More Than Words:

Quantifying Language to Measure Firms' Fundamentals

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Abstract

We examine whether a simple quantitative measure of language can be used to predict individual firms' accounting earnings and stock returns. Our three main findings are: 1) the fraction of negative words in firm-specific news stories forecasts low firm earnings; 2) firms' stock prices briefly underreact to the information embedded in negative words; and 3) the earnings and return predictability from negative words is largest for the stories that focus on fundamentals. Together these findings suggest that linguistic media content captures otherwise hard-to-quantify aspects of firms' fundamentals, which investors quickly incorporate in stock prices.

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"Language is conceived in sin and science is its redemption"

– W.V. Quine, *The Roots of Reference*, p. 68.

There is a voluminous literature that examines the extent to which stock market prices incorporate quantitative information. Although few researchers study the impact of qualitative verbal information, there are compelling theoretical and empirical reasons to do so.[1] Theoretically, efficient firm valuations should be equal to the expected present discounted value of their cash flows conditional on investors' information sets, which include qualitative descriptions of firms' business environments, operations, and prospects in the financial press. Empirically, Shiller (1981), Roll (1988) and Cutler, Poterba, and Summers (1989) find that substantial movements in firms' stock prices do not seem to correspond to changes in quantitative measures of firms' fundamentals, suggesting that qualitative variables may help explain stock returns.

In this paper, we quantify the language used in financial news stories in an effort to predict firms' accounting earnings and stock returns. Our study builds on Tetlock (2006) who examines how qualitative information—the fraction of negative words in a particular news column about the stock market—is incorporated in aggregate market valuations. We extend that analysis to address the impact of negative words in all *Wall Street Journal* (*WSJ*) and *Dow Jones News Service* (*DJNS*) stories about individual S&P 500 firms from 1980 to 2004.[2] In addition to studying individual firms' stock returns, we investigate whether negative words can be used to improve expectations of firms' future cash flows. Overall, this study sheds light on whether and why quantifying language provides novel information about firms' earnings and returns.

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[1] Recent studies that examine qualitative verbal information include Busse and Green (2002), Antweiler and Frank (2004) and Tetlock (2006).

[2] We follow Tetlock (2006) in using negative words from the General Inquirer classification dictionary. The results are similar for alternative measures that include positive words (see footnote 10).

Our first main result is that negative words convey negative information about firm earnings, above and beyond stock analysts' forecasts and historical accounting data. In other words, qualitative verbal information does not merely echo easily quantifiable traditional measures of firm performance.

A natural next step is to test whether stock market prices rationally reflect the effect of negative words on firms' expected earnings. Our second result is that stock market prices exhibit a delayed response to the information embedded in negative words on the subsequent trading day. As a result, we identify potential profits from using trading strategies based on the words in a timely news source (*DJNS*), but not from strategies based on a news source that primarily disseminates information from the prior calendar day (*WSJ*).[3] Accounting for reasonable transaction costs could eliminate the profitability of the high-frequency trading strategy, suggesting that short-run frictions play an important role in how information is incorporated in asset prices.

To interpret these results further, we separately analyze negative words in news stories whose content focuses on firms' fundamentals. We find that negative words in stories about fundamentals predict earnings and returns more effectively than negative words in other stories. Collectively, our three findings suggest that linguistic media content captures otherwise hard-to-quantify aspects of firms' fundamentals, which investors quickly incorporate in stock prices.

Before delving into our tests, we call attention to two significant advantages to using the language in everyday news stories to predict firms' earnings and returns. First, by quantifying language, researchers can examine and judge the directional impact of a limitless variety of events, whereas most studies focus on one particular event type, such as earnings announcements, mergers, or analysts' recommendations. Analyzing a more

[3] The *DJNS* is a continuous intra-day news source, whereas the *WSJ* is released each morning.

complete set of events that affects firms' fundamental values allows researchers to identify common patterns in firm responses and market reactions to events.[4] Broadening the range of events also limits the scope for data mining.

Second, for most human beings, including investors, language is the predominant medium for communicating information. Virtually no stock market investors physically observe a statistically representative sample of production activities for the firms in which they invest. Their two main sources of information about firms are quantifiable publicly disclosed accounting variables and verbal descriptions of firms' current and future profit-generating activities. Investors who are unfamiliar with mathematical valuation principles may rely exclusively on linguistic descriptions of firms' valuations. Even investors who are valuation experts often pay attention to language because it summarizes qualitative information in a more natural and familiar way than quantitative valuation models.

As an example of our linguistic quantification method, consider the opening sentence of an October 11, 2005 *DJNS* article about Microsoft: "Microsoft Corp. (MSFT) released nine security patches Tuesday, including one for a flaw that could allow an attacker to create an outbreak similar to the Sasser worm that crippled computers worldwide." We hypothesize that investors' reactions to this sentence depend on the fraction of negative words that the sentence contains (Tetlock (2006)). According to the classification dictionary that we use, this sentence ranks in the 99th percentile of sentences in terms of the fraction of negative words that it contains, which is largely

[4] Studying the ability of past returns to predict future fundamentals and future returns has this same benefit. The negative words measure used here is complementary to various measures of past returns, which we include as control variables in our earnings and return predictability tests that follow. Because the vast majority of variation in negative words is orthogonal to past returns, our predictability tests are not merely regressing returns on returns.

consistent with intuition.[5] We do not claim that our crude quantitative measure of language subsumes or dominates traditional accounting measures of firms' fundamentals. Instead, we investigate whether the fraction of negative words in firm-specific news stories can improve our understanding of firms' underlying values and whether firms' stock market prices appropriately incorporate linguistic information.

The layout of the paper is as follows. In the next section, we discuss the properties of the news stories used in this study. In the Appendix, we explain how we match firms' common names used in news stories to firms' corresponding financial identifier variables. Section II presents the main tests for whether negative words predict firms' earnings and stock returns. In Section III, we assess whether earnings and return predictability is strongest for timely (*DJNS*) news articles that focus on firms' fundamentals. In Section IV, we present our conclusions and outline directions for further research on media content.

I. Stylized Facts about Firm-specific News Stories

We concentrate our analysis on the fraction of negative words in *DJNS* and *WSJ* stories about S&P 500 firms from 1980 through 2004 inclusive. We choose the S&P 500 constituents for reasons of importance and tractability. Firms in the S&P 500 index compose roughly three-quarters of the total U.S. market capitalization, and appear in the news sufficiently often to make the analysis interesting. However, there are not so many

[5] There are three negative words (flaw, cripple, and outbreak) among the 31 total words in the sentence, or 9.7%, which easily exceeds the cut-off for the 99^{th} percentile in 2004. In this instance, the opening sentence is representative of the entire article, which contains 8.2% negative words and ranks in the top percentile.

firms in the S&P 500 that the manual labor required to identify firms' common names is prohibitively costly.[6]

We obtain the list of S&P index constituents and stock price data from CRSP, analyst forecast information from I/B/E/S and accounting information from CompuStat. Merging the news stories and the financial information for a given firm is a non-trivial task because firms are identified by their common names in news stories but by their permnos, CUSIPs, or gvkeys in the above financial data sets. Although the common names in news stories usually resemble the company names appearing in financial data sets, a perfect match is an exception, not the rule.

To obtain the common names that we use as search strings for news stories, we begin with the string from the company name field in the CRSP data for all S&P 500 index constituents during the relevant time frame. We use the CRSP company name change file to identify situations in which a firm in the index changes its name. Throughout the analysis, we focus on news stories featuring the company name most directly related to the stock. Thus, for conglomerates, we use the holding company name, not the subsidiary names—*e.g.*, PepsiCo, Inc., or Pepsi for short, rather than Gatorade or Frito-Lay.

As our source for news stories, we use the Factiva news database. To find the name that media sources use to refer to a firm, we use a combination of four different methods that are described in detail in the Appendix. Because of the large number of firms and corresponding news stories, we implement an automated story-retrieval system. For each S&P 500 firm, the system constructs a query that specifies the characteristics of the stories to be retrieved. The system then submits the query and records the retrieved stories.

[6] Because some firms in the S&P 500 index appear in our news sources fewer than three times per year, we suspect that there is an insufficient quantity of non-S&P 500 firms to make the analysis interesting.

In total, we retrieve over 350,000 qualifying news stories—over 260,000 from *DJNS* and over 90,000 from *WSJ*—containing over 100,000,000 words. We find at least one story for 1063 of 1110 (95.8%) of the firms in the S&P 500 from 1980 to 2004 (see Appendix for details). We include a news story in our analysis only if it occurs while the firm is a member of the S&P index and within our 25-year time frame.[7]

Each of the stories in our sample also meets the requirements that we impose to eliminate irrelevant stories and blurbs. Specifically, we require that each firm-specific story mentions the firm's official name at least once within the first 25 words, including the headline, and the firm's popular name at least twice within the full story. In addition, we require that each story contains at least 50 words in total, at least five non-unique "Positive" and "Negative" words, and at least three unique "Positive" and "Negative" words.[8] We rely on the Harvard psychosocial dictionary word classifications labeled POSITIV (NEGATIV) to categorize positive (negative) words in each news story. This dictionary has been used extensively by psychologists employing a well-known semantic text analysis program called the General Inquirer.[9]

As our primary measure of media content, we compute the standardized fraction of negative words in each news story following Tetlock (2006).[10,11] We standardize the

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[7] We also exclude stories in the first week after a firm has been newly added to the index to prevent the well-known price increase associated with a firm's inclusion in the S&P 500 index (*e.g.*, Shleifer (1986)) from affecting our analysis.
[8] We impose these three word count filters to eliminate stories that contain only tables or lists with company names and quantitative information, and to limit the influence of outliers on the negative words measure described below. Changing these three cut-offs does not have a material impact on the results.
[9] Please refer to the Harvard-IV dictionary definitions on the General Inquirer's Web site for the complete word lists. See Riffe, Lacy and Fico (1998) for a survey of content analysis and its application to the media.
[10] We find very similar results using combined measures of positive (P) and negative (N) words, such as $(P - N) / (P + N)$ and $\log((1 + P) / (1 + N))$. In general, using positive words in isolation produces much weaker results, especially after controlling for negative words. One possible explanation is that positive words are more frequently used in combination with negations, such as "not good," which obscures the relationship between positive word counts and the intended meaning of the phrase. By contrast, the phrase "not bad" is used less frequently and preserves some of the negative tone of "bad."
[11] When a firm has multiple qualifying news stories on a given trading day, we combine all of these stories into a single composite story before counting word categories. Our results change very little if we treat stories on these firm-days separately.

fraction of negative words in each news story by subtracting the prior year's mean and dividing by the prior year's standard deviation of the fraction of negative words.[12] Formally, we define two negative words measures:

$$Neg = \frac{\#\text{ of negative words}}{\#\text{ of total words}}$$

$$neg = \frac{Neg - \mu_{Neg}}{\sigma_{Neg}}$$

where μ_{Neg} is the mean of *Neg* and σ_{Neg} is the standard deviation of *Neg* over the prior calendar year. This definition of *neg* produces a stationary measure of media content that we employ in our regression analyses.

Before analyzing the predictive power of linguistic media content, we document an important stylized fact: there are many more firm-specific news stories in the days immediately surrounding a firm's earnings announcement. For each firm-specific news story, we calculate the number of days until the firm's next earnings announcement and the number of days that have passed since the firm's previous earnings announcement. We plot a histogram of both variables back-to-back in Figure 1. Thus, each story is counted exactly twice in Figure 1, once after the previous announcement and once before the next announcement, except the stories that occur exactly on the earnings announcement day.

[Insert Figure 1 around here.]

Figure 1 provides striking evidence that news stories concentrate disproportionately around earnings announcement days. If news stories were randomly distributed throughout the year, then the histograms in the figure would be flat. The three adjacent spikes in the middle of Figure 1 reveal that there are abnormally many firm-specific news stories one day before, on the same day as, and one day after a firm's

[12] We also have data on news stories in 1979, which we use only for standardizing negative words in 1980.

earnings announcement. This fact suggests that news stories could play an important role in communicating and disseminating information about firms' fundamentals. In the next two sections, we provide further support for this interpretation of Figure 1.

II. Using Negative Words to Predict Earnings and Returns

Equipped with this qualitative insight about media coverage, we now formally investigate whether the language used by the media provides new information about firms' fundamentals and whether stock market prices appropriately incorporate this information. In Section II.A, our main finding is that negative words reliably forecast negative earnings, even after controlling for analysts' forecasts, stock returns and accounting information. In Section II.B, we show that market prices eventually incorporate the information embedded in negative words, but that this response is somewhat slower than a frictionless efficient market model would predict. In Section II.C, we compute the trading profits from a strategy that exploits the market's underreaction to negative words.

A. Predicting Earnings

In order to affect stock returns, negative words must convey novel information about either firms' expected earnings or investors' discount factors.[13] Our tests in this section focus on whether negative words can predict earnings, whereas the return predictability tests in Section II.B address the second possibility. The idea underlying our earnings predictability tests is that negative words in a firm's news stories prior to the firm's

[13] This statement implicitly relies on a present value decomposition of prices that rules out prices that grow forever at a rate greater than investors' required returns—*e.g.*, Campbell and Shiller (1987).

earnings announcement could measure otherwise hard-to-quantify unfavorable aspects of the firm's business environment.

We use two measures of firms' quarterly accounting earnings as dependent variables in our predictability tests. Our main tests compute each firm's standardized unexpected earnings (*SUE*) following Bernard and Thomas (1989), who use a seasonal random walk with trend model for each firm's earnings:

$$UE_t = E_t - E_{t-4}$$
$$SUE_t = \frac{UE_t - \mu_{UE_t}}{\sigma_{UE_t}}$$

where E_t is earnings in quarter t, and the trend and volatility of unexpected earnings (*UE*) are equal to the mean (μ) and standard deviation (σ) of the firm's previous 20 quarters of unexpected earnings data, respectively.[14] We also use standardized analysts' forecast errors (*SAFE*) as an alternative measure to ensure robustness. *SAFE* is equal to the median stock analyst's earnings forecast error divided by earnings volatility (σ), which is the same as the denominator of *SUE*. We use the median analyst forecast from the most recent I/B/E/S statistical period prior to three days before the earnings announcement.[15] Despite the well-known biases in stock analysts' earnings forecasts, we find remarkably similar results using *SUE* and *SAFE*.[16]

Our measure of negative words ($neg_{-30,-3}$) is the standardized number of negative words in all news stories between 30 and three trading days prior to an earnings

[14] As in Bernard and Thomas (1989), we require that each firm has non-missing earnings data for the most recent 10 quarters and assume a zero trend for all firms with fewer than four years of earnings data. Whereas Bernard and Thomas (1989) use *SUE* deciles in their tests, we winsorize the 1% tails of *SUE* to limit the impact of estimation error in the *SUE* calculation. Winsorizing preserves the continuity of *SUE* for our regression tests and is consistent with our treatment of analyst forecast variables.
[15] We winsorize all analyst forecast variables, including the control variables below, at the 1% level to reduce the influence of extreme outliers. Using the unwinsorized analyst variables (or winsorizing at a lower level) would reduce the significance of the analyst controls and make our results stronger.
[16] Several studies argue that analyst earnings forecasts are too optimistic (*e.g.*, Easterwood and Nutt (1999)), overreact to certain pieces information (*e.g.*, De Bondt and Thaler (1990)), and underreact to other information (*e.g.*, Abarbanell and Bernard (1992)) among other biases.

announcement divided by the total number of words in these news stories. That is, we construct the measure exactly analogous to the story-specific measure (*neg*) defined earlier, where we treat all the words in the [-30,-3] time window as though they form a single composite news story. [17] The timing of this measure is designed to include news stories about the upcoming quarter's earnings announcement. Because 30 trading days is roughly one half of a calendar quarter, it is likely that most of the news stories in the [-30,-3] time window focus on the firm's upcoming announcement rather than its previous quarter's announcement. [18] In addition, we allow for two full trading days between the last news story included in this measure and the earnings announcement because CompuStat earnings announcement dates may not be exact.

In all earnings predictability regressions, we include control variables based on firms' lagged earnings, log firm sizes, log book-to-market ratios, three measures of firms' recent stock returns, analysts' earnings forecast revisions, and analysts' forecast dispersion. We measure lagged earnings using last quarter's *SUE* or *SAFE* measure, according to which of these two variables is the dependent variable in the regression.[19] We measure firm size and book-to-market at the end of the preceding calendar year, following Fama and French (1992).

Our three control variables for a firm's past returns are based on a simple earnings announcement event study methodology. [20] We estimate benchmark returns using the Fama-French (1993) three-factor model with an estimation window of [-252,-31] trading days prior to the earnings announcement. [21] We include two control variables for a firm's recent returns, the cumulative abnormal return from the [-30,-3] trading day window

[17] We standardize this fraction of negative words as described earlier, by subtracting the prior year's mean and dividing by the prior year's standard deviation.
[18] Using the most recent 20 or 40 trading days, rather than 30, does not change our qualitative results.
[19] The inclusion of additional lags of the dependent variables does not change the results.
[20] Controlling for alternative measures of past returns such as raw event returns and the past calendar year's return does not change our qualitative results.
[21] There are roughly 252 trading days in a typical year.

(*FFCAR*$_{-30,-3}$) and the abnormal return on the day -2 (*FFCAR*$_{-2,-2}$). These return windows end one trading day after our [-30,-3] news story time window to ensure that we capture the full price impact of the news stories. Our third control variable (*FFAlpha*$_{-252,-31}$) is the estimated intercept from the event study regression that spans the [-252,-31] time window. We interpret the *FFAlpha*$_{-252,-31}$ measure as the firm's in-sample cumulative abnormal return over the previous calendar year, skipping the most recent month.[22]

In all our earnings regressions, we include control variables for the median analyst's quarterly forecast revision and analysts' quarterly forecast dispersion. We compute the median analyst's three-month earnings forecast revision following Chan, Jegadeesh and Lakonishok (1996).[23] This variable is equal to the three-month sum of scaled changes in the median analyst's forecast, where the scaling factor is the firm's stock price in the prior month. We compute analysts' forecast dispersion as the standard deviation of analysts' earnings forecasts in the most recent time period prior to the announcement scaled by earnings volatility (σ)—*i.e.*, the denominator of *SUE* and *SAFE*. We construct both of these control variables using quarterly analyst forecasts to match our dependent variables, which are based on quarterly earnings measures. Because analysts' quarterly forecasts are unavailable from I/B/E/S between 1980 and 1983 and for firms without analyst coverage, the earnings predictability regressions that we report do not include these observations.[24]

[22] The *FFAlpha*$_{-252,-31}$ variable is related to the Jegadeesh and Titman (1993) return momentum effect, which is based on firms' relative returns over the previous calendar year excluding the most recent month.
[23] We use three-month revision periods rather than six-month periods because these revisions capture new information after the forecast preceding last quarter's earnings announcement, which is already included in our regressions as a separate control.
[24] Fortunately, because there are very few S&P 500 firms without analyst coverage and few news stories in the early years of our data, we lose fewer than 10% of our observations by including the analyst control variables. If we omit the two analyst variables and include these remaining observations in our regressions, we find very similar results.

We estimate the ability of negative words ($neg_{-30,-3}$) to predict earnings (*SUE* or *SAFE*) using pooled ordinary least squares (OLS) regressions.[25] Because firms' realized earnings are undoubtedly correlated within calendar quarters, we allow for arbitrary correlations between firms' earnings by computing clustered standard errors (Froot (1989)).[26] We run separate regressions for two sub-periods of our time period, pre-1995 and 1995-2004, with the reasoning that media coverage changed significantly in 1995 with the introduction of the Internet—*e.g.*, *WSJ* launched WSJ.com on April 29, 1995.

In Table I, we report the results from 18 (2*3*3) OLS regressions. We estimate the dependence of two different dependent variables (*SUE* and *SAFE*) in each of three different time periods (1984 to 1994, 1995 to 2004, and 1984 to 2004) on each of three different negative words measures (from *DJNS*, from *WSJ* and from both). The key result is that negative words (*neg*) consistently predict lower earnings in both time periods, regardless of whether we use the *SUE* or *SAFE* measure, and regardless of whether we use stories from *DJNS* or *WSJ*.[27] All of the full period estimates and most of the sub-

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[25] We report only pooled OLS estimates because these standard errors are the most conservative, which could be because the estimates are inefficient. If we use fixed- or random-effects models instead, the point estimates of the key coefficients change by very little and the standard errors decline. This robustness is comforting because fixed-effects estimators and pooled OLS estimators for dynamic panel data models with lagged dependent variables show opposite small sample biases (see Nickell (1981)). The bias in the fixed effects estimator bias diminishes quickly (as T^{-1}) as the time dimension (T) of the panel becomes large, which it is in this application. In addition, the bias in our pooled OLS estimator is relatively minor because the fixed effects explain so little of the overall variation in unexpected earnings (less than 15%) and returns (less than 1%). The fixed effects also have extremely low correlations with earnings forecasts (less than 0.01) and return forecasts (around 0.05) based on the other independent variables. These facts help to explain why the pooled OLS, fixed-effects and random-effects coefficient estimates are so similar.

[26] We choose the quarterly clustering methodology to be conservative. We also find that clustering errors by firm, by year or by industry-quarter does not change our qualitative results. In addition, we find qualitatively similar estimates using quarterly cross-sectional Fama-MacBeth (1973) regressions along with Newey-West (1980) standard errors for the time series of the coefficients. Similarly, including yearly time dummies in the pooled OLS regressions does not affect our results.

[27] Although negative words (*neg*) from *WSJ* stories appear to predict *SUE* slightly better than *neg* from *DJNS* stories, the *WSJ* coefficient estimates of *neg* are not statistically different from the *DJNS* estimates.

period estimates of the dependence of earnings on *neg* are statistically significant at the 99% level.[28]

[Insert Table I around here.]

We now analyze the *SUE* and *SAFE* full period regressions that include stories from both news sources in greater detail. The first two columns in Table II display the full set of coefficient estimates for all variables in these two regressions. As one would expect, several control variables exhibit strong explanatory power for future earnings. For example, lagged earnings, variables based on analysts' forecasts and recent stock returns ($FFCAR_{-30,-3}$) are all powerful predictors of earnings.

[Insert Table II around here.]

To gain intuition for the importance of language in predicting fundamentals, we compare the abilities of negative words in firm-specific news stories ($neg_{-30,-3}$) and firms' recent stock returns ($FFCAR_{-30,-3}$) to predict future earnings. The logic of this comparison is that these two variables should be related to each other and to future earnings in theory.[29] In addition, both variables are measured over the same time horizon. This is a particularly tough comparison for language because the firm's abnormal return measures the representative investor's interpretation of firm-specific news, which is undoubtedly based on a more sophisticated reading of the same linguistic content that we quantify. In this respect, it is surprising that quantified language has any explanatory power above and beyond market returns. Indeed, one could view a firm's abnormal return ($FFCAR_{-30,-3}$) measured over the time horizon in which there is news ([-30,-3]) as an alternative quantification of news (*e.g.*, Chan (2003)).[30]

[28] As a general rule, the greater number of news stories in the second half of the sample leads to greater statistical significance for this time period.
[29] The correlation between these negative words and returns measures is strongly statistically significant, but less than -0.05 in magnitude.
[30] In the tests reported below and in additional unreported tests, we find that this alternative measure of news content has similar predictive properties to our direct linguistic measure ($neg_{-30,-3}$).

Nevertheless, the first two columns in Table II reveal that negative words and recent stock returns have almost the same statistical impact and comparable economic impacts on future earnings.[31] After standardizing the coefficients to adjust for the different variances of the two independent variables, we find that the economic impact of past returns is 0.1275 *SUE* and the impact of negative words is 0.0786 *SUE*—*i.e.*, 61.6% as large. This demonstrates that incorporating directly quantified language in earnings forecasts significantly improves upon using stock returns alone to quantify investors' reactions to news stories.

Even though the stock return control variable ($FFCAR_{-30,-3}$) includes all of the information embedded in news stories during the [-30,-3] time window, it is possible that these stories are more recent than the most recent analyst forecast control variables included in Table II. Indeed, many *WSJ* and *DJNS* news stories explicitly mention stock analysts, suggesting negative words in these stories may draw some of their predictive power from analysts' qualitative insights. To guard against the possibility that negative words predict returns solely because they appear more recently than the *quantitative* analyst forecasts, we recalculate the negative words measure ($neg_{-30,-3}$) including only the stories that occur at least one trading day prior to the date of the most recent consensus analyst forecast.[32]

The last two columns in Table II show that negative words ($neg_{-30,-3}$) robustly predict both *SUE* and *SAFE* even after we exclude words from the most recent stories. Surprisingly, the respective $neg_{-30,-3}$ coefficients diminish in magnitude by only 12.3% and 12.9%, and both remain strongly significant at any conventional level (p-values < 0.001). In summary, we find that a crude quantification of qualitative fundamentals

[31] In unreported tests, we find that the coefficients on negative words roughly double in magnitude when we omit all of the control variables from the regressions.

[32] Because I/B/E/S reviews and updates the accuracy and timing of analyst forecasts even after the date of the consensus forecast, it is unlikely that news stories from one trading day earlier contain information not reflected in the consensus. In addition, allowing three trading days does not change our qualitative results.

($neg_{-30,-3}$) predicts earnings above and beyond more recent measures of market prices and analysts' forecasts.

We now examine the long-run time series behavior of earnings surrounding the release of negative words in firm-specific news. Figure 2 compares the earnings of firms with negative and positive news stories from 10 fiscal quarters prior to an earnings announcement up to 10 fiscal quarters after the earnings announcement. The dependent variable in Figure 2 is a firm's cumulative *SUE* beginning 10 quarters prior to the earnings announcement associated with the media content.[33] We define positive (negative) news as news in which the variable $Neg_{-30,-3}$ is in the bottom (top) quartile of the previous year's distribution of $Neg_{-30,-3}$.[34]

[Insert Figure 2 around here.]

Figure 2 shows that firms with negative news stories before an earnings announcement experience large negative shocks to their earnings that endure for the next two announcements. Although there are noticeable differences between firms with positive stories and those with many negative stories that appear before the news is released (0.645 cumulative *SUE*), the greatest discrepancy between the cumulative earnings of the two types of firms (1.375 cumulative *SUE*) appears in the third fiscal quarter after the news. It appears as though some of the impact of negative words on cumulative earnings is permanent—0.771 cumulative *SUE* after 10 quarters, which is 0.126 cumulative *SUE* more than prior to the news. However, it is difficult to judge the magnitude and duration of the effect based on just 10 ten-quarter periods.[35]

[33] Our cumulative *SUE* computation does not discount earnings in different time periods. Using a positive discount rate would make the effect of negative words on earnings appear larger and more permanent.
[34] As one would expect, the fractions of positive and negative words in news stories are negatively correlated (-0.18, p-value < 0.001). For this reason, defining positive stories as those with relatively few negative words also produces stories with relatively more positive words.
[35] Long-horizon earnings regressions also yield inconclusive results because the standard errors are large for estimates based on our short time period. We note that our estimate of the permanent impact of negative words is similar in magnitude to our estimates of the immediate impact on next period's *SUE* in Table II.

From the analysis above, we conclude that negative words in firm-specific stories leading up to earnings announcements significantly contribute to a useful measure of firms' fundamentals. One view is that this result is surprising because numerous stock analysts and investors closely monitor the actions of S&P 500 firms. Yet even after controlling for recent stock returns, analyst forecasts and revisions, and other measures of investors' knowledge, we find that a rudimentary linguistic measure of negative news still forecasts earnings. Furthermore, we will demonstrate in Section III that it is possible to improve substantially upon this basic negative word count measure.

On the other hand, one could argue that negative words appear to be informative measures of firms' fundamentals simply because they do not suffer from the same shortcomings as the control variables that we use to forecast earnings. For example, it is well-known that stock analysts' earnings forecasts exhibit significant biases that limit their forecasting power. In addition, stock market returns reflect revisions in investors' expectations of the present value of all future earnings as opposed to next quarter's earnings, which is the dependent measure in our regressions. Even if investors and stock analysts are fully aware of the information embedded in negative words, negative words may appear to have significant incremental explanatory power for future earnings because the control variables in the regressions are not accurate representations of investors' expectations.

The permanent impact is the 0.126 cumulative *SUE* difference between the top and bottom quartiles of negative words, whereas the temporary impact is 0.181 *SUE*. The latter figure is the difference between the Table II estimates at +1.15 and -1.15 standard deviations of negative words, which are the top and bottom quartile midpoints (12.5% and 87.5%) assuming that standardized negative words are normally distributed.

B. Predicting Returns in Story Event Time

We subject the two competing views described above to empirical scrutiny in our return predictability tests. Having established that negative words in news stories are related to fundamentals, we now examine whether they provide novel information not already represented in stock market prices. Unfortunately, we cannot test this conjecture by looking at contemporaneous market returns. Although there is a significant negative relationship between negative words and concurrent market returns, it is impossible to know which variable causes the other.

Instead, we hypothesize that investors do not immediately fully respond to the news embedded in negative words. To test this theory, we explore whether negative words in firm-specific news stories predict future stock returns. In this section, we focus on OLS regression estimates of the effect of negative words on future stock returns in event time—*i.e.*, relative to the release of the news story. In Section II.C, we estimate the same effects using calendar time methods.

In our first tests, we assess whether standardized fractions of negative words in firm-specific news stories predict firms' close-to-close stock returns on the following day. For all *DJNS* stories, we obtain precise time stamp data to exclude stories that occur after 3:30pm—*i.e.*, 30 minutes prior to market closing.[36] This ensures that traders have at least 30 minutes, and usually much longer, to digest and trade on information embedded in these stories.[37] For all *WSJ* stories, we assume that stories printed in the morning's *WSJ* are available to traders well before the market close on the same day.

[36] To be conservative, we use the last time stamp for each story, which indicates when the story was most recently updated. Thus, in many cases, the negative words in *DJNS* stories became known to investors much earlier, often by one hour, than we assume.
[37] The qualitative results are similar for alternative time cut-off choices, such as 15 minutes and one hour. Intuition suggests that traders have many opportunities to transact large amounts in the 30-minute time intervals that we allow them. The typical 30-minute transaction volume for a firm in the S&P 500 index

In each regression, we include several standard control variables to assess whether negative words predict returns above and beyond already known sources of predictability, including both firms' characteristics (Daniel, Grinblatt, Titman and Wermers (1997)) and firms' covariances with priced risk factors (Fama and French (1993)). We include all of the characteristic controls in the earnings predictability regressions, except the two analyst earnings forecast variables.[38] That is, we include the firm's most recent earnings announcement (*SUE*) and close-to-close abnormal returns on the day of the news story ($FFCAR_{0,0}$), each of the previous two trading days ($FFCAR_{-1,-1}$ and $FFCAR_{-2,-2}$), the previous month ($FFCAR_{-30,-3}$) and the previous year ($FFAlpha_{-252,-31}$). These controls are designed to capture return predictability from past earnings (*e.g.*, Ball and Brown (1968)) and past returns (*e.g.*, Jegadeesh and Titman (1993)), which may be distinct phenomena (*e.g.*, Chan, Jegadeesh and Lakonishok (1996)). In addition, we control for firm size and book-to-market ratios using each firm's log of market capitalization and log of book-to-market equity measured at the end of the most recent end of June.[39] These controls mimic the variables that Fama and French (1992) use to predict returns.

We also run two sets of regressions to ensure that firms' return covariances with priced risk factors do not drive our results. In the first set of regressions, we use each firm's next-day abnormal return as the dependent variable, where the Fama-French three-factor model is the benchmark for expected returns.[40] To ensure that our results are not

ranges between $1 million and $100 million. Volume is usually higher for firms that frequently appear in the news. Volume is also higher following a news story and during the last 30 minutes of the trading day.

[38] When we include the two analyst forecast variables, we find that both revisions and dispersion are statistically and economic insignificant predictors of returns in our sample. The coefficients on the key variables do not change materially. Thus, we omit the analyst variables to include the few S&P 500 firms without analyst coverage and the first four years of our sample in the regression results.

[39] For parsimony, we omit controls for market-wide return measures, such as lagged market, size, book-to-market, and momentum factor returns. These controls are insignificant and do not change the results if they are included.

[40] We also find that including time dummies for each trading day—*i.e.*, demeaning returns by trading day—does not change our regression results. This suggests that there is not an omitted common news factor driving our results.

driven by the benchmarking process, we run a second set of regressions in which we use each firm's next-day raw return as the dependent variable.

Table III reports the results from 18 (2*3*3) OLS regressions, two different dependent variables (raw and abnormal next-day returns) in each of three different time periods (1980 to 1994, 1995 to 2004, and 1980 to 2004) regressed on each of three different negative words measures (from *DJNS*, from *WSJ* and from both). The table shows the coefficients on negative words in firm-specific news stories and their associated t-statistics. We compute clustered standard errors (Froot (1989)) to account for the correlations between firms' stock returns within trading days. The table reports the number of clusters—*i.e.*, trading days—and the adjusted R-squared for each regression.

[Insert Table III around here.]

The main result in Table III is that negative words in firm-specific news stories strongly predict lower returns on the following trading day. The coefficients on negative words (*neg*) are strongly negatively significant in all 12 of the regressions where news stories from *DJNS* are included. However, the coefficients on negative words are two to three times smaller and usually statistically insignificant in the six regressions where only *WSJ* stories are included. One interpretation of this evidence is that the *DJNS* releases intra-day stories with extremely recent information before the information is fully priced. By contrast, a number of the morning *WSJ* stories are recapitulations of the previous day's events—some of which appeared in the *DJNS*—that may already be incorporated in market prices.

We now examine the market's apparently sluggish reaction to negative words in firm-specific news stories in the four weeks surrounding the story's release to the public. Figure 3 graphs a firm's abnormal event returns from 10 trading days preceding a story's release to 10 trading days following its release. Again, we use the Fama-French three-factor model to estimate abnormal returns. We label all news stories with a fraction of negative words (*Neg*) in the previous year's top (bottom) quartile as negative (positive) stories. We separately examine the market's response to positive and negative *DJNS* and *WSJ* stories. We also compute the difference between the reaction to positive and negative news stories for each source.

[Insert Figure 3 around here.]

The top line in Figure 3 demonstrates that the 12-day market reaction, from day -2 to day 10, to *WSJ* stories is virtually complete after the first two trading days—7.5 basis points (bps) of underreaction after day one and only 2.4 bps after day two. By contrast, the second line in Figure 3 shows that much more of the 12-day market reaction to *DJNS* stories persists beyond the first two days—16.8 bps after day one and 6.2 bps after day two. The positive and negative *DJNS* lines show that the day one delayed reaction to positive *DJNS* news stories (6.6 bps) is somewhat larger than the delayed reaction to negative stories (4.0 bps).[41,42] Although the total one-day delayed reaction to *DJNS* news stories is 10.6 bps (see the difference line), this magnitude is relatively small (17.2%) compared to the total 12-day reaction of roughly 61.6 bps. The market appears even more efficient in its reaction to *WSJ* stories, where the one-day delayed reaction (5.2 bps) is only 7.1% of the 12-day reaction (73.3 bps).[43]

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[41] Of course, the contemporaneous reactions to positive news stories are also larger. We observe the opposite asymmetry for the positive and negative news stories about fundamentals that we examine in Section III.

[42] There appears to be a slight upward drift in the returns of firms with both positive and negative news stories, consistent with the old adage: "there's no such thing as bad publicity."

[43] It is also possible that there is underreaction to *WSJ* stories within the close-to-close trading day that encompasses the morning release of the newspaper.

C. Predicting Returns in Calendar Time

The lingering difference between the abnormal returns of firms with positive and negative *DJNS* news stories suggests that a simple trading strategy could earn excess risk-adjusted profits. In this section, we explore this possibility, focusing on the apparent short-run underreaction to negative words in the *DJNS*.

Specifically, at the close of each trading day, we form two equal-weighted portfolios based on the content of each firm's *DJNS* news stories during the prior trading day.[44] We use the same definitions for positive and negative stories, based on the distribution of words in the prior year, as we did in the previous section. We include all firms with positive *DJNS* news stories during the preceding day in the long portfolio, and put all firms with negative stories in the short portfolio.[45] We hold both the long and short portfolios for one full trading day and rebalance at the end of the next trading day. To keep the strategy simple, we exclude the rare days in which either the long or the short portfolio contains no qualifying firms. Ignoring trading costs, the annualized cumulative returns of the long-short strategy would be 21.1%.

Table V shows the risk-adjusted daily returns from this daily news-based trading strategy for three different time periods (1980 to 1994, 1995 to 2004 and 1980 to 2004). We use the Fama-French three-factor (1993) and Carhart four-factor (1997) models to adjust the trading strategy returns for the returns of contemporaneous market, size, book-to-market, and momentum factors. Table V reports the alpha and loadings from the time series regression of the long-short news-based portfolio returns on the four factors. The first three columns report the results with the Fama-French benchmark, whereas the last

[44] Forming two story-weighted or value-weighted portfolios produces very similar results. The traditional motivation for value weights is less compelling in this application because all S&P 500 firms have sufficient size and liquidity to enable investors to execute large trades cost-effectively.
[45] Again, to be conservative, we exclude all news stories that occur within 30 minutes of the market close.

three columns report the results with the Carhart benchmark. We compute all coefficient standard errors using the Huber-White (1980) heteroskedasticity-consistent covariance matrix.

[Insert Table V around here.]

Consistent with the results in Tables III and IV, Table V shows that the daily news-based trading strategy would earn substantial risk-adjusted returns in a frictionless world with no trading costs or price impact. Specifically, the risk-adjusted return (Fama-French alpha) from news-based trading would be 9.2 bps per day from 1980 to 1994 and 11.8 bps per day from 1995 to 2004. Regardless of the benchmark model for returns, the alpha from the trading strategy is highly significant in all three time periods. Interestingly, the returns from news-based trading are not strongly related to any of the three Fama-French factors or the momentum factor.[46] Indeed, the R-squared statistics reveal that the vast majority of the trading strategy risk is firm-specific.

Next, we analyze the yearly distribution of the trading strategy returns over time. Over the 25 years between 1980 and 2004, the median strategy return is 10.2 bps per day. In 18 out of 25 years, the news-based strategy earns positive excess returns. Thus, we can reject the null hypothesis that yearly news-based strategy returns follow the binomial distribution with an equal likelihood of positive and negative returns (p-value = 0.0216). Moreover, if we restrict the trading strategy to exclude days in which either the long or short portfolio contains only one firm, then the trading strategy has the same daily return (9.5 bps) and produces positive returns in 21 out of 25 years (p-value < 0.0005).

Figure 4 depicts the distribution of the yearly returns for the news-based trading strategy. There is only one year (1980) out of 25 in which the strategy lost more than 2.5 bps per day (-3.0 bps). By contrast, in 16 out of 25 years, the strategy gained more than

[46] The strategy's negative loading on HML is a minor exception, which may be caused by the large number positive media stories about growth firms during the late 1990s.

2.5 bps per day. This analysis suggests the news-based trading strategy is not susceptible to catastrophic risks that second moments of returns could fail to capture.

[Insert Figure 4 around here.]

Finally, we estimate the impact of reasonable transaction costs on the trading strategy's profitability. To judge how sensitive the profits are to trading costs, we recalculate the trading strategy returns under the assumption that a trader must incur a round-trip transaction cost of between 0 and 10 bps.[47] Table VI displays the annualized cumulative news-based strategy returns under the assumptions of 0, 1, 2, 3 … and 10 bps round-trip costs.

[Insert Table VI around here.]

From the evidence in Table VI, we see that the simple news-based trading strategy explored here is no longer profitable after accounting for reasonable levels of transaction costs—*e.g.*, 10 bps.[48] Of course, we cannot rule out the possibility that more sophisticated trading rules that exploit the time series and cross-sectional properties of news stories and economize on trading costs would be profitable.[49]

[47] Because the daily return on the strategy is roughly 10 bps, it does not make sense to implement the strategy if transactions costs are greater than 10 bps.

[48] As a typical example, consider an individual day trader using an E-Trade account to execute a round trip trade for 500 shares of an actively traded S&P 500 firm. The firm could have a bid-ask spread equal to one cent (as most S&P firms do) and an ask price of $40 (which is near the median for S&P firms). The trader would incur a round trip cost of 500 shares * $0.01 = $5 from the spread and a cost of 2 trades * $7 per trade = $14 for the two commissions. The total cost would be $19, or 9.5 bps of the trader's 500 shares * $40 = $20,000 of capital. With costs of 9.5 bps per round trip trade, the trader would not earn any abnormal profits (see Table VI). In general, the trading strategy's profitability depends critically on the amount of capital employed, the degree of price improvement or quote improvement, and other factors that influence transaction costs.

[49] For example, the next subsection investigates a refined measure of negative words that predicts greater market underreactions to particular negative words.

III. Interpreting the Earnings and Return Predictability

The key stylized facts documented thus far are: 1) news stories about firms are concentrated around their earnings announcements; 2) negative words in firm-specific stories predict low firm earnings in the next quarter; and 3) negative words about firms predict low firm stock returns on the next trading day. In this section, we explore further whether the ability of negative words to predict returns stems from underreaction to news about firms' fundamentals that is embedded in language.

Our specific hypothesis is that negative words in news stories that mention the word stem "earn" contain more information about firms' fundamentals than other stories. If this is the case, then we should observe three effects. First, the ability of negative words to predict earnings should be greater for stories that include the word stem "earn." Second, the contemporaneous relationship between firm-specific negative words and firms' returns should be stronger for stories that contain the word stem "earn." Third, because these stories probably better capture news about hard-to-quantify fundamentals, the magnitude of the market's underreaction to negative words should be greater for stories that contain the word stem "earn."

Before testing these three predictions, we establish an intuitive property of this measure of fundamentals: the news stories near earnings announcements (see Figure 1) are far more likely to mention the word stem "earn"—*e.g.*, the word "earnings" or any form of the verb "earn." We construct a dummy variable (*Fund*) that indicates whether a news story contains any words beginning with "earn." We find that only 18.9% of the stories that are more than one day away from an earnings announcement contain the word stem "earn," whereas 72.5% of the stories within a day of the announcement mention earnings-related words.[50]

Having established that stories around earnings announcements are likely to be about firms' fundamentals, we now test whether negative words in these stories predict earnings better than negative words in other stories. We add two new independent variables to the regressions for *SUE* and *SAFE* shown earlier in the first two columns of Table II. The first new variable ($Fund_{-30,-3}$) is the total number of words in news stories between day -30 and day -3 that contain the word stem "earn" divided by the total number of words in all news stories between day -30 and day -3. It is designed to capture the fraction of words between day -30 and day -3 that are likely to provide relevant information about firms' fundamentals. The second new variable ($neg_{-30,-3}*Fund_{-30,-3}$) is the interaction between $Fund_{-30,-3}$ and the negative words measure ($neg_{-30,-3}$). The coefficient on the interaction term measures the extent to which negative words "about" fundamentals are more useful predictors of firms' earnings than other negative words.

[Insert Table VII around here.]

Table VII shows that the coefficients for both of the new independent variables in the *SUE* and *SAFE* regressions are negative and statistically significant at any conventional level. The coefficient on the interaction term ($neg_{-30,-3}*Fund_{-30,-3}$) in the *SUE* regression shows that negative words that are "about" fundamentals are much better predictors of firms' earnings. The sum of the coefficient on the interaction ($neg_{-30,-3}*Fund_{-30,-3}$) and the coefficient on negative words alone ($neg_{-30,-3}$) estimates the dependence of firm earnings on negative words for announcements in which all (100%) of the news stories between day -30 and day -3 contain the stem "earn." The direct effect

[50] We confirm that this relationship remains very strong using logistic regressions of *Fund* on an earnings announcement dummy and firms' characteristics. Another notable finding is that stories about large firms, growth firms and firms with poor recent returns are more likely to mention earnings.

of negative words alone (*neg*$_{-30,-3}$) estimates the dependence of firm earnings on negative words when none (0%) of the news stories between day -30 and day -3 contain the stem "earn." The point estimate of the sum of the interaction term and the direct effect (-0.3400) is an order of magnitude greater than the direct effect alone (-0.0291), suggesting that negative words have much greater predictive power when they appear in earnings-related stories. Similarly, negative words in earnings-related stories have a much greater ability—again, by an order of magnitude—to predict analyst forecast errors (*SAFE*). Negative words in other stories (*neg*$_{-30,-3}$) still weakly forecast lower earnings (*SUE* or *SAFE*), but this effect is much less important in both statistical and economic terms.

We now test the other two predictions of our hypothesis: contemporaneous market reactions and subsequent market underreactions should be larger for stories that mention the word stem "earn" than for other stories. As in the previous section and Tables III and IV, we use pooled OLS regressions with clustered standard errors to estimate the relationship between negative words and returns. We also use the same set of firm characteristic and stock return control variables discussed earlier. To conserve space, we report only the results where we use firms' abnormal returns as the dependent variable and negative words in firm-specific stories from *DJNS* as the key independent variable.[51] We use *DJNS* stories to explore the underreaction hypothesis because Table III reveals that there is only minimal underreaction to *WSJ* stories.

The first three columns in Table VIII report the contemporaneous (same-day) relationship between abnormal returns and negative words. There are two new independent variables in these regressions: the dummy variable that is equal to one if a story mentions the word stem "earn" (*Fund*) and the interaction (*neg*Fund*) between this

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[51] As in Section III, we include only the *DJNS* stories that occur more than 30 minutes before the market closes.

dummy variable and standardized negative words (*neg*). The first three columns in Table VIII report the coefficient estimates for the full period and two sub-periods divided according to whether the news story appears within one day of an earnings announcement. We use the one-day time window because each of the three days centered on the announcement day have over twice as many news stories as any other day (see Figure 1).[52]

[Insert Table VIII around here.]

Unsurprisingly, the first two columns of Table VIII reveal that there is a strong relationship between negative words (*neg*) and contemporaneous returns in both time periods. More importantly, the coefficient on the interaction between negative words and the "earn" word stem dummy (*neg*Fund*) is statistically significant and negative for the full period (see third column). The sum of the coefficient on *neg* by itself (-0.0821%) and the coefficient on the *neg*Fund* term (-0.3264%) provides an estimate of the contemporaneous market response to negative words in news stories that mention earnings (-0.4085%). In economic terms, the coefficient magnitudes mean that the market response to negative words is about five times as large when these negative words appear in news stories that mention the word stem "earn." This large market reaction to negative words in earnings-related stories is yet another piece of evidence consistent with the idea that negative words convey otherwise hard-to-quantify information about fundamentals.

The second and first columns in Table VIII show that contemporaneous market responses to negative words (*neg*) are somewhat larger around earnings announcements versus other times (-0.1445% vs. -0.0821%). More interestingly, the interaction term coefficients (*neg*Fund*) show that negative words have a much greater impact—by at least a factor of two—when they appear in earnings-related stories, whether or not the

[52] Fortunately, very little changes if we use one-day or five-day periods centered on the earnings announcement, instead of the three-day periods.

earnings-related story occurs near an earnings announcement.[53] This means that a story's impact on market returns depends not only on the timing of the story, but also on what the story says. Stories about fundamentals have consistently strong relationships with stock returns at all times. This fact is somewhat surprising given that the earnings announcement time window is measured much more precisely than our crude fundamental content variable (*Fund*).

Next, we redo the first three regressions in Table VIII using firms' next-day abnormal returns as the dependent variable. The results of this analysis are displayed in the last three columns of Table VIII. The main result is that the same variables that elicit the greatest contemporaneous market responses also predict the greatest subsequent market underreaction. For example, the coefficient on the interaction term (*neg**Fund*) is highly negative for the full period (sixth column in Table VIII), suggesting that negative words in earnings-related stories predict greater market underreactions than negative words in other stories (*neg*). In fact, although the sign of the direct effect of negative words (*neg*) remains the same as before, the market's underreaction to negative words in stories that fail to mention earnings is cut in half (-0.0161% vs. -0.0320% in Table IV). The magnitude of the underreaction to negative words about fundamentals is about seven times greater than the underreaction to negative words in other stories (-0.1197% vs. -0.0161%).

It is useful to gauge the degree of market efficiency by comparing the sizes of the contemporaneous reaction to negative words about fundamentals and the two-day reaction to negative words. Table VIII allows us to make this comparison both near and away from earnings announcements. The sums of the coefficients on *neg* and *neg**Fund*

[53] We note that the negative market responses to earnings-related words themselves (*Fund*) are significantly larger away from earnings announcements. This could be related to earnings warnings that firm management sometimes issues prior to earnings announcements.

in the second column (-0.3267%) and fifth column (-0.1037%) measure the day-zero and day-one reactions near earnings announcements. The sums in the first column (-0.4085%) and fourth column (-0.1062%) measure the day-zero and day-one reactions away from announcements. Based on these coefficients, we infer that the market's initial one-day reaction to negative words about fundamentals composes the vast majority of its two-day reaction both near (75.9%) and away from (79.4%) earnings announcements.[54] One interpretation of this evidence is that investors remain almost equally attuned to the importance of linguistic information about fundamentals even when there is compelling quantitative earnings information to distract them.

All three tests in this section suggest that negative words in stories about firms' fundamentals are driving the earnings and return predictability results. Although news stories that do not mention earnings have some relevance for forecasting earnings and are associated with contemporaneous market returns, these stories have very little ability to forecast future market returns. By contrast, contemporaneous market responses are much larger to negative words in earnings-related stories, which they should be because negative words in these stories are better predictors of firms' subsequent earnings. However, the initial market responses to negative words, especially those contained in earnings-related stories, are insufficiently large to prevent return continuations on the next trading day. Investors seem to recognize that there is a difference between earnings-related stories and the rest, but they do not fully account for the importance of linguistic information about fundamentals.

[54] The same comparison for negative words that do not accompany the word stem "earn" shows that the market reacts even more efficiently (84.2%) to these words (see *neg* in columns three and six in Table VIII).

IV. Conclusion

Our first main result is that negative words in the financial press forecast low firm earnings. That is, the words contained in news stories are not merely redundant information, but instead capture otherwise hard-to-quantify aspects of firms' fundamentals. Our second result is that stock market prices gradually incorporate the information embedded in negative words over the next trading day. We demonstrate large potential profits from using a simple trading strategy based on the words in a timely news source (*DJNS*), but find that these profits could easily vanish after accounting for reasonable levels of transaction costs. Finally, we show that negative words in stories about fundamentals are particularly useful predictors of both earnings and returns.

Our overall impression is that the stock market is relatively efficient with respect to firms' hard-to-quantify fundamentals. The market's underreaction to negative words is typically small as compared to the market's initial reaction to negative words. Even if economists have neglected the possibility of quantifying language to measure firms' fundamentals, stock market investors have not.

Nevertheless, we do find that market prices consistently underreact to negative words in firm-specific news stories, especially those that relate to fundamentals. Although frictionless asset pricing models may not be able to explain these findings, models in which equilibrium prices induce traders to acquire costly information—*e.g.*, Grossman and Stiglitz (1980)—are broadly consistent with our results. Without some slight underreaction in market prices, traders would have no motivation to monitor and read the daily newswires. Future research that quantifies the information embedded in written and spoken language has the potential to improve our understanding of the mechanism in which information is incorporated in asset prices.

Appendix

To match firms' names in CRSP with their common names used in the media, we employ a combination of four methods. Our first method works well for firms that are currently members of the S&P 500 index. We download common names for these firms from the "S&P constituents" spreadsheet posted on Standard and Poor's Web site, http://www.standardpoor.com/. We match these common names by hand to CRSP name strings, which is not difficult once both lists are alphabetically ordered. The matched names form the basis for our Factiva news queries for the 473 firms in the S&P at the end of our data period (12/31/04) that remained in the index on the date that we downloaded the spreadsheet. We identify the common names of the other 27 S&P 500 firms at the end of 2004 using the methods described below.

The other three methods entail matching the CRSP name strings with common firm names from one of three Web-based data sources: Mergent Online, the Securities and Exchange Commission (SEC) or Factiva. For all companies that exist after 1993, we use the Mergent Online company search function to identify firms' common names (336 firms). For the few post-1993 companies without Mergent data, we use the SEC company name search function (20 firms). Finally, we identify the common names of firms prior to 1993 using the Factiva company name search function (285 firms).

In many cases, we manually tweak the CRSP names to improve the quality of the company search. For example, if we do a company search for the CRSP name string "PAN AMERN WORLD AWYS INC," Factiva returns no results. Logically, we look for "Pan American," which seems to retrieve the appropriate company name: "Pan American World Airways Inc." Although this matching process introduces the possibility of minor judgmental errors, our searches uniquely identify matching firms in all cases, suggesting our methods are reasonable.

We construct search queries for news stories using the common names that we match to the CRSP name string. For most firms, our initial queries appear to retrieve most of the relevant news stories from *DJNS* and *WSJ*. We examine the results returned by our automatically constructed search queries and reassess the queries for firms with fewer than 10 news stories. For all firms with no stories initially retrieved, we manually search for common names using the Internet and other resources.

Ultimately, our search methods retrieve at least one news story for 1063 of 1110 (95.8%) of the firms in the S&P 500 from 1980 to 2004. In addition, we lose another 80 of the 1063 firms with news stories (7.5%) because these firms did not make the news during the time in which they were in the S&P 500 between 1980 and 2004.[55] Finally, after deleting all stories with fewer than three unique positive and negative words or fewer than five total positive and negative words, we lose another three firms, leaving us with 980 qualifying firms.[56]

It is possible that we retrieve no news stories for the missing 4.2% of the initial set of 1110 S&P 500 firms because of errors in our matching algorithm. Fortunately, although the exact magnitude of our results depends on the matching methodology employed, the sign and significance of all key coefficients does not change for the firms that have been matched using each of the four different processes. In addition, there are no significant differences in the magnitudes for the predictive coefficients of negative words on earnings or returns. Thus, we infer that it is unlikely that matching errors introduce sufficient *systematic* errors in our tests that would significantly change the

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[55] This time frame is brief if a firm exits the S&P index shortly after 1980. Also, Factiva's coverage of news stories from 1980 to 1984 appears somewhat incomplete, possibly leading to missing news stories.
[56] The median firm has 156 news stories and 929 of 980 firms have at least 10 news stories.

results. Moreover, our key results depend on cross-sectional and time series variation in earnings and returns but not the levels of these variables, which could be affected by survivorship bias.

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Table I: Predicting Earnings Using Negative Words

This table shows estimates of the ability of negative words ($neg_{-30,-3}$) to predict quarterly earnings (*SUE* or *SAFE*) using ordinary least squares (OLS) regressions. The coefficients on $neg_{-30,-3}$ and summary statistics from 18 (2*3*3) different regressions are displayed below: two different dependent variables (*SUE* and *SAFE*) in each of three different time periods (1984-1994, 1995-2004 and 1984-2004) regressed on negative words from each of three different news sources (*Dow Jones News Service*, *The Wall Street Journal*, and both sources). Our measure of negative words ($neg_{-30,-3}$) is the standardized number of negative words in the news stories from 30 trading days prior up to three trading days prior to an earnings announcement divided by the total number of words in these news stories. Only the coefficient estimates for $neg_{-30,-3}$ are shown below. However, all regressions include control variables for lagged firm earnings, firm size, book-to-market, recent and distant past stock returns, and analysts' quarterly forecast revisions and dispersion (see text for details). To allow for correlations among announced firm earnings within the same calendar quarter, we compute clustered standard errors (Froot (1989)).

		SUE			*SAFE*		
Stories Included		1984-1994	1995-2004	1984-2004	1984-1994	1995-2004	1984-2004
Both Sources	$neg_{-30,-3}$	-0.0333	-0.0948	-0.0797	-0.0224	-0.0192	-0.0202
		(1.64)	(4.31)	(4.47)	(2.52)	(5.03)	(5.44)
	Obs.	8982	22705	31687	8543	21243	29786
	Adj. R-sq.	0.1312	0.1214	0.1215	0.1227	0.1069	0.1214
Dow Jones News Service	$neg_{-30,-3}$	-0.0396	-0.0669	-0.0619	-0.0237	-0.0167	-0.0193
		(1.65)	(3.06)	(3.52)	(2.57)	(4.80)	(5.41)
	Obs.	8213	22172	30385	7814	20745	28559
	Adj. R-sq.	0.1319	0.1196	0.1204	0.1274	0.1054	0.1229
Wall Street Journal	$neg_{-30,-3}$	-0.0584	-0.1461	-0.1185	-0.0376	-0.0168	-0.0239
		(2.59)	(4.23)	(4.67)	(3.29)	(2.58)	(4.14)
	Obs.	6805	14199	21004	6485	13411	19896
	Adj. R-sq.	0.1307	0.1254	0.1235	0.1242	0.1013	0.1224

Robust t-statistics in parentheses.

Table II: Detailed Predictions of Earnings Using Negative Words

This table reports the results from four OLS regressions with two different dependent variables (*SUE* and *SAFE*) regressed on two measures of negative words ($neg_{-30,-3}$). All four regressions include all news stories from both news sources (*Dow Jones News Service* and *The Wall Street Journal*) over the time period from 1984 through 2004. The measure of negative words ($neg_{-30,-3}$) is the standardized number of negative words in the news stories from 30 trading days prior up to three trading days prior to an earnings announcement divided by the total number of words in these news stories. The first two regressions compute $neg_{-30,-3}$ using all stories in the [-30,-3] time window, whereas the last two regressions use only the stories occurring one trading day before the most recent consensus analyst forecast. All regressions include control variables for lagged firm earnings, firm size, book-to-market equity, recent and distant past stock returns, and analysts' quarterly forecast revisions and dispersion (see text for construction). To allow for correlations among announced firm earnings within the same calendar quarter, we compute clustered standard errors (Froot (1989)).

	All Stories		Before Analyst Forecasts	
	SUE	*SAFE*	*SUE*	*SAFE*
$neg_{-30,-3}$	-0.0797	-0.0202	-0.0699	-0.0176
	(4.47)	(5.44)	(3.56)	(3.56)
Lag(Dependent Variable)	0.2206	0.2518	0.2173	0.2331
	(10.88)	(10.56)	(10.45)	(9.55)
Analyst Forecast Dispersion	-0.9832	-0.2799	-0.9714	-0.2688
	(8.30)	(6.12)	(7.58)	(5.03)
Analyst Forecast Revisions	21.7568	0.5517	22.7160	0.4760
	(7.72)	(1.03)	(7.21)	(0.76)
Log(Market Capitalization)	-0.0138	0.0224	-0.0113	0.0213
	(0.61)	(4.03)	(0.48)	(3.84)
Log(Book-to-Market Equity)	0.0198	-0.0047	0.0220	-0.0085
	(0.64)	(0.68)	(0.64)	(1.14)
Log(Share Turnover)	-0.1405	0.0290	-0.1321	0.0305
	(2.89)	(3.03)	(2.65)	(3.07)
$FFAlpha_{-252,-31}$	1.9823	0.1626	1.9464	0.1389
	(7.22)	(3.25)	(6.76)	(2.61)
$FFCAR_{-30,-3}$	0.0113	0.0061	0.0112	0.0055
	(6.47)	(13.58)	(5.54)	(11.15)
$FFCAR_{-2,-2}$	0.0168	0.0070	0.0240	0.0089
	(2.35)	(3.37)	(2.82)	(3.60)
Observations	31687	29786	25764	24309
Clusters	80	79	78	78
Adjusted R-squared	0.1215	0.1214	0.1189	0.1102

Robust t-statistics in parentheses.

Table III: Predicting Returns Using Negative Words

This table shows the relationship between standardized fractions of negative words (*neg*) in firm-specific news stories and firms' stock returns on the following day ($Return_{+1,+1}$ or $FFCAR_{+1,+1}$). The coefficients on $neg_{-30,-3}$ and summary statistics from 18 (2*3*3) different regressions are displayed below: two different dependent variables ($Return_{+1,+1}$ and $FFCAR_{+1,+1}$) in each of three different time periods (1984-1994, 1995-2004 and 1984-2004) regressed on negative words from each of three different news sources (*Dow Jones News Service*, *The Wall Street Journal*, and both). For all *DJNS* stories, we exclude stories that occur after 3:30pm (30 minutes prior to market closing). For all *WSJ* stories, we assume that stories printed in the morning's *WSJ* are available to traders before the market close on the same day. The two dependent variables are the firm's raw close-to-close return ($Return_{+1,+1}$) and the firm's abnormal return ($FFCAR_{+1,+1}$). We use the Fama-French three-factor model with a [-252,-31] trading day estimation period relative to the release of the news story as the benchmark for expected returns. The table shows only the coefficient for the key independent variable *neg*, which is the fraction of negative words in each news story standardized using the prior year's distribution. Each regression also includes control variables for the firm's most recent earnings announcement (*SUE*), market capitalization, book-to-market equity, share turnover, and close-to-close returns on the day of the news story, each of the previous two trading days, and the previous calendar year. To allow for correlations among firms' stock returns within the same trading day, we compute clustered standard errors (Froot (1989)).

		$Return_{+1,+1}$			$FFCAR_{+1,+1}$		
Stories Included		1980-1994	1995-2004	1980-2004	1980-1994	1995-2004	1980-2004
Both Sources	*neg*	-0.0232	-0.0216	-0.0221	-0.0266	-0.0243	-0.0253
		(3.15)	(2.40)	(3.72)	(4.07)	(3.10)	(4.88)
	Clusters	3753	2519	6272	3753	2519	6272
	Adj. R-sq.	0.0034	0.0014	0.0018	0.0043	0.0012	0.0019
Dow Jones News Service	*neg*	-0.0297	-0.0268	-0.0277	-0.0273	-0.0353	-0.0320
		(3.05)	(2.47)	(3.67)	(3.11)	(3.75)	(4.83)
	Clusters	3741	2519	6260	3741	2519	6260
	Adj. R-sq.	0.0033	0.0022	0.0024	0.0039	0.0021	0.0026
Wall Street Journal	*neg*	-0.0143	-0.0050	-0.0105	-0.0207	0.0028	-0.0102
		(1.38)	(0.36)	(1.24)	(2.32)	(0.23)	(1.37)
	Clusters	3710	2519	6229	3710	2519	6229
	Adj. R-sq.	0.0037	0.0010	0.0014	0.0054	0.0008	0.0014

Robust t-statistics in parentheses.

Table IV: Detailed Predictions of Returns Using Negative Words

This table reports the full set of coefficient estimates for the two full period *Dow Jones News Service* regressions from Table III. Each regression measures the dependence of firms' stock returns following firm-specific news on negative words in the news (*neg*) and control variables. The two dependent variables are the firm's next-day raw return ($Return_{+1,+1}$) and abnormal return ($FFCAR_{+1,+1}$) constructed using the methodology described in Table III. The key independent variable is *neg*, which is the fraction of negative words in each news story standardized using the prior year's distribution. The main purpose of this additional table is to show the coefficients on the control variables, which include the firm's most recent earnings announcement (*SUE*), market capitalization, book-to-market equity, share turnover, and close-to-close returns on the day of the news story, each of the previous two trading days, and the previous calendar year. To allow for correlations among firms' stock returns within the same trading day, we compute clustered standard errors (Froot (1989)).

	$Return_{+1,+1}$	$FFCAR_{+1,+1}$
Neg	-0.0277	-0.0320
	(3.67)	(4.83)
$FFCAR_{0,0}$	0.0285	0.0259
	(5.28)	(5.00)
$FFCAR_{-1,-1}$	-0.0272	-0.0254
	(3.63)	(3.86)
$FFCAR_{-2,-2}$	-0.0215	-0.0207
	(3.16)	(3.10)
$FFCAR_{-30,-3}$	-0.0005	0.0004
	(0.30)	(0.28)
$FFAlpha_{-252,-31}$	0.0559	0.1201
	(0.57)	(1.36)
Standardized Unexpected Earnings (SUE)	0.0160	0.0152
	(2.84)	(3.46)
Log(Market Equity)	-0.0152	-0.0120
	(2.02)	(2.19)
Log(Book-to-Market Equity)	-0.0027	-0.0246
	(0.18)	(2.12)
Log(Annual Turnover)	-0.0324	-0.0189
	(1.66)	(1.35)
Observations	141541	141541
Clusters	6260	6260
Adjusted R-squared	0.0024	0.0026

Robust t-statistics in parentheses.

Table V: Risk-Adjusted News-Based Trading Strategy Returns

This table shows the daily risk-adjusted returns from a news-based trading strategy for three different time periods (1980 to 1994, 1995 to 2004 and 1980 to 2004). The first three regressions use the Fama-French (1993) three-factor model to adjust the trading strategy returns for the impact of contemporaneous market, size and book-to-market factors. The last three regressions use the Carhart (1997) four-factor model to account for incremental impact of the momentum factor. Table V reports the alpha and loadings from the time series regression of the long-short news-based portfolio returns on each of the four factors. We compute all coefficient standard errors using the Huber-White (1980) heteroskedasticity-consistent covariance matrix. We assemble the portfolio for the trading strategy at the close of each trading day. We form two equal-weighted portfolios based on the content of each firm's *Dow Jones News Service* stories during the prior trading day. We label all news stories with a fraction of negative words in the previous year's top (bottom) quartile as negative (positive) stories. We include all firms with positive news stories in the long portfolio and all firms with negative news stories in the short portfolio. We hold both the long and short portfolios for one full trading day and rebalance at the end of the next trading day. We exclude the rare days in which there are no qualifying firms in either the long or the short portfolio.

	1980-1994	1995-2004	1980-2004	1980-1994	1995-2004	1980-2004
Alpha	0.0919	0.1175	0.1031	0.0952	0.1131	0.1013
	(2.83)	(3.93)	(4.55)	(2.81)	(3.78)	(4.38)
Market	-0.0994	-0.1087	-0.0983	-0.0831	-0.1001	-0.0999
	(0.93)	(1.99)	(1.86)	(0.75)	(1.87)	(1.87)
SMB	-0.0767	0.0475	-0.0081	-0.0647	0.0341	-0.0128
	(0.35)	(0.70)	(0.08)	(0.29)	(0.49)	(0.12)
HML	-0.1869	-0.2590	-0.2372	-0.1819	-0.2500	-0.2365
	(1.24)	(2.81)	(2.94)	(1.20)	(2.75)	(2.93)
UMD				-0.0911	0.0930	0.0444
				(0.74)	(2.01)	(0.90)
Trading Days	3398	2497	5895	3398	2497	5895
Adj. R-sq.	0.0003	0.0081	0.0026	0.0004	0.0106	0.0027

Robust t-statistics in parentheses.

Table VI: Sensitivity of News-Based Trading Returns to Trading Cost Assumptions

This table shows estimates of the impact of transaction costs on the news-based trading strategy's profitability (see the text or Table V for strategy details). We recalculate the trading strategy returns for 11 alternative assumptions about a trader's round-trip transaction costs: 0, 1, 2, 3 … or 10 basis points (bps) per round-trip trade. The annualized cumulative news-based strategy returns for each assumption appear below.

Trading Costs (bps)	Annualized Returns (%)
0	21.07
1	18.25
2	15.49
3	12.80
4	10.17
5	7.60
6	5.09
7	2.64
8	0.25
9	-2.09
10	-4.37

Table VII: Predicting Earnings Using Negative Words about Fundamentals

This table reports the results from two OLS regressions with different dependent variables (*SUE* and *SAFE*) regressed on negative words ($neg_{-30,-3}$), fundamental words ($Fund_{-30,-3}$), and the interaction between these words ($neg_{-30,-3}*Fund_{-30,-3}$). Both regressions include all news stories from both news sources (*Dow Jones News Service* and *The Wall Street Journal*) over the time period from 1984 through 2004. The measure of negative words ($neg_{-30,-3}$) is the standardized fraction of words that are negative in the news stories from 30 trading days prior up to three trading days prior to an earnings announcement. Fundamental words ($Fund_{-30,-3}$) is the fraction of words that are contained in news stories that mention the word stem "earn" from 30 trading days prior up to three trading days prior to an earnings announcement. All regressions include control variables for lagged firm earnings and numerous firm characteristics (see text for details). To allow for correlations among announced firm earnings within the same calendar quarter, we compute clustered standard errors (Froot (1989)).

	SUE	*SAFE*
$neg_{-30,-3}$	-0.0291	-0.0070
	(1.75)	(1.70)
$neg_{-30,-3}*Fund_{-30,-3}$	-0.3109	-0.0766
	(5.83)	(6.15)
$Fund_{-30,-3}$	-0.4710	-0.0866
	(5.85)	(5.04)
Lag(Dependent Variable)	0.2190	0.2515
	(11.18)	(10.55)
Analyst Forecast Dispersion	-0.9696	-0.2765
	(8.28)	(6.05)
Analyst Forecast Revisions	21.5752	0.5594
	(7.80)	(1.04)
Log(Market Capitalization)	-0.0154	0.0224
	(0.68)	(3.99)
Log(Book-to-Market Equity)	0.0122	-0.0059
	(0.40)	(0.83)
Log(Share Turnover)	-0.1211	0.0332
	(2.61)	(3.52)
$FFAlpha_{-252,-31}$	1.9376	0.1532
	(7.26)	(3.10)
$FFCAR_{-30,-3}$	0.0098	0.0058
	(5.52)	(13.18)
$FFCAR_{-2,-2}$	0.0156	0.0069
	(2.25)	(3.31)
Observations	31687	29786
Clusters	80	79
Adjusted R-squared	0.1303	0.1257

Robust t-statistics in parentheses.

Table VIII: Firms' Returns and Negative Words about Fundamentals

This table shows the relationship between negative words in firm-specific news stories (*neg*) and firms' close-to-close abnormal stock returns on the same day ($FFCAR_{+0,+0}$) and the following day ($FFCAR_{+1,+1}$). The stories include all *Dow Jones News Service* articles from 1980 through 2004, but exclude stories that occur after 3:30pm (30 minutes prior to market closing). The coefficients and summary statistics from six (2*3) OLS regressions appear below: two different dependent variables ($FFCAR_{+0,+0}$ and $FFCAR_{+1,+1}$) and three different time spans (far, near and both), categorized according to whether the news story is published within one trading day of an earnings announcement. The key independent variable is negative words (*neg*), which is the fraction of negative words in each news story standardized using the prior year's distribution. The independent variable *Fund* is a dummy indicating whether a story mentions the word stem "earn"; and *neg*Fund* is the interaction between negative words (*neg*) and this dummy. All regressions include numerous control variables for lagged firm returns and other firm characteristics (see text for details). To allow for correlations among firms returns within the same trading day, we compute clustered standard errors (Froot (1989)).

	$FFCAR_{+0,+0}$			$FFCAR_{+1,+1}$		
Stories' Proximity to Earnings Announcement	Far	Near	Both	Far	Near	Both
Neg	-0.0821	-0.1445	-0.0857	-0.0162	-0.0078	-0.0161
	(10.55)	(3.50)	(11.16)	(2.36)	(0.19)	(2.35)
*neg*Fund*	-0.3264	-0.1822	-0.3127	-0.0900	-0.0959	-0.1036
	(8.70)	(2.96)	(10.75)	(3.59)	(1.71)	(4.52)
Fund	-0.4316	-0.1708	-0.3250	-0.0772	-0.0452	-0.0342
	(12.96)	(3.19)	(12.84)	(3.63)	(0.99)	(1.96)
$FFCAR_{+0,+0}$				0.0219	0.0339	0.0255
				(3.56)	(3.99)	(4.91)
$FFCAR_{-1,-1}$	0.0360	-0.0842	0.0181	-0.0227	-0.0430	-0.0256
	(4.00)	(5.32)	(2.23)	(3.16)	(3.01)	(3.89)
$FFCAR_{-2,-2}$	-0.0112	-0.0945	-0.0220	-0.0156	-0.0532	-0.0209
	(1.26)	(5.67)	(2.72)	(2.14)	(3.20)	(3.13)
$FFCAR_{-30,-3}$	0.0029	-0.0045	0.0020	0.0013	-0.0056	0.0004
	(1.51)	(1.14)	(1.17)	(0.80)	(1.35)	(0.23)
$FFAlpha_{-252,-31}$	-0.0285	-0.7700	-0.1425	0.1172	0.1042	0.1136
	(0.26)	(2.74)	(1.36)	(1.34)	(0.37)	(1.29)
SUE	0.0053	0.1218	0.0234	0.0074	0.0527	0.0146
	(0.91)	(7.39)	(4.16)	(1.66)	(3.79)	(3.33)
Observations	118276	23357	141633	118186	23355	141541
Clusters	6258	4082	6260	6258	4082	6260
Adjusted R-squared	0.0058	0.0112	0.0045	0.0021	0.0064	0.0028

Robust t-statistics in parentheses.

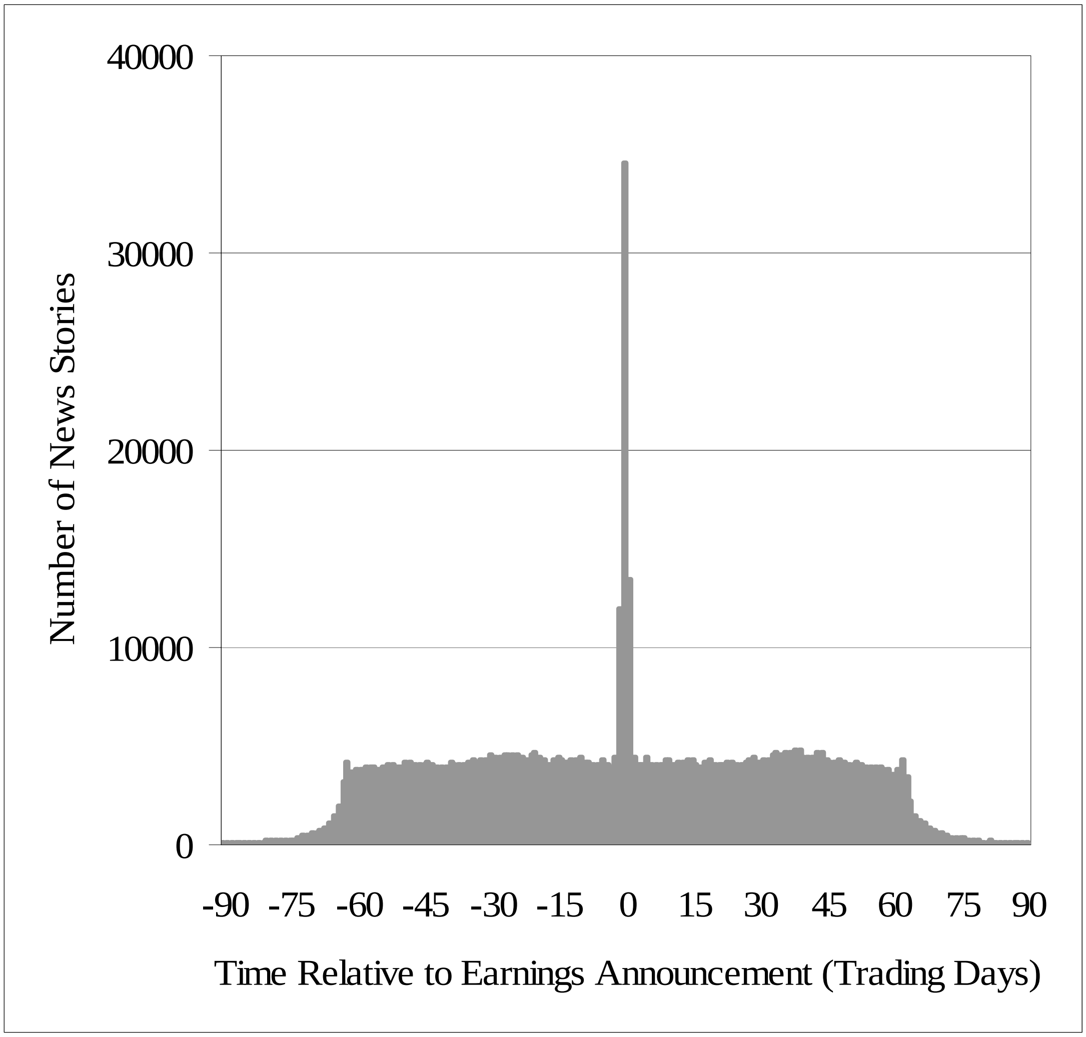

Figure 1. Media Coverage around Earnings Announcements. This figure depicts the relationship between the number of firm-specific news stories and the number of days away from a firm's earnings announcement. All stories included in the figure are about S&P 500 firms, appear in either *Dow Jones News Service* or *The Wall Street Journal* from 1980 through 2004, and meet basic minimum word requirements (see text for details). For each news story, we calculate the number of days until the firm's next earnings announcement and the number of days that have passed since the firm's last earnings announcement. We plot a histogram of both variables back-to-back in Figure 1. Thus, each story is counted twice in Figure 1, once before and once after the nearest announcement, except the stories occurring on the earnings announcement day.

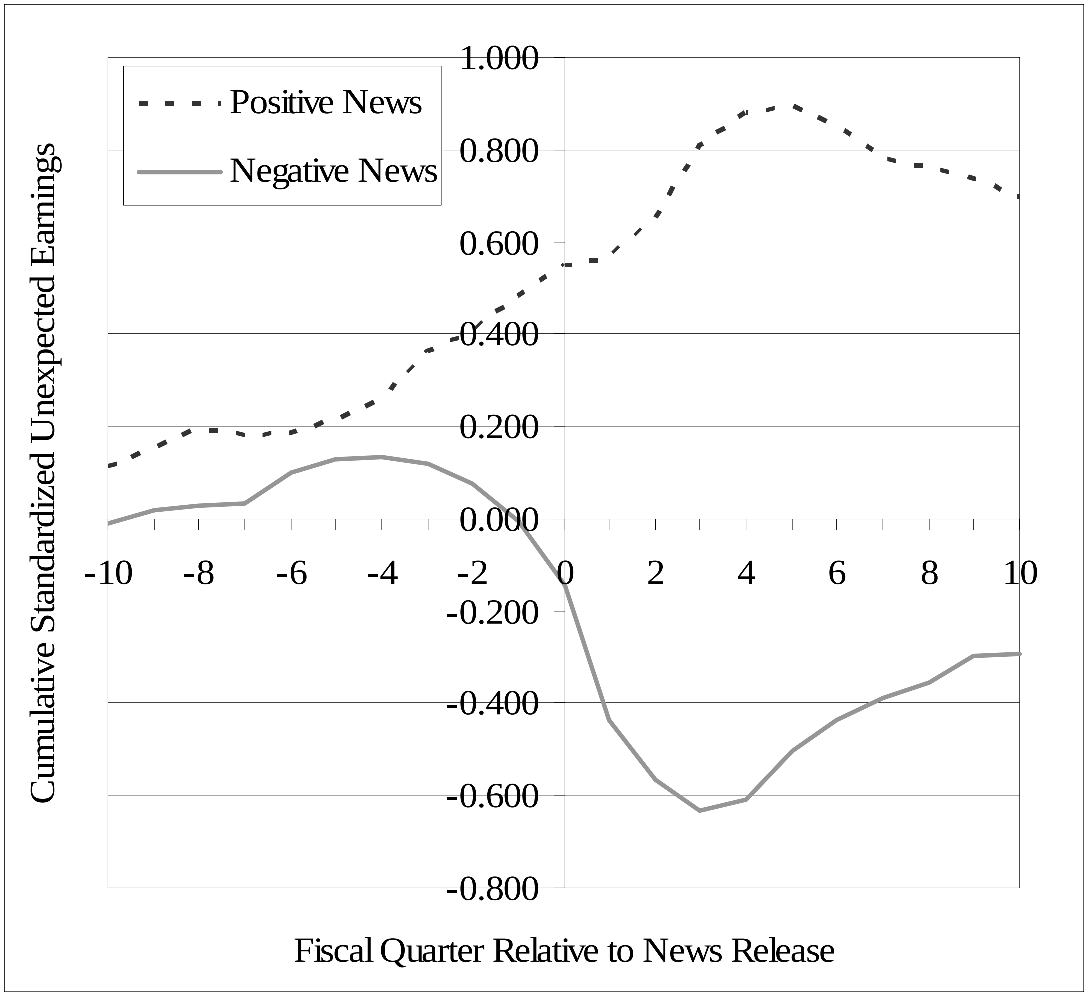

Figure 2. Firms' Fundamentals around Positive and Negative News Stories. In this figure, we graph firms' cumulative standardized unexpected earnings (*SUE*) from 10 fiscal quarters preceding media coverage of an earnings announcement to 10 quarters after the media coverage. We define media coverage of the announcement as positive (negative) when it contains a fraction of negative words ($Neg_{-30,-3}$) in the previous year's top (bottom) quartile. The measure of negative words ($Neg_{-30,-3}$) is the fraction of words that are negative in the news stories from 30 trading days prior up to three trading days prior to an earnings announcement. We separately analyze the firms with positive and negative media coverage prior to their earnings announcements. We compute the cumulative *SUE* for both sets of firms, beginning 10 quarters prior to the news and ending 10 quarters after the news.

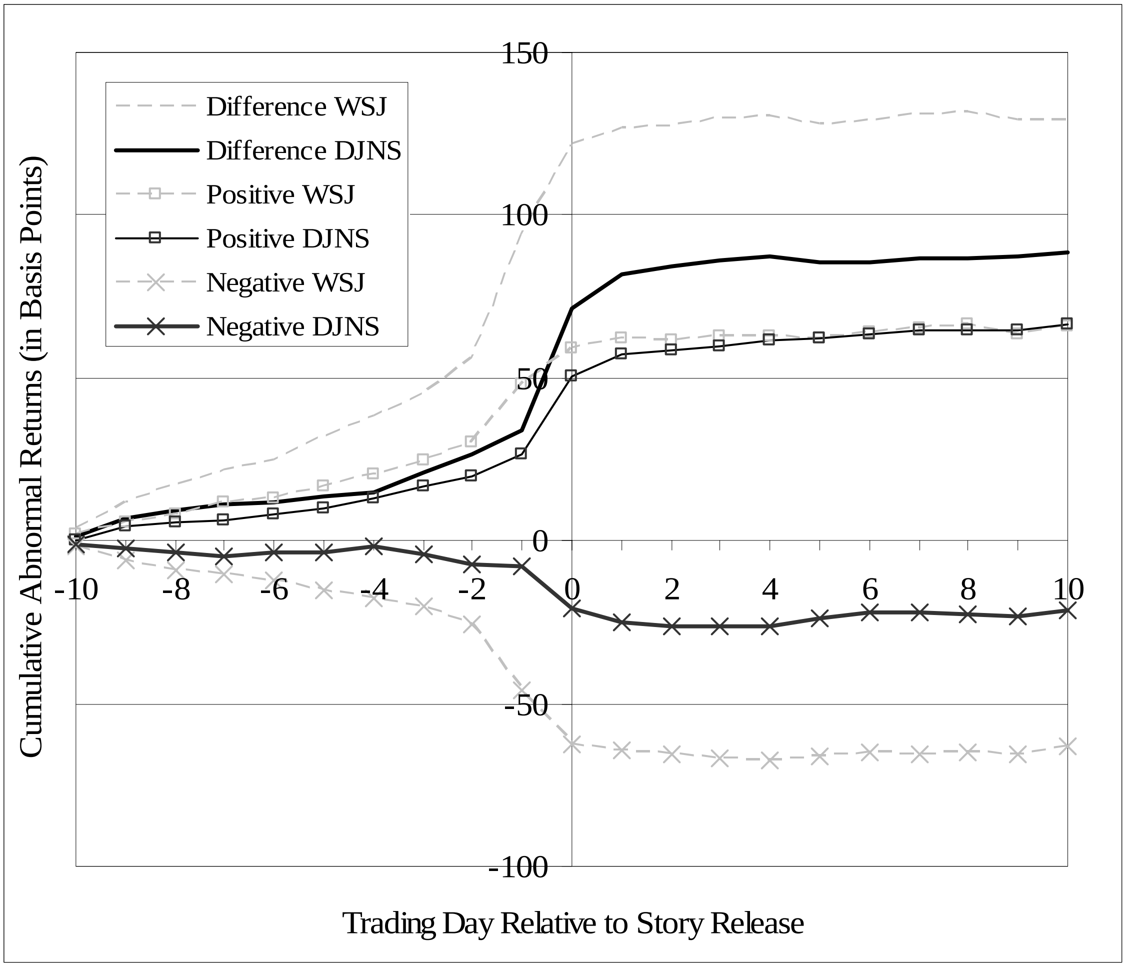

Figure 3. Firms' Valuations around Positive and Negative News Stories. In this figure, we graph a firm's abnormal event returns from 10 trading days preceding a news story's release to 10 trading days following its release. All news stories focus on S&P 500 firms and come from either *Dow Jones News Service* or *The Wall Street Journal* between 1980 and 2004 inclusive. For all *DJNS* stories, we exclude stories that occur after 3:30pm (30 minutes prior to market closing). For all *WSJ* stories, we assume that stories printed in the morning's *WSJ* are available to traders well before the market close on the same day. We use the Fama-French three-factor model with a [-252,-31] trading day estimation period relative to the release of the news story as the benchmark for expected returns. We label all news stories with a fraction of negative words (*Neg*) in the previous year's top (bottom) quartile as negative (positive) stories. We separately examine the market's response to positive and negative *DJNS* and *WSJ* stories. We also compute the difference between the reaction to positive and negative news stories for each source.

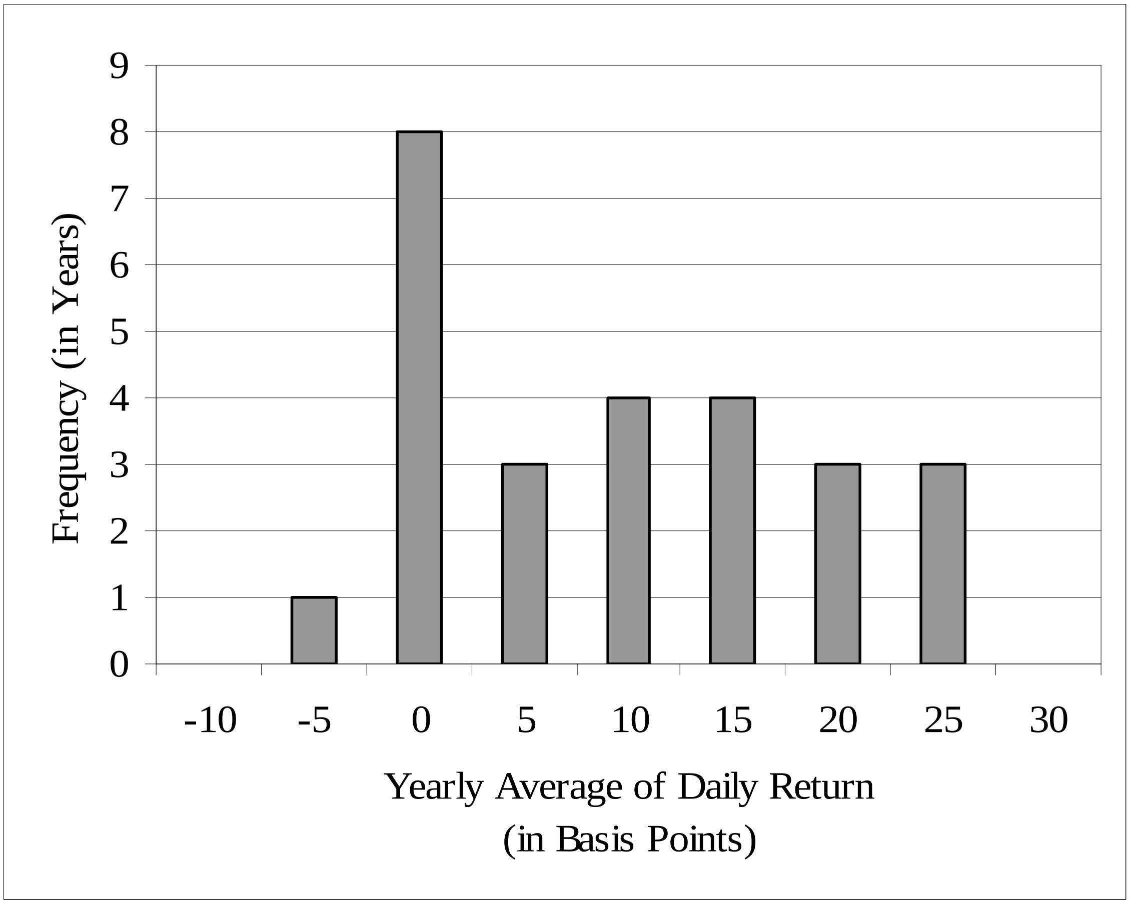

Figure 4. Distribution of Yearly Returns for the News-Based Trading Strategy. This figure shows the frequency of yearly raw returns from the daily news-based trading strategy described below. Each frequency bin encompasses a 5% range of returns around the bin's midpoint—*e.g.*, the frequency of the 15% return bin (four) is the number of years in which the trading strategy returns are between 12.5% and +17.5%. We assemble the portfolio for the news-based trading strategy at the close of each trading day. We form two equal-weighted portfolios based on the content of each firm's *Dow Jones News Service* stories during the prior trading day. We label all news stories with a fraction of negative words in the previous year's top (bottom) quartile as negative (positive) stories. We include all firms with positive news stories in the long portfolio and all firms with negative news stories in the short portfolio. We hold both the long and short portfolios for one full trading day and rebalance at the end of the next trading day. We exclude the rare days in which either the long or the short portfolio contains no qualifying firms.