Company produces the *WSJ* and the "Abreast of the Market" column focuses on the stocks in the Dow Jones index, I test whether pessimism forecasts daily returns on the Dow Jones Industrial Average (*Dow*). In addition, because previous authors (*e.g.*, DeLong et al. (1990a)) have suggested that investor sentiment plays a larger role in the pricing of small stocks, I consider whether pessimism forecasts the returns to the Fama-French daily small minus big (*SMB*) factor. As a measure of volume, I look at the detrended log of daily volume (*Vlm*) on the New York Stock Exchange (NYSE).[10]

I obtain a time series of daily returns from January 1, 1984, to September 17, 1999, from the Wharton Research Data Services' access to the historical Dow Jones Industrial Averages. This sample period encompasses almost 4,000 observations of market returns; each year consists of only about 250 data points because the U.S. stock market is idle on weekends and national holidays.

All VAR estimates include all lags up to five days prior to market activity. The endogenous variables in the first VAR are *Dow*, the pessimism media factor (*BdNws*), and *Vlm*.[11] The exogenous variables include five lags of the detrended squared *Dow* residuals to proxy for past volatility,[12] dummy variables for day-of-the-week and January to control for other potential return anomalies, and a dummy variable for the October 19, 1987 stock market crash to ensure the results are not driven by this single observation.[13] Newey-West robust standard errors account for any heteroskedasticity and auto-correlation in the residuals up to five lags.

It is convenient to define a variable *Exog* that represents all of the exogenous variables. I also define a lag operator $L5$ that transforms any variable x_t into a row vector consisting of the five lags of x_t—*i.e.*, $L5(x_t) = \begin{bmatrix} x_{t-1} & x_{t-2} & x_{t-3} & x_{t-4} & x_{t-5} \end{bmatrix}$ With these definitions, the returns equation for the first VAR can be expressed as:

$$\begin{aligned} Dow_t &= \alpha_1 + \beta_1 \cdot L5(Dow_t) + \gamma_1 \cdot L5(BdNws_t) \\ &\quad + \delta_1 \cdot L5(Vlm_t) + \lambda_1 \cdot Exog_{t-1} + \varepsilon_{1t} \end{aligned} \tag{1}$$

To account for time-varying return volatility, I assume the disturbance term ε_t is heteroskedastic across time. Because the disturbance terms in the volume and media variables equations have no obvious relation to disturbances in the returns equation, I assume these disturbance terms are independent. Relaxing the assumption of independence across equations does not affect the results.

Assuming independence allows me to estimate each equation separately using standard ordinary least squares (OLS) techniques. Thus, the VAR estimates are equivalent to the Granger causality tests first suggested by Granger (1969). The OLS estimates of the coefficients γ_1 in equation (1) are the primary focus of this study. These coefficients describe the dependence of the Dow Jones index on the pessimism factor. Table II summarizes the estimates of γ_1.

[Insert Table II around here]

The p-value for the null hypothesis that the five lags of the pessimism factor do not forecast returns is only 0.006, which strongly implies that pessimism is associated in some way with future returns. The table shows that the pessimism media factor exerts a statistically and economically significant negative influence on the next day's returns (t-statistic = 3.94; p-value < 0.001). The average impact of a one standard deviation change in pessimism on the next day's Dow Jones returns is 8.1 basis points, which is larger than the unconditional mean of Dow Jones returns (5.4 basis points).

Consistent with the model in Campbell, Grossman, and Wang (1993), this negative influence is only temporary and is almost fully reversed later in the trading week. The magnitude of the reversal in lags 2 through 5 is 6.8 basis points, which is significantly different from zero at the 5% level. Thus, I can reject the hypothesis of no reversal and the hypothesis of return continuation following pessimistic news. However, I cannot reject the hypothesis that the 6.8 basis point reversal in lags 2 through 5 exactly offsets the initial decline in returns of 8.1 basis points–*i.e.*, the sum of the coefficients on the five lags of pessimism (-1.3 basis points) is not significantly different from zero. Assuming the newspaper column contains no relevant information about fundamentals, the market's *long-run* reaction is consistent with market efficiency and provides no support for theories of over- or underreaction to news.

The evidence of an initial decline and subsequent reversal is consistent with neither the new information theory nor the stale information theory of the newspaper column. If the column contained new information about fundamentals, there could be an initial decline in returns, but this would not be followed by a complete return reversal. If the column contains only information already incorporated into prices, media pessimism would not significantly influence returns. The evidence is, however, consistent with temporary downward price pressure caused by pessimistic investor sentiment.

The second and third regressions in Table II examine whether the GI word categories, Negative and Weak, underlying the pessimism factor also serve as proxies for investor sentiment. All independent variables in the second and third regressions are the same as in the original specification except that the pessimism factor has been replaced by the Negative category and the Weak category, respectively. If the pessimism factor is truly a proxy for negative investor sentiment, then it is reasonable to expect that the GI word categories comprising pessimism should bear the same qualitative relationship to future returns as the pessimism factor. The Negative and Weak word categories capture the psychological intuition behind investor sentiment.

Table II shows that one standard deviation increases in Negative words and Weak words predict the Dow Jones will fall by 4.4 and 6.0 basis points, respectively. Both magnitudes are statistically and economically significant, and are comparable to the pessimism effect. The table also shows that the return reversals in days 2 through 5 following increases in Negative and Weak words are even larger than the reversal following pessimism. The delayed increase in returns is 9.5 basis points for Negative words and 10.7 basis points for Weak words, both of which are strongly economically and statistically significant (p-values < 0.01).

All three measures of pessimism exert an effect on returns that is an order of magnitude greater than typical bid-ask spreads for Dow Jones stocks. So bid-ask bounce is unlikely to explain the results. Based on the evidence in Table II, I conclude that the negative sentiment has a significant temporary impact on future Dow Jones returns that is fully reversed within a week.[14]

It is also interesting to look at the effect of returns and other economic variables on the content of the newspaper column. If the pessimism factor is a reasonable measure of the content of the column, then economic variables from the recent past may predict the values of the pessimism factor. The VAR equation given below describes this relationship:

$$\begin{aligned} BdNws_t &= \alpha_2 + \beta_2 \cdot L5(Dow_t) + \gamma_2 \cdot L5(BdNws_t) \\ &\quad + \delta_2 \cdot L5(Vlm_t) + \lambda_2 \cdot Exog_{t-1} + \varepsilon_{2t} \end{aligned} \tag{2}$$

Table III presents OLS estimates of β_2, which represents the impact of past Dow Jones returns on pessimism, for all three measures of pessimism. Table III reverses the causal link posited in Table II. The table shows negative returns predict more pessimism in the next day's *WSJ* column, which is consistent with the positive feedback trading theory in DeLong et al. (1990b). The magnitude of the pessimism coefficient implies that a 1% decrease in the prior day's returns on the Dow leads to a significant increase in pessimism equal to 5.8% of one standard deviation of the pessimism media factor (p-value = 0.003).

[Insert Table III around here]

The VAR equation that models NYSE volume provides another measure of the pessimism factor's influence on market activity. Prior research suggests financial media coverage could be related to exchange volume. Other measures of communication such as those used in Coval and Shumway (2001) and Antweiler and Frank (2004) are related to the costs of trading, liquidity, and volume. If pessimism proxies for trading costs, then increases in pessimism will lead to declines in trading volume.

The model in Campbell, Grossman, and Wang (1993) provides another rationale for why pessimism could be related to volume. For simplicity, suppose the mean value of media pessimism is zero. High absolute values of pessimism indicate that a group of liquidity traders will suddenly decide to buy or sell equity. Market makers must absorb the demands for equity from these liquidity traders in order to restore equilibrium, inducing abnormally high trading volume. So high absolute values of pessimism should forecast high trading volume until liquidity trading subsides. Although DeLong et al. (1990a) do not explicitly model trading volume, their model makes similar predictions about the behavior of liquidity traders when the absolute value of sentiment is high.

In summary, theories of media pessimism as a proxy for trading costs predict pessimism decreases volume, whereas theories of pessimism as a proxy for sentiment such as Campbell, Grossman, and Wang (1993) and DeLong et al. (1990a) predict the absolute value of pessimism will increase volume. Accordingly, I add five lags of the pessimism factor and the absolute value of this factor to the OLS specification for volume:

$$\begin{aligned} Vlm_t &= \alpha_3 + \beta_3 \cdot L5(Dow_t) + \gamma_3 \cdot L5(BdNws_t) \\ &\quad + \psi_3 \cdot L5(|BdNws_t|) + \delta_3 \cdot L5(Vlm_t) + \lambda_3 \cdot Exog_{t-1} + \varepsilon_{3t} \end{aligned} \tag{3}$$

Table IV depicts the coefficients γ_3 and ψ_3 on the pessimism factor. Each coefficient in the table describes the impact of a one standard deviation increase in pessimism on detrended log NYSE volume. Again, I estimate the impact of pessimism using all three measures of pessimism.

[Insert Table IV around here]

There is some evidence that pessimism plays a direct role in forecasting volume, tentatively supporting the idea that pessimism is a proxy for trading costs. The first lags of Negative and Weak words are significant negative predictors of volume. However, this result is attenuated when I winsorize the 1% outliers. Nevertheless, I cannot completely rule out theories that posit a direct link between pessimistic communication and volume.

An interpretation of pessimism as a measure of risk aversion or sentiment receives much more support from the volume regressions. Consistent with the theories of Campbell, Grossman, and Wang(1993) and DeLong et al. (1990a), the absolute value of pessimism significantly predicts increases in volume on the next trading day. This result holds regardless of whether pessimism is measured by the pessimism factor, Negative words or Weak words (p-values $<$ 0.01).[15] The straightforward interpretation is that high absolute values of pessimism are a proxy for disagreement between noise traders and rational traders, which leads to increases in trading volume on the next trading day.[16]

Next, I consider the effect of the pessimism factor on measures of market returns other than the Dow Jones index. It is well-known that small stocks have the highest individual investor ownership. If the pessimism factor measures the investor sentiment of individual investors, then perhaps it should predict the returns on small stocks. To test this theory, I obtain data on the daily Fama-French small-minus-big (*SMB*) factor constructed as in Fama and French (1993). I use this factor rather than an index of small stocks, because its performance does not correlate highly with Dow Jones returns. The results above already show that the media factors predict the returns on the Dow. The tests here examine whether the media factors predict small stock returns independent of their ability to predict returns on the Dow.

To predict the *SMB* factor, I adopt an analogous regression specification to the VAR equations above. In other words, I control for five lags of returns on the Dow, five lags of detrended log NYSE volume, and five lags of *SMB* factor returns in addition to the variables defined in *Exog* above. The resulting regression equation is:

$$\begin{aligned} SMB_t &= \alpha_4 + \beta_4 \cdot L5(Dow_t) + \gamma_4 \cdot L5(BdNws_t) \\ &\quad + \delta_4 \cdot L5(Vlm_t) + \pi_4 \cdot L5(SMB_t) + \lambda_4 \cdot Exog_{t-1} + \varepsilon_{4t} \end{aligned} \tag{4}$$

Table V shows the coefficients γ_4 on the pessimism factor in the *SMB* factor regression. Each coefficient in the regression measures the impact in basis points of a one standard deviation increase in pessimism on daily *SMB* factor returns.

[Insert Table V around here]

The main result is that all three pessimism measures significantly predict negative returns to the *SMB* factor over the following week (p-values of 0.034, 0.008, and 0.018 for pessimism, Negative and Weak). Relative to its effect on the Dow Jones returns, the effect of negative sentiment on *SMB* returns appears to be longer lasting. The sum of the coefficients on each of the three negative sentiment measures in Table V is statistically and economically significant (p-values < 0.020 and magnitude of roughly five basis points). Thus, negative sentiment seems to have a longer-lasting and larger impact on small stocks.

The results up to this point suggest pessimism in the *WSJ* column predicts lower returns on the Dow and lower returns on the Dow predicts increased pessimism. Yet a reasonable reader could be skeptical of these conclusions. If the afternoon *WSJ* column (written at the close of the prior trading day) contains late-breaking information not completely incorporated in closing prices, then investors may continue to react to news in the column on the next trading day. If this is the source of predictability in the regressions above, then the results are generally consistent with conventional models in finance that do not allow for the existence of liquidity or noise traders. For example, theories of media content as a proxy for information about fundamental asset values could be consistent with some of the regression results shown above.[17] In the next section, I investigate this possibility and report the findings from other robustness and sensitivity tests.

B. Robustness and Sensitivity Analysis

The newswires containing the information necessary to calculate the pessimism factor appear at the close of afternoon trading, which is the beginning of the close-to-close return measurement period for the next day. Thus, it seems possible that a slight lag time between the release of the *WSJ* column and its incorporation into prices is driving the return and volume predictability results shown above. The question is whether the predictive power of the pessimism factor is concentrated in after-hours and opening hour returns or is dispersed uniformly throughout the trading day.

To address this issue, I re-estimate the regressions above with a return window that allows traders more time to react to any information released in the afternoon newswires. I also allow traders some time to react to the *same* information reprinted in the paper *WSJ* the next morning. Specifically, I use a return window that begins on 10 a.m. the day after the column is released on the newswires. I also add control variables in the return regressions to capture the influence of closing and opening returns and volume. I use data on intraday Dow Jones index levels from Global Financial Data, Inc. to measure the returns on the Dow Jones from the close of the prior trading day to 10 a.m. on the current trading day. I re-estimate equation (1) with the more conservative return window.[18]

Even if the predictive power of the pessimism factor comes from its ability to predict investor sentiment and is dispersed uniformly throughout the trading day, the coefficients on the lags of pessimism in equation (1) should decline in magnitude after eliminating close-to-open and opening-30-minute returns from the dependent variable. This decline occurs because the ability of the pessimism factor to predict returns is presumably dispersed throughout the period that includes after-hours and opening-30-minute trading. It is possible, in fact, that pessimism has its greatest causal impact on returns just after traders have read the afternoon newswires or the morning newspaper. Indeed, over 25% of daily trading volume on the NYSE occurs within this time frame. Unfortunately, there is no way to disentangle this early impact of pessimism from the hypothesis that traders slowly react to information released in the column.

Table VI reports the results from estimating equation (1) with the new return window as the dependent variable. For all three measures of sentiment, the hypothesis that negative sentiment does not predict the next day's returns on the Dow Jones between 10 a.m. and market closing time can be rejected at the 99% level. Moreover, the magnitude of the next day's coefficients in Table VI fall by at most 25% relative to the corresponding coefficients in Table II. A decline of at least 25% would be expected if the negative effect of sentiment is uniformly distributed across trading volume. This suggests that, if anything, the measures of negative sentiment considered in this paper have their largest impact later in the trading day.

Also consistent with the results from earlier, Table VI shows the impact of negative sentiment on returns is either fully or mostly reversed over the next few days, depending on the exact sentiment measure used. The reversal is complete and strongly statistically significant for Negative and Weak words; and the reversal accounts for over 85% of the decline and is marginally statistically significant for the pessimism factor. Based on Table VI, I conclude that negative sentiment predicts returns throughout the ensuing trading day and subsequent reversals later in the week, which is inconsistent with the hypothesis that traders slowly react to information released in the column.

[Insert Table VI around here]

I also scrutinize the relationship between NYSE volume and the measures of pessimism to assess whether pessimism's effect on trading volume endures beyond any plausible immediate response to the release of information about pessimism. Specifically, I subtract the next trading day's opening-hour NYSE volume from the dependent variable in the regression specification in equation (3) to obtain a measure of after-morning volume.

To retest the hypothesis that pessimism is a proxy for trading costs, I assess whether yesterday's pessimism media factor directly forecasts today's after-morning volume. The insignificant coefficients on $BdNws_{t-1}$ in Table VII suggest none of the three measures of pessimism plays this role. That is, the direct effect of pessimism on volume is mostly attributable to its effect on opening-hour volume. It seems that pessimism does not directly forecast volume, but may still be a proxy for past or contemporaneous trading costs.

[Insert Table VII around here]

Interestingly, the results in Table VII suggest that the absolute values of the measures of pessimism still have strong effects on the next day's NYSE volume above and beyond their immediate impact on opening-hour volume. For all three sentiment measures, after-morning volume increases by over 1% when sentiment is above or below its mean by one standard deviation. This impact is statistically significant at the 99% level for Negative and Weak words and the 95% level for the pessimism factor. These results are again consistent with interpretations of the absolute value of pessimism as a proxy for unusually high or low demand from liquidity traders as in Campbell, Grossman, and Wang (1993) or noise traders as in DeLong et al. (1990a).

I perform a similar test to that used in Table VII to examine the robustness of the effect of pessimism on the Fama-French *SMB* factor. Again, the goal is to assess whether *SMB* returns are affected by pessimism measures long after information about pessimism has been released. Because the prices of small stocks are particularly slow to adjust to information, I do not use the prior day's pessimism factor to try to predict the *SMB* factor. To err on the side of caution, I use only negative sentiment measures based on newspaper columns printed *over* 24 hours in advance of market activity. With the exception of modifying the timing of sentiment in equation (4), I follow the same estimation procedure used to develop Table V.

Table VIII displays the robustness check for predicting the *SMB* factor with lags two through six of the pessimism measures. The qualitative results from Table V remain valid in Table VIII, suggesting that the forecasting ability of negative sentiment for *SMB* returns persists beyond one day's worth of trading activity. Each of the three measures of pessimism strongly predicts *SMB* returns (p-values of 0.014, 0.005, and 0.005). The sums of the five coefficients are all significantly negative from a statistical perspective (p-values < 0.002) and an economic perspective (roughly 7 basis points). This evidence demonstrates that the enduring and large effect of negative sentiment on the *SMB* factor is robust to changes in the timing of the return window.

[Insert Table VIII around here]

From the similarities between Tables II and VI, Tables IV and VII, and Tables V and VIII, it appears that the market response to pessimism is dispersed throughout the following trading week. It is likely that much of the immediate response to true information contained in the column has already occurred even before the column has been written. This result is consistent with the stated practice of the *WSJ* "Abreast of the Market" columnist, who claims the column is written before the end of the prior trading day.

There are reasons to suspect the effect of negative sentiment is stronger during particular time periods. For example, many economists and practitioners have suggested that market valuations during the bull market of the 1990s were affected by "irrationally exuberant" traders. Under this hypothesis, the sentiment measures examined in this study will exert a larger impact during the second half of the sample. To investigate this possibility, I split the sample into two equal-sized sub-periods: 1984 to 1991 and 1992 to 1999. For each time period and each sentiment measure, I repeat the estimation of VAR equation (1), which predicts Dow Jones returns using negative sentiment and various control variables.

Table IX reveals that negative sentiment predicts immediate negative returns and gradual reversals during the 1990s, but has a somewhat different effect during the earlier time period. In fact, the joint hypothesis that sentiment does not predict returns during the 1984 to 1991 period can only be rejected for two of the three measures at the 10% significance level. By contrast, in the 1992 to 1999 period, the magnitudes of the initial negative impact of sentiment and subsequent return reversal are economically large and strongly statistically significant. These estimates in the 1990s are so large relative to the 1980s that they appear to dominate the full sample results.

[Insert Table IX around here]

Although the impact of sentiment in the two time periods looks quite different on the surface, there are some interesting similarities. The average impact of negative sentiment on 3-day cumulative returns is -3.3 basis points in the earlier period and -7.4 basis points in the later period.[19] The average impact of negative sentiment on day 4 and 5 cumulative returns is 7.8 basis points in the early period and 6.8 basis points in the later period. In other words, both periods show qualitatively similar 3-day declines and 2-day reversals. I conclude that sentiment has a quantitatively larger and more immediate impact in the 1990s, but I cannot rule out the hypothesis that sentiment has a similar qualitative impact in the earlier time period.

Until this point, I have relied exclusively on parametric estimates of the effect of the media factors. Using a semi-parametric approach to forecasting Dow Jones returns, I can assess whether there are any asymmetries or nonlinearities in the relationship between the pessimism media factor and stock returns. The semi-parametric procedure consists of a parametric and a nonparametric stage. First, I estimate equation (1), omitting only the lags of the negative sentiment measures from the linear regression, to obtain an estimate of the unexplained (residual) daily Dow Jones return.[20] Second, I form a nonparametric estimate of the effect of negative sentiment on this residual Dow Jones return. I use a standard locally weighted regression or lowess method to derive the nonparametric estimates. I repeat this procedure for all three measures of negative sentiment: the pessimism media factor, the GI category Negative words, and the GI category Weak words.

The lowess procedure runs a local regression in the neighborhood of each data point, repeatedly estimating the effect of negative sentiment on Dow Jones returns. Under the assumption that the conditional expectation of Dow Jones returns on sentiment is a continuous and differentiable function, this procedure combines the point estimates in a smooth conditional expectation function. I use a smoothing bandwidth equal to half the sample to generate the function shown in Figure 2. In each local regression, I use the standard tricube weighting function from Cleveland (1979) to weigh data points from nearby values of sentiment.

[Insert Figure 2 around here]

Figure 2 displays the results from the three locally weighted regressions for the three measures of negative sentiment. The nonparametric estimates of the effect of negative sentiment on Dow Jones returns are broadly consistent with the qualitative results from the linear parametric structure imposed in the VAR equations. With the possible exception of a short interval near the vertical axis, the conditional expectation of returns on the Dow monotonically decreases as negative sentiment increases. This remains true for all three measures of sentiment.

The effect of negative sentiment on the Dow appears to be strongest near the extreme values of returns and sentiment. To assess whether the estimated relationship between these variables is a statistical fluke driven by outliers, I have replicated the results using independent and dependent variables that are winsorized at the 1% level. Neither the parametric nor the nonparametric estimates of the effect of negative sentiment on returns change substantially as a consequence of the winsorizing process.

Figure 2 shows that the Dow Jones index returns roughly 25 basis points more on the days in which negative sentiment is very low (bottom 5%) as compared to the days in which negative sentiment is very high (top 5%). The effect of changes in sentiment near the middle of the sentiment distribution is much smaller—the change in expected returns between -1 and +1 standardized sentiment is only about 5 basis points. Overall, the qualitative shape and quantitative estimates of the sentiment effect are very similar for all three measures of sentiment. In further robustness tests not reported here, I find that the semi-parametric results in Figure 2 become slightly stronger, but remain qualitatively similar, when I eliminate the control variables in the first-stage parametric regression.

The statistical results in this section show sentiment plays a significant role in forecasting temporary market-wide declines in valuation. Sentiment predicts especially large and persistent declines in the returns of small stocks, suggesting sentiment measures individual traders' views. Sentiment has a much larger and more sudden impact on returns during the 1990s, suggesting sentiment affected valuations more during this time period. In summary, the tests here identify return and volume patterns consistent with the hypothesis that the three variables selected by a factor analysis of words in the *WSJ* are valid sentiment indicators.

C. The Economic Importance of the Results

Table II (or VI) shows that a one standard deviation increase in pessimism in the *WSJ* column predicts a decrease in Dow Jones returns equal to 8.1 (or 6.2) basis points over the next day. Comparisons to other daily returns suggest the economic magnitude of the pessimism effect is large. For example, the average daily return on the Dow Jones over the sample period is 6.3 basis points, which would be completely offset by a one standard deviation increase in pessimism.

The explanatory power of the sentiment measures for forecasting returns is also quite large relative to other standard variables. The five lags of the pessimism factor explain just 1.52% of the residual variation in Dow Jones returns, which may seem small because the magnitude of daily variation in the Dow Jones index is very large relative to the average daily return on the Dow; however, the other economic control variables used in this study such as five lags of Dow returns, five lags of volume, and five time period dummies explain only 0.16%, 0.30%, and 0.17% respectively.[21]

The success of pessimism in forecasting returns suggests investors who read the Dow Jones Newswires can devise profitable trading strategies based on daily variation in pessimism. For example, a straightforward computer program, similar to the one written to collect and analyze the data in this paper, could automatically process the electronic text of the Dow Jones Newswires "Abreast of the Market" column immediately after the column is released on the newswires. The program could calculate the daily value of pessimism and use predetermined coefficients, from predictability regressions just like those presented above, to forecast future returns. Depending on whether this forecast is positive or negative, the media-based trading strategy would go long or short on the Dow Jones index.

Rather than attempt to construct the optimal real-world trading strategy based on negative sentiment, I adopt a basic hypothetical trading strategy as a benchmark. I use the

GI category Negative words as a proxy for negative sentiment in the trading strategy to minimize the computational burden on the trader. This category also seems to be the most intuitive measure of negative investor sentiment. To ensure that the success of the trading strategy is not driven by bid-ask bounce or day-of-the-week effects, I compute the residual from a regression of Negative words demeaned by day-of-the-week on five lags of past Dow Jones returns.[22]

Following days in which Negative words are in the bottom third of the prior year's Negative word distribution, I borrow at the riskless rate to purchase all the stocks in the Dow Jones index and sell them back one day later. One day after Negative words are in the top third of the prior year's Negative word distribution, I borrow all the stocks in the Dow Jones index, receiving the riskless rate, and buy them back one day later.[23] Although this strategy is neither perfectly optimal nor perfectly realistic, it represents a useful benchmark for evaluating the potential of media content to predict returns.

The strategy buys the index 1,281 times and sells the index 1,254 times in the over 3,700 trading days between 1985 and 1999. The average daily return of this zero-cost strategy is 4.4 basis points, which is slightly larger than the average daily excess return on the Dow Jones itself, and statistically significant at the 99% level. The annualized return of the pessimism-based strategy is 7.3%, which seems economically important.[24]

To assess the robustness and riskiness of this strategy, I examine its performance in yearly subsamples. For each of the 15 years, I calculate an estimate of expected trading returns equal to the difference in the arithmetic means of the Dow returns on the buy and sell days. In 12 of the 15 years, the estimated expected returns are positive, which is unlikely to occur by chance (p-value $= 0.018$).[25] This consistent performance suggests the pessimism-based trading strategy is robust and relatively safe.

An important disclaimer renders this hypothetical trading strategy less attractive than it first appears. First, any daily trading strategy will incur transaction costs, price impact costs and capital gains taxes that may be prohibitive. Typical trading commissions on the Dow Jones index futures contracts listed on the Chicago Board of Trade are less than one basis point for a round trip transaction.[26] However, commissions do not include the price impact of trades or capital gains taxes. Depending on the size of the transaction, costs attributable to bid-ask spreads and finite market depth may exceed 4.4 basis points per trade—the cutoff value for eliminating the profitability of a pessimism-based trading strategy.[27] A formal investigation of the price impact and short-run capital gains taxes incurred by these trading strategies lies beyond the scope of this paper.

Although the statistical results above establish a relationship between investor sentiment and stock returns, the nature of this relationship requires further study before investors can implement reliable news-based trading strategies. The next section addresses this concern.

IV. Interpreting the Results

To assess whether the pessimism factor relates to investor sentiment, I attempt to identify the GI categories most closely related to pessimism. These tests may suggest a specific behavioral mechanism underlying the regression results above.[28] A decomposition of the pessimism factor into its constituents may suggest candidates for direct measures of investor sentiment that could be tested in future research. In this spirit, I test whether the GI categories underlying pessimism predict similar patterns in returns and volume. Tables II through IX examine the two categories, Negative and Weak, that have the highest correlations with pessimism and the highest weightings in the linear combination of categories that comprises pessimism.[29]

A. Do the Factors Relate to Investor Sentiment?

The GI categories, Negative and Weak words, are easier to interpret than the factor itself, which consists of a linear combination of all 77 GI categories. Because these two categories capture most of the variation in the pessimism factor, it seems likely that they convey the same semantic ideas to readers of the column and, therefore, exhibit the same relationship to stock market activity.

The results reported in Tables II through VIII support this interpretation of the pessimism factor. First and foremost, in both sets of return regressions, Negative and Weak words forecast the same temporary decline and reversal predicted by the pessimism factor. This remains true whether or not the regressions use dependent variables that include after-hour and opening-hour returns and volume. Although the magnitude of the coefficients diminishes slightly in some specifications, all results remain significant at the 5% level.

Second, changes in Negative words and changes in Weak words robustly forecast increases in volume. The absolute values of Negative and Weak words are slightly stronger predictors of increases in next day's volume—in magnitude and significance—than pessimism. Third, similar to the pessimism factor, Negative and Weak words tend to follow market declines. This effect is comparable statistically and economically to the effect of the market on pessimism.

Taken as a whole, these tests suggest the GI categories, Negative and Weak, underlying the pessimism factor are reasonable proxies for the factor in terms of their ability to forecast market activity. This finding demonstrates the results are not only robust, but also easily interpretable in terms of well-established psychological variables.[30]

In unreported tests, I examine whether the pessimism media factor and the underlying GI category variables are proxies for decreases in volatility. The risk premium hypothesis is that investors require *lower* returns on the Dow Jones on days in which there are many

Negative words in the *WSJ* column because holding the Dow Jones stocks is less risky on these days.

Unfortunately, as Ghysels, Santa-Clara, and Valkanov (2004) note, tests of the risk-return trade-off over short samples may not have sufficient power to identify the true relationship. Indeed, using my sample of 16 years (which is roughly five times shorter than theirs), I am unable to detect any significant change in daily expected returns on the Dow in response to changes in the volatility of the Dow, calling the risk-return relationship into question for these variables in this sample. Notwithstanding these concerns about measurement, I test the risk premium hypothesis and find that the conditional volatility of the Dow appears to be higher (not lower) when the pessimism factor is high. Thus, even if there is a meaningful risk-return trade-off in daily Dow Jones returns, it does not appear that media pessimism contributes to lower expected future returns through its effects on conditional volatility.

V. Conclusions

This study systematically explores the interactions between media content and stock market activity. I construct a straightforward measure of media content that appears to correspond to either negative investor sentiment or risk aversion. Pessimistic media content variables forecast patterns of market activity that are consistent with the DeLong et al. (1990a) and Campbell, Grossman, and Wang (1993) models of noise and liquidity traders. High values of media pessimism induce downward pressure on market prices; and unusually high or low values of pessimism lead to temporarily high market trading volume. Furthermore, the price impact of pessimism appears especially large and slow to reverse itself in small stocks. This is consistent with sentiment theories under the assumption that media content is linked to the behavior of individual investors, who own a disproportionate fraction of small stocks.

By contrast, the hypothesis that pessimism represents negative fundamental information not yet incorporated into prices receives very little support from the data. The changes in market returns that follow pessimistic media content are dispersed throughout the trading day, rather than concentrated after the release of information. Moreover, the negative returns following negative sentiment are reversed over the next few days of market activity, casting further doubt on an information interpretation of media content.

Pessimism, which predicts temporary decreases in returns, does not appear to be related to decreases in risk measures. In fact, pessimism weakly predicts increases in market volatility. In summary, the results are inconsistent with theories that view media content as either a proxy for new information about fundamentals, a proxy for market volatility, or an irrelevant noisy variable.

The fact that different measures of negative sentiment—*i.e.*, the pessimism factor, Negative words and Weak words—bear the same relationship to future market activity is reassuring in two ways. First, because the raw GI word categories were designed by psychologists, they have natural interpretations as measures of negative sentiment. Second, reporting tests based on multiple measures of sentiment mitigates the potential for data mining.

It is possible to construct a hypothetical zero-cost trading strategy using Negative words that yields non-trivial excess returns—7.3% per year—with little risk. But implementing this strategy would require frequent portfolio turnover, leading to significant costs from commissions, bid-ask spreads, limited market depth and capital gains taxes. It is unclear whether, after accounting for these costs, a sentiment-based trading strategy would remain profitable. Indeed, these limits to high-frequency arbitrage may prevent markets from responding efficiently to the information embedded in media content.

Appendix: Content Analysis of News Articles

Some examples of the 77 categories in this dictionary include: Negative, 2,291 words pertaining to negative things; Strong, 1,902 words implying strength; Passive, 911 words implying a passive orientation; Pleasure, 168 words indicating enjoyment of a feeling; Arousal, 166 words indicating excitation; Economic, 510 words of an economic, commercial or business orientation; and IAV, 1,947 verbs giving an interpretive explanation of an action.

The GI draws nuanced distinctions between words with identical appearances but different meanings. For example, the word "account" has eight different entries in the Harvard dictionary, which map into eight different category classifications. By examining the context of the word in the *WSJ* column, the GI can recognize one preposition form, five noun forms, one verb form and one adverb form of the word "account." When "account" means "because" as in the phrase "on account of," the GI categorizes it as Causal, which includes words denoting presumption that occurrence of one phenomenon is necessarily preceded, accompanied or followed by the occurrence of another. When "account" means "explain" as in the phrase "to account for," the GI places "account" in the following categories: Active, words with an active orientation; Solve, words associated with the mental process of problem solving; and IAV, interpretive verbs.

Unfortunately, the GI is a pure word count program, so it does not categorize combinations of words that often possess different meanings from the constituent words. As an example of this fault, consider the sentences: "No, the economy is not strong" and "It is not that the economy is not strong." The GI understands and categorizes all of the important words in both sentences, but pure category counts would suggest that these sentences have identical meanings. In fact, the sentences have opposite meanings. Even though semantic and stylistic noise partially obscure interpretations of the *Wall Street Journal* column based on the GI, the GI may still provide interesting raw data that is correlated with important semantic components of the column.

Notes

[1]Sources: circulation and subscription data from Dow Jones and Company's filing with the Audit Bureau of Circulations, September 30, 2003; circulation rankings from 2004 Editor and Publisher International Yearbook.

[2]This statement reflects my knowledge of newspaper columns available electronically as of December 2001.

[3]Most models in finance focus on trades *between* groups of noise traders and rational traders. Traditional no-trade theorems suggest that within-group trades among rational traders should not occur. Furthermore, for noise traders to have an impact on prices, there must be a common component in the variation in their beliefs. This paper focuses on the common component of noise trader beliefs that could affect prices.

[4]Of course, it is possible that new information produces divergence in opinion, which would lead to increases in volume. On the other hand, it seems equally likely that agents' beliefs would converge when all agents observe the same piece of public information.

[5]In an earlier version of this paper, I consider the top three factors, some of which have interesting interpretations. Adding additional factors to the regressions shown here does not substantially alter the results because all factors are mutually orthogonal by construction.

[6]For example, investors may not care how many religious words appear in the column each day. Nevertheless, the GI dictionary devotes an entire category to tracking these words.

[7]Intuitively, the number of Positive and Negative words in the column are strongly negatively correlated, holding constant the total number of words. Thus, it is natural that one media factor captures the variation in both Positive and Negative words.

[8]Journalists, not economic or financial experts, write the column. A typical writer has a B.A. degree in Journalism and has taken few, if any, courses in economics. The column writers sometimes leave their offices in Jersey City to go to the floor of the stock exchange in Manhattan in search of opinion quotes from strategists and traders, but usually they ask market participants questions by telephone. On the whole, the writers consider their columns "more art than science."

[9]Bid-ask spreads can induce negative autocorrelation in the return time series when trades alternately occur at the bid and ask prices. Non-synchronous trading causes spurious cross-correlations and autocorrelations in stock returns because quoted closing prices are not equally spaced at 24-hour intervals (see Campbell, Lo, and Mackinlay (1995)). Transaction costs such as trading fees and short-run capital gains taxes preclude arbitrage strategies that would mitigate return predictability.

[10]I focus on detrended log volume because the level of log volume is not stationary. I use a detrending methodology based on Campbell, Grossman, and Wang (1993). Specifically, I calculate the volume trend as a rolling average of the past 60 days of log volume. All results below are robust to using 30-day and 360-day averages.

[11]The time series of daily NYSE volume comes from the NYSE database.

[12]Specifically, I demean the *Dow* variable to obtain a residual, square this residual, and subtract the past 60-day moving average of the squared residual. All results below are robust to using alternative detrended measures of past volatility in which I subtract the past 30-day or 360-day moving average of squared residuals from current squared residuals. The results for other volatility measures such as the CBOE's volatility index (VIX) are qualitatively similar.

[13]Interestingly, measures of pessimism seem to have been abnormally high prior to the 1987 crash, which is consistent with the findings below. I have also verified that winsorizing all variables at the 0.5% upper and lower tails of their distributions does not affect the results.

[14]To assess whether the power of the statistical tests is the driving force behind the significant pessimism effects, I have also examined the estimates of β_1, δ_1, and λ_1 in VAR equation (1), which measure the impact of past returns, volatility, volume and other controls. After omitting the 1% outliers, none of these variables has a statistically significant impact on future Dow Jones returns at the 10% level. This suggests even relatively weak statistical tests can resolve the effects of pessimism on returns.

[15]The subsequent reversal in volume is strongly significant for the pessimism factor, but not for Negative or Weak words. Theories of sentiment make ambiguous predictions about whether this volume reversal should occur depending on the exact mechanism of price adjustment. Volume may remain high if liquidity traders repurchase their former positions when sentiment reverts to its mean or volume may subside because prices adjust without substantial trading.

[16]Intuitively, the absolute value of pessimism is also associated with high contemporaneous trading volume.

[17]The return reversals above would still be difficult to reconcile with theories of pessimism as a proxy for information about fundamentals.

[18]Including additional controls for opening-hour returns and log NYSE volume does not change the results. See *infra* for a description of these variables.

[19]This is an equal-weighted average over the three sentiment measures of the sum of the first three coefficients in Table IX.

[20]The control variables in the first-stage linear regression are the same as in equation (1).

[21]The five lags of volatility explain 3.29% of variation in Dow returns, but this is almost attributable to extreme negative returns. Winsorizing the most extreme 1% of returns reduces the explanatory power of volatility to far less than that of media pessimism.

[22]I use the prior year's day-of-the-week means to compute the means to avoid any hindsight bias. This implies that I cannot use the first year of my news sample, 1984, in the trading strategy.

[23]These two strategies are equivalent to going long and short on a Dow Jones futures contract. Ignoring margin and capital requirements, both strategies are zero-cost strategies.

[24]The trading strategy returns has positive returns of 7.1 and 1.7 basis points on days in which the hypothetical strategy buys and sells the index, respectively. Because the former strategy has a beta of 1 and the latter has a beta of -1, the return difference is consistent with the existence of a daily market risk premium of roughly 2.7 basis points or an annualized risk premium of about 10%, which is a reasonable estimate in light of the high returns during the 1990s.

[25]The strategy has negative expected returns in the years 1986, 1988 and 1990, when Dow Jones returned 23%, 12% and -4% respectively, suggesting the strategy has very little systematic risk. In fact, the daily correlation between the strategies' returns and the market is significantly negative.

[26]For example, as of September 13, 2004, the discount brokerage TradeStation Securities charged only $5 per round-trip transaction in Dow Jones futures valued at over $50,000 per

contract.

[27]Typically, the spread at the inside quote for the Dow Jones E-mini contract is about 1 basis point, but a large trade of contracts having a $10,000,000 notional value would incur a spread of 5 basis points or more. Moreover, this particular Dow Jones futures contract did not exist until relatively recently. Instruments available to traders in the past may have had larger spreads.

[28]The theories of DeLong et al. (1990) and Campbell, Grossman, and Wang (1993), which are consistent with the results above, do not explicitly model the psychology behind sentiment. DeLong et al. (1990a) assumes that noise traders' beliefs change randomly from period to period without specifying why. Similarly, Campbell, Grossman, and Wang (1993) simply assumes the existence of shocks to investors' discount factors that drive liquidity demand.

[29]It is not a foregone conclusion that the two categories most highly correlated with pessimism would also receive the highest weightings in the linear combination of categories that comprises pessimism.

[30]The pessimism factor, Negative words and Weak words are all significantly negatively correlated with the measures of (positive) investor sentiment proposed by Whaley (2000) and Baker and Wurgler (2005). Neither the Whaley (2000) nor the Baker and Wurgler (2005) sentiment measure subsumes the explanatory power of the sentiment measures presented here.

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Table I
Correlations of the Media Factors Constructed Yearly

The table data come from the General Inquirer program. This table shows correlations between media factors constructed using factor analysis on the GI categories in different years. The mean pairwise correlation for a given yearly factor excludes the factor's correlation with itself. Each yearly media factor is the linear combination of GI categories that captures the maximum variance in GI categories in that year. The factor analysis method is principal components analysis, which is equivalent to a singular value decomposition. Each yearly factor analysis is based on news columns from roughly 250 trading days per year. All GI category variables have been demeaned by day of the week using the prior year's mean.

Year	'84	'85	'86	'87	'88	'89	'90	'91	'92	'93	'94	'95	'96	'97	'98
1984	1.00														
1985	0.95	1.00													
1986	0.94	0.98	1.00												
1987	0.95	0.97	0.98	1.00											
1988	0.94	0.96	0.97	0.97	1.00										
1989	0.92	0.92	0.94	0.96	0.96	1.00									
1990	0.93	0.93	0.93	0.96	0.95	0.95	1.00								
1991	0.95	0.96	0.97	0.97	0.98	0.97	0.96	1.00							
1992	0.92	0.97	0.97	0.95	0.98	0.94	0.94	0.95	1.00						
1993	0.91	0.96	0.97	0.95	0.97	0.93	0.95	0.97	0.97	1.00					
1994	0.90	0.95	0.96	0.94	0.96	0.93	0.92	0.94	0.97	0.97	1.00				
1995	0.95	0.95	0.97	0.97	0.97	0.98	0.96	0.98	0.96	0.96	0.94	1.00			
1996	0.92	0.96	0.98	0.96	0.97	0.96	0.96	0.97	0.87	0.98	0.97	0.97	1.00		
1997	0.91	0.93	0.92	0.92	0.96	0.91	0.93	0.94	0.95	0.94	0.94	0.94	0.94	1.00	
1998	0.93	0.95	0.96	0.96	0.97	0.94	0.96	0.96	0.97	0.96	0.96	0.97	0.97	0.97	1.00
Mean	0.93	0.95	0.96	0.96	0.97	0.94	0.95	0.96	0.96	0.96	0.95	0.96	0.96	0.94	0.96

Table II
Predicting Dow Jones Returns Using Negative Sentiment

The table data come from CRSP, NYSE, and the General Inquirer program. This table shows OLS estimates of the coefficient γ_1 in equation (1). Each coefficient measures the impact of a one standard deviation increase in negative investor sentiment on returns in basis points (one basis point equals a daily return of 0.01%). The regression is based on 3,709 observations from January 1, 1984, to September 17, 1999. I use Newey-West standard errors that are robust to heteroskedasticity and auto-correlation up to five lags. Bold denotes significance at the 5% level; italics and bold denotes significance at the 1% level.

Regressand	Dow Jones Returns		
News Measure	Pessimism	Negative	Weak
$BdNws_{t-1}$	***-8.1***	***-4.4***	***-6.0***
$BdNws_{t-2}$	0.4	**3.6**	2.0
$BdNws_{t-3}$	0.5	-2.4	-1.2
$BdNws_{t-4}$	**4.7**	***4.4***	***6.3***
$BdNws_{t-5}$	1.2	2.9	**3.6**
$\chi^2(5)[Joint]$	***20.0***	***20.8***	***26.5***
p-value	0.001	0.001	0.000
Sum of 2 to 5	**6.8**	***9.5***	***10.7***
$\chi^2(1)[Reversal]$	**4.05**	***8.35***	***10.1***
p-value	0.044	0.004	0.002

Table III
Predicting Negative Sentiment Using Dow Jones Returns

The table data come from CRSP, NYSE, and the General Inquirer program. This table shows OLS estimates of the coefficient β_2 in equation (2). Each coefficients measures the effect of a 1% increase in Dow Jones returns on negative investor sentiment in units of standard deviations. The regression is based on 3,709 observations from January 1, 1984, to September 17, 1999. I use Newey-West standard errors that are robust to heteroskedasticity and auto-correlation up to five lags. Bold denotes significance at the 5% level; italics and bold denotes significance at the 1% level.

Regressand	Pessimism	Negative	Weak
Dow_{t-1}	***-5.8***	***-7.6***	***-5.6***
Dow_{t-2}	2.3	-0.7	0.7
Dow_{t-3}	2.1	1.2	1.9
Dow_{t-4}	2.3	0.3	1.7
Dow_{t-5}	**4.2**	1.5	1.0
$\chi^2(5)[Joint]$	***16.6***	**14.1**	**12.1**
p-value	0.006	0.015	0.033

Table IV
Predicting Log NYSE Volume Using Sentiment

The table data come from CRSP, NYSE, and the General Inquirer program. This table shows OLS estimates of the coefficient γ_3 in equation (3). The two sets of coefficients describe the impact of one standard deviation increases in negative sentiment and the absolute value of sentiment on detrended log NYSE volume growth. The regression is based on 3,709 observations from January 1, 1984, to September 17, 1999. I use Newey-West standard errors that are robust to heteroskedasticity and auto-correlation up to five lags. Bold denotes significance at the 5% level; italics and bold denotes significance at the 1% level.

Regressand		Volume	
News Measure	Pessimism	Negative	Weak
$BdNws_{t-1}$	**-0.80**	-0.18	**-0.80**
$BdNws_{t-2}$	-0.16	-0.16	0.29
$BdNws_{t-3}$	0.31	0.04	0.68
$BdNws_{t-4}$	-0.11	0.33	***0.87***
$BdNws_{t-5}$	0.18	0.13	0.15
$\|BdNws_{t-1}\|$	***1.34***	***1.51***	***1.34***
$\|BdNws_{t-2}\|$	***-1.50***	-0.37	-0.34
$\|BdNws_{t-3}\|$	-0.10	0.38	-0.30
$\|BdNws_{t-4}\|$	0.71	0.41	0.60
$\|BdNws_{t-5}\|$	***-1.97***	0.15	-0.62
$\chi^2(5)$ $[BdNws]$	6.6	2.2	***15.4***
p-value	0.256	0.823	0.009
$\chi^2(5)$ $[\|BdNws\|]$	***34.9***	**13.2**	10.7
p-value	0.000	0.022	0.058

Table V
Predicting the Small-Minus-Big Factor Using Negative Sentiment

The table data come from CRSP, NYSE, Professor Kenneth French's Web site, and the General Inquirer program. This table shows OLS estimates of the coefficient γ_4 in equation (4). Each coefficient measures the impact of a one standard deviation increase in negative investor sentiment on returns in basis points (one basis point equals a daily return of 0.01%). The regression is based on 3,709 observations from January 1, 1984, to September 17, 1999. I use Newey-West standard errors that are robust to heteroskedasticity and auto-correlation up to five lags. Bold denotes significance at the 5% level; italics and bold denotes significance at the 1% level.

Regressand	Small-Minus-Big Returns		
News Measure	Pessimism	Negative	Weak
$BdNws_{t-1}$	-2.0	-1.2	-0.9
$BdNws_{t-2}$	1.1	-0.5	-0.6
$BdNws_{t-3}$	-0.4	0.1	0.3
$BdNws_{t-4}$	**-2.4**	***-2.4***	***-2.7***
$BdNws_{t-5}$	-0.9	-1.6	-2.0
$\chi^2(5)[Joint]$	**12.1**	***15.5***	**13.7**
p-value	0.034	0.008	0.018
Sum 1 to 5	**-4.6**	***-5.6***	**-5.9**
$\chi^2(1)[Sum]$	**5.5**	***11.7***	**9.5**
p-value	0.019	0.001	0.020

Table VI
Robustness of Dow Jones Return Forecasts Using Negative Sentiment

The table data come from CRSP, NYSE, and the General Inquirer program. This table shows OLS estimates of the coefficient γ_1 in equation (1). The return time window for the dependent variable in equation (1) has been shortened to include only the returns from 10 a.m. to market closing time on the day after the news column is released.. Each coefficient measures the impact of a one standard deviation increase in negative investor sentiment on returns in basis points (one basis point equals a daily return of 0.01%). The regression is based on 3,709 observations from January 1, 1984, to September 17, 1999. I use Newey-West standard errors that are robust to heteroskedasticity and auto-correlation up to five lags. Bold denotes significance at the 5% level; italics and bold denotes significance at the 1% level.

Regressand	Dow Jones Returns		
News Measure	Pessimism	Negative	Weak
$BdNws_{t-1}$	***-6.2***	**-3.7**	***-4.5***
$BdNws_{t-2}$	0.9	1.9	1.2
$BdNws_{t-3}$	-0.9	-2.8	-2.2
$BdNws_{t-4}$	***4.9***	***4.0***	***5.3***
$BdNws_{t-5}$	0.5	2.5	3.0
$\chi^2(5)[Joint]$	***17.5***	***21.5***	***24.0***
p-value	0.004	0.001	0.000
Reversal 2 to 5	5.4	**5.6**	***7.3***
$\chi^2(5)[Reversal]$	3.6	**5.4**	***6.8***
p-value	0.058	0.021	0.009

Table VII
Robustness of Log NYSE Volume Forecasts Using Sentiment

The table data come from CRSP, NYSE, and the General Inquirer program. This table shows OLS estimates of the coefficient γ_3 in equation (3). The definition of volume in equation (3) has been modified to include only trades occurring between 10 a.m. and market closing time on the day after the news column is released. The two sets of coefficients describe the impact of one standard deviation increases in negative sentiment and the absolute value of sentiment on detrended log NYSE volume growth. The regression is based on 3,709 observations from January 1, 1984, to September 17, 1999. I use Newey-West standard errors that are robust to heteroskedasticity and auto-correlation up to five lags. Bold denotes significance at the 5% level; italics and bold denotes significance at the 1% level.

Regressand		Volume	
News Measure	Pessimism	Negative	Weak
$BdNws_{t-1}$	-0.52	0.01	-0.49
$BdNws_{t-2}$	-0.07	-0.09	0.22
$BdNws_{t-3}$	0.43	-0.49	**0.88**
$BdNws_{t-4}$	-0.12	0.42	***1.01***
$BdNws_{t-5}$	0.08	0.38	0.14
$\|BdNws_{t-1}\|$	**1.17**	***1.51***	***1.34***
$\|BdNws_{t-2}\|$	***-1.52***	-0.43	-0.16
$\|BdNws_{t-3}\|$	0.01	0.42	-0.33
$\|BdNws_{t-4}\|$	**1.02**	0.51	0.42
$\|BdNws_{t-5}\|$	***-1.88***	0.13	-0.63
$\chi^2(5)$ $[BdNws]$	3.2	2.0	**14.1**
p-value	0.676	0.852	0.015
$\chi^2(5)$ $[\|BdNws\|]$	***31.8***	**12.0**	8.4
p-value	0.000	0.035	0.137

Table VIII
Robustness of SMB Return Forecasts Using Negative Sentiment

The table data come from CRSP, NYSE, Professor Kenneth French's web site and the General Inquirer program. This table shows OLS estimates of the coefficient γ_4 in equation (4); however, equation (4) has been modified to include the second through sixth lags of the pessimism factor rather than the first through fifth lags. Each coefficient measures the impact of a one standard deviation increase in negative investor sentiment on returns in basis points (one basis point equals a daily return of 0.01%). The regression is based on 3,709 observations from January 1, 1984, to September 17, 1999. I use Newey-West standard errors that are robust to heteroskedasticity and auto-correlation up to five lags. Bold denotes significance at the 5% level; italics and bold denotes significance at the 1% level.

Regressand	Small-Minus-Big Returns		
News Measure	Pessimism	Negative	Weak
$BdNws_{t-2}$	0.2	-1.1	-1.2
$BdNws_{t-3}$	-0.8	-0.0	-0.0
$BdNws_{t-4}$	**-2.8**	***-2.7***	***-3.0***
$BdNws_{t-5}$	-1.3	**-2.0**	**-2.3**
$BdNws_{t-6}$	**-2.0**	-1.0	-1.6
$\chi^2(5)[Joint]$	**14.3**	***16.6***	***16.6***
p-value	0.014	0.005	0.005
Sum 2 to 6	***-6.7***	***-6.8***	***-8.0***
$\chi^2(1)[Sum]$	***9.7***	***14.8***	***13.8***
p-value	0.002	0.000	0.000

Table IX
Predicting Dow Jones Returns Using Negative Sentiment

The table data come from CRSP, NYSE, and the General Inquirer program. This table shows OLS estimates of the coefficient γ_1 in equation (1). Each coefficient measures the impact of a one standard deviation increase in negative investor sentiment on returns in basis points (one basis point equals a daily return of 0.01%). Each regression is based on 3,709 observations from January 1, 1984 to September 17, 1999. I use Newey-West standard errors that are robust to heteroskedasticity and auto-correlation up to 5 lags. Bold denotes significance at the 5% level; and italics and bold denotes significance at the 1% level.

Regressand	Dow Jones Returns					
Time Period	1984–1991			1992–1999		
News Measure	Pessimism	Negative	Weak	Pessimism	Negative	Weak
$BdNws_{t-1}$	-0.5	3.1	-0.1	***-13.6***	***-10.9***	***-9.8***
$BdNws_{t-2}$	-3.7	0.7	-1.2	3.3	**5.8**	3.3
$BdNws_{t-3}$	-2.3	-3.1	-2.8	2.4	-2.3	-0.5
$BdNws_{t-4}$	**6.7**	**5.0**	**9.3**	3.1	3.4	4.6
$BdNws_{t-5}$	-2.8	2.6	2.7	2.9	2.6	3.8
$\chi^2(5)[Joint]$	5.9	9.3	9.3	***42.2***	***31.1***	***28.3***
p-value	0.316	0.099	0.098	0.000	0.000	0.000
Sum of 2 to 5	-2.1	5.2	8.0	***11.7***	**9.5**	***11.3***
$\chi^2(1)[Reversal]$	0.2	1.4	1.8	***6.7***	**10.7**	***7.2***
p-value	0.681	0.234	0.183	0.010	0.018	0.007

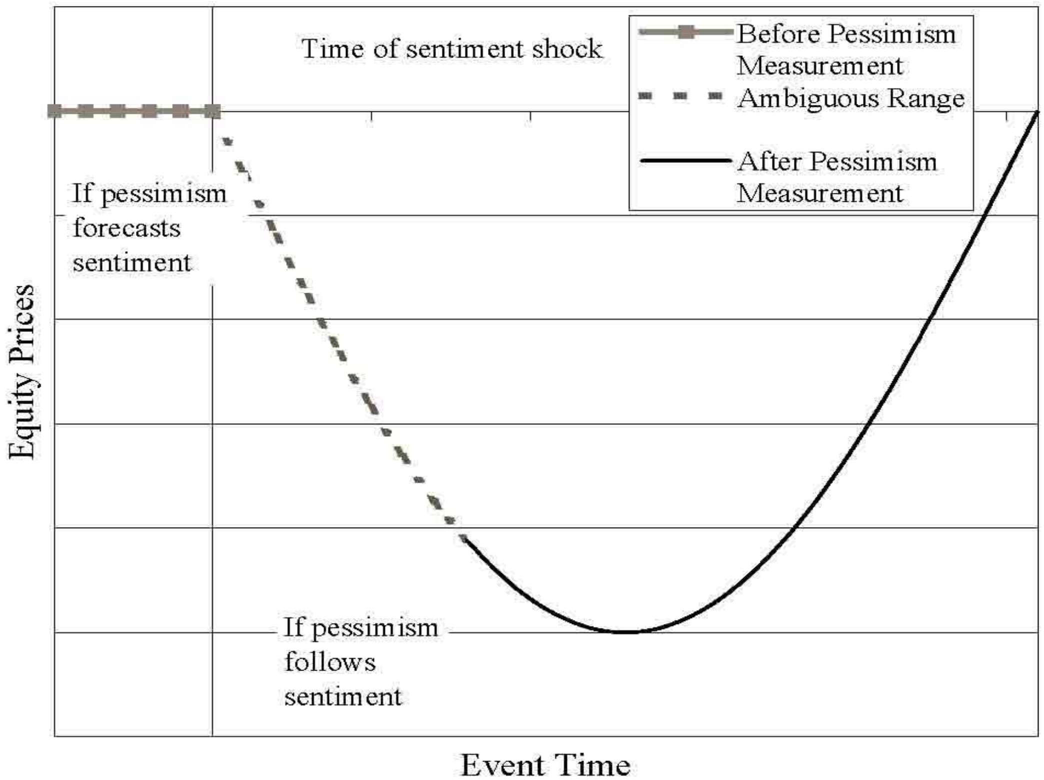

Figure 1. Impact of a negative sentiment shock on prices. The graph depicts the theoretical impact of a one-time increase in negative investor sentiment on equity prices. If the media pessimism measure is a predictor of investor sentiment, it will predict low short-horizon returns followed by high long-horizon returns of approximately equal magnitude. If the media pessimism measure follows past investor sentiment, it will predict low short-horizon returns followed by high long-horizon returns of greater magnitude than the short-horizon returns.

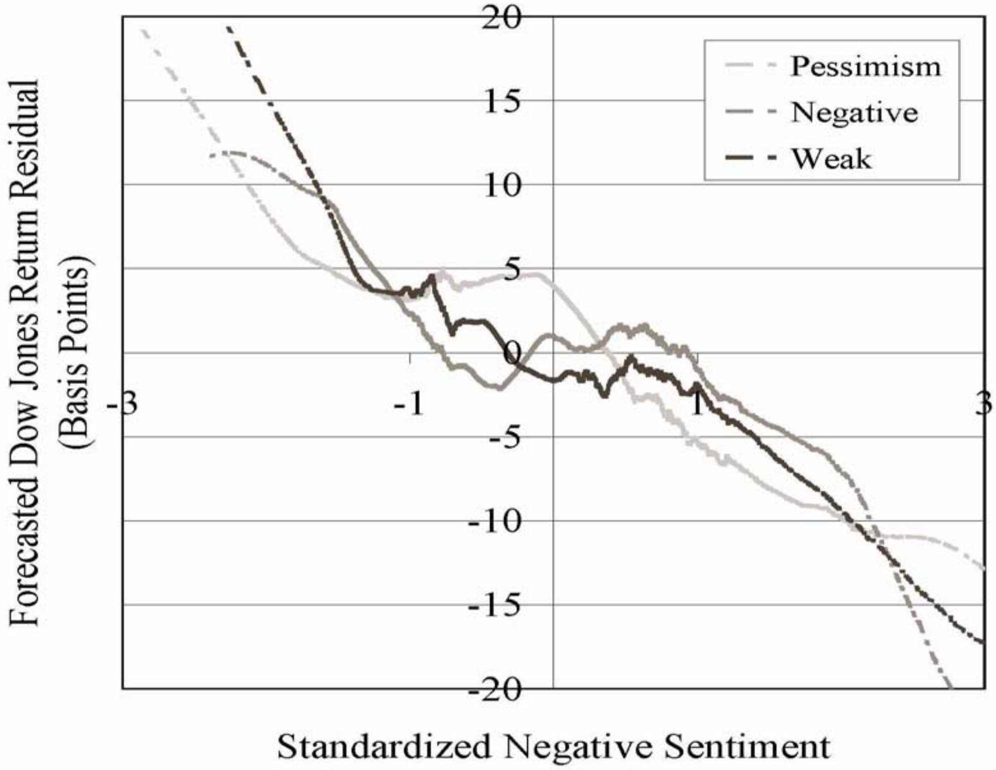

Figure 2. The effect of negative sentiment on Dow Jones returns. Data from author's application of the General Inquirer program to the *Wall Street Journal* column from January 2, 1984, to September 17, 1999. The Dow Jones residuals come from the regression depicted in equation (1). The three measures of negative sentiment are calculated using the factor analysis procedure described in Section III. In the original unsmoothed data, there are 3,709 observations on daily residual Dow Jones returns and negative sentiment. Each smoothed data point represents the fitted value from a locally weighted least squares regression of residual Dow Jones returns on negative sentiment. In each local regression, I apply local weightings from the standard tricube weighting function to only neighboring values of negative sentiment. The neighborhood for each data point is centered around the data point and includes one half of the sample.