No news is good news: A time-varying story of how firm-specific textual sentiment drives firm-level performance

Research paper
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Khurshid Ahmad, Colm Kearney, and Sha Liu

Abstract

Using panel estimates, vector autoregressive models and rolling regressions, we show how firm-specific textual sentiment extracted from news stories is related to trading volumes and stock returns in 20 large US corporations. Negative firm-specific textual sentiment predicts future firm-level returns; the latter predict future firm-specific textual sentiment; and trading volumes act as an important transmission mechanism linking firm-specific sentiment to firm-level returns. Intuitively, we show how negative firm-specific textual sentiment affects firm-level performance in a time-varying manner. It follows that firm-specific textual sentiment is a potential time-varying factor in equity pricing models.

Key words:
Textual sentiment analysis, news, trading volumes and returns, market efficiency

Contact details

Khurshid Ahmad, School of Computer Science and Statistics, Trinity College Dublin, College Green, Dublin 2, Ireland. Email: kahmad@cs.tcd.ie

Colm Kearney, Faculty of Business and Economics, Monash University, Sir John Monash Drive, Melbourne, Australia. Tel: +61 3 99051021, Email: colmpkearney@gmail.com

Sha Liu, Business School, Trinity College Dublin, College Green, Dublin 2, Ireland. Email: lius2@tcd.ie.

1 Introduction

The effects of sentiment on equity returns have been examined by many researchers over the past three decades. Broadly speaking, two types of sentiment have been studied. The first is investor sentiment – beliefs about future cash flows and investment risks that are not justified by the facts at hand (Baker and Wurgler (2007)). The second is textual sentiment, which refers to the degree of positivity or negativity in texts such as corporate disclosures, financial news articles or internet postings. In the fast-growing textual sentiment literature, a number of studies have extracted sentiment from news articles or commentaries. Tetlock (2007) and Garcia (2012) generate sentiment series from general business, economic, and financial news stories and assess its effect from a market-wide and time-series perspective. Tetlock et al. (2008), Engelberg (2008) and Ferguson et al. (2012) have studied the cross-sectional effects of firm-specific sentiment (from firm-specific news stories) on firm fundamentals and performance measures. The time-series patterns of the role of firm-specific sentiment on individual firms and their returns have not been previously examined. This raises interesting questions: What are the overall time-series effects of firm-specific sentiment on individual stocks? Is the role of firm-specific sentiment similar to that of market-level sentiment?

In this paper, we examine the interrelations among firm-specific textual sentiment, firm-level equity returns and trading volumes for 20 large non-financial firms from the *Fortune 500* list over the 10-year period from January 2001 to December 2010. The consecutive firm-specific sentiment is extracted from firm-specific news stories and media articles. We first employ panel data regressions to test six hypotheses regarding the relation between firm-specific sentiment, firm-level equity returns and trading volumes. We then employ vector autoregression (VAR) models to test the hypotheses on individual firms separately. Finally, we use 1-year rolling-window regressions to examine the time-varying effects of firm-specific sentiment on firm-level equity returns, and we further explore the indirect effects of sentiment on returns that operate through trading volumes.

Our research contains some novel features. *First*, by generating daily, firm-specific, textual sentiment, we show how it relates to firm-level trading volumes and equity returns. This fills a gap in the literature as nobody has hitherto examined the time-series patterns of how sentiment impacts on individual firms and their returns. *Second*, we study the relation between firm-specific textual sentiment, trading volumes and firm-level returns in a manner consistent with the mixture of distributions hypothesis (Clark (1973)) that allows us to shed light on the extent to which firm-specific sentiment acts as a previously unconsidered source of information that drives firm-level returns by first working through trading volumes. *Third*, we extend previous research by showing that firm-specific textual sentiment has time-varying effects on firm-level trading volumes and returns that have not been previously examined.

Amongst the main findings of this paper are that negative firm-specific sentiment predicts future firm-level returns; better firm-level returns predict less subsequent negative firm-specific sentiment; and greater trading volumes are associated with greater subsequent negative sentiment. Moreover, there is strong evidence of indirect effects of sentiment on equity returns: sentiment causes trading volumes which in turn drive returns. Meanwhile, firm-specific sentiment has time-varying effects on firm-level returns that tend to be concentrated during discrete periods that most likely align with significant news-worthy episodes for each firm. Overall, our analysis constitutes strong evidence for the consideration of firm-specific textual sentiment as a potentially important time-varying factor in equity pricing models.

The remainder of our paper is structured as follows. Section 2 provides a review of the most relevant literature. Section 3 describes the process of creating corpora and generating firm-specific sentiment, and contains the descriptions of the textual sentiment and equity data. Section 4 outlines the hypotheses regarding the interrelations between our measures of firm-specific sentiment, trading volumes and firm-level returns. Section 5 tests the hypotheses by treating the dataset as a panel. Three groups of regressions are studied. The first group examines whether sentiment and trading volumes cause equity returns, the second examines whether returns and trading volumes cause sentiment, and the third examines whether returns and sentiment cause trading volumes. Section 6 examines each of the 20 individual firms, testing the hypotheses both over the full sample period and over rolling-window samples. Section 7 summarizes our main findings and draws together our conclusions.

2 Research on textual sentiment analysis

The qualitative information that has been analyzed by researchers comes mainly from three sources: public corporate disclosures/filings (Li (2006), Feldman et al (2008), Henry(2008), Henry and Leone (2009), Li (2010), Davis et al. (2011), Davis and Tama-Sweet (2011), Demers and Vega (2011), Doran et al. (2010), Huang et al. (2011), Loughran and McDonald (2011a, 2011b), Davis et al. (2012), Ferris et al. (2012), Jegadeesh and Wu (2012), Price et al. (2012), and Loughran and McDonald (2013)); news stories and analysts' reports (Tetlock (2007), Engelberg(2008), Tetlock et al. (2008), Sinha (2010), Carretta et al. (2011), Engelberg et al. (2012), Ferguson et al. (2012), Garcia (2012), Rees and Twedt (2012), and Huang et al. (2013)); and internet postings (Antweiler and Frank (2004), Das and Chen (2007) and Chen et al. (2013)). The sentiment embodied in these texts conveys market participants' information or views about financial markets, and it also reflects how investor sentiment responds to developments in financial markets.

The most closely related papers to ours are the studies that use news stories as the information source and employ the dictionary-based approach in content analysis (see, *inter alia*, Tetlock (2007), Tetlock et al. (2008), and Ferguson et al. (2012)). Tetlock (2007) collect daily news stories from the *Wall Street Journal* 'Abreast of the Market' column over the 16-year period 1984-1999. The pessimism factor is identified by implementing principal component analysis on the 77 *General Inquirer* (GI) categories in the Harvard IV-4 psychosocial dictionary. Tetlock performs VAR analysis that incorporates the pessimism factor and other two media factors, *DJIA* index returns, *NYSE* volumes and the SMB factor. He shows that negative sentiment or a large increase in negative sentiment causes immediate downward pressure on market prices, and pessimism measures significantly predict negative returns to the SMB factor over the following week. Tetlock et al. (2008) collect all *Wall Street Journal* and *Dow Jones News Service* stories about individual *S&P 500* firms from 1980 to 2004. They use negative words in the news stories from 30 to 3 trading days prior to an earnings announcement to predict earnings, and use firms' negative sentiment in a day to predict stock returns on the following day. They show that the fraction of negative words in firm-specific news stories forecasts low subsequent earnings, firms' stock prices briefly underreact to the information embedded in negative words, and negative words in the stories that focus on fundamentals have the largest predictability on earnings and returns. Ferguson et al. (2012) is the first study that generates firm-specific textual sentiment for non-US stocks. Their sample consists of 264,647 firm-specific UK news media articles between 1981 and 2010 from *The Financial Times*, *The Times*, *The Guardian and Mirror*, covering FTSE 100 firms. They have performed similar analysis as in Tetlock (2007) and Tetlock et al. (2008).

Loughran and McDonald (2011a) is another closely-related and important study, although their information source is 50,115 firm-year 10-Ks between 1994 and 2008. Their most important contribution is that they discover that almost three quarters of the word counts in the Harvard negative word list are attributable to words that are typically not negative in a financial context, so they create a list of 2,337 words that typically have negative implications in a financial sense[1]. They suggest the use of their financial word lists to avoid those words in the Harvard list that might proxy for industry or other unintended effects.

3 Data and methodology

The first step in sentiment extraction is to select the sample of firms. The firms being considered are large multinational corporations (MNCs), which are more likely to have a stable news flow at daily frequency for an intended 10-year research period between 01/01/2001 and 31/12/2010. The most common database of large MNCs used in international business and financial research is the *Fortune 500* list. We select 20 firms from the top 50 non-financial public firms on the 2011 *Fortune 500* list[2]. We omit financial firms because of their differing fundamentals compared with non-financial firms, and because their news stories may contain much information regarding transactions with their client companies, making it more difficult to separate the firm-specific sentiment. There are a total of 17 companies meeting the criteria (i.e. stable daily news flow[3], non-financial firm, top 50 Fortune 500 firm): Apple, AT&T, Boeing, Cisco Systems, Dell, Ford Motor, General Electric, Hewlett Packard, Home Depot, IBM, Intel, Johnson & Johnson, Merck, Microsoft, Pfizer, Verizon Communications, and Wal-mart Stores. Another 3 companies have sufficient news stories only in the latest five or six years. They are ConocoPhillips and Chevron (ranges from 01/01/2006 to 31/12/2010), and Exxon Mobil (ranges from 01/01/2005 to 31/12/2010). These 3 firms are also incorporated in the sample. The final sample consists of 20 large MNCs.

The next step is to search for relevant news articles during the pre-specified time range to form a text corpus from which to extract the firm-specific sentiment. The electronic news database used is '*LexisNexis News and Business*', a popular news database. We search for articles that contain the firm name in the headline, and at least 5 mentions of the firm name in the body. By choosing the option 'Strong references only', the retrieved articles are ensured to be highly relevant to the firm[4]. The source we choose is 'All English Language News', which includes articles from newspapers, newswires and press releases, magazines, journals and web-based publications. The purpose is to retrieve as many qualified articles as possible to ensure there is at least one article each day, and preferably multiple articles to get unbiased sentiment scores. Choosing all available English-language articles also lowers the possibility of getting biased sentiment from a small number of pre-specified sources. Unlike Tetlock (2007) and Garcia (2012) who use only one or two news commentary columns from the *Wall Street Journal* or the *New York Times* as the information source, our texts have the advantage of being more objective because they are based on a much wider set of news articles. We omit articles with high similarity to stories that have been previously published. The downloaded files are individual text files containing up to 500 articles.

A custom 'splitter' program is then used to split the text files into individual articles. This program also extracts date and time information for each article. We move all articles on weekends to Friday, and when there are multiple stories in one day, they are considered to be one story per day. Articles on holidays are omitted because few market participants pay attention to the very few, if any, firm-specific news stories that appear on holidays. In addition, our examinations confirm that barely any articles are collected on holidays. Table 1 reports the average number of articles and words collected per day for each firm in our sample. Because the 20 firms are large and well known, they each have at least 10 news articles per day – with Microsoft and Boeing each having more than 40 articles every day.

We use *Rockesteady*, a content analysis program developed by *Treocht Ltd*[5], to calculate the daily sentiment scores by counting the frequency of words in the Loughran and McDonald's (2011) 'Finance Negatve' (*FN*) category relative to the total words in a day. By setting the sentiment score to be zero on days where there is no article, the final *FN* series are obtained. Table 2 summarizes the descriptive statistics of the *FN* series, including mean, variance, skewness, excess kurtosis, the Jarque-Bera (J-B) test of normality, the Ljung-Box Q test for autocorrelation, and the Dickey-Fuller unit-root test. The skewness and excess kurtosis of a normal distribution are expected to be zero. The J-B column denotes the p-value of tests against the null hypothesis that the *FN* data is normally distributed. Clearly, none of the *FN* series is normally distributed. The Q10 column displays the p-value of tests for autocorrelation up to the 10th lag. All results indicate that the *FN* series are serially correlated. Dickey-Fuller unit-root tests were also calculated to test that whether each of the *FN* series is stationary. With the absolute values of all t-statistics greater than 25, the existence of a unit root is easily rejected for each series.

We collected the daily closing prices and trading volumes of each of our 20 sample stocks from *Datastream*. The data range is from 2001-2010, with exceptions for Exxon Mobil from 2005-2010 and for Chevron and ConocoPhillips from 2006-2010. The closing prices are adjusted for dividends and splits, and the trading volumes have also been adjusted for capital events and divided by 1,000. Log returns are computed. Table 3 provides descriptive statistics of the daily firm-level stock returns and trading volumes, including skewness, excess kurtosis, the Jarque-Bera (J-B) test of normality, the Ljung-Box Q test for autocorrelation and the Dickey-Fuller unit-root test. The J-B column denotes the p-value of tests against the null hypothesis that the data is normally distributed. Results reveal that none of the return or volume data is normally distributed. The Q10 column displays the p-value of tests for autocorrelation up to the 10th lag. Results indicate that all the volume series are serially correlated. All return series except Merck is serially correlated at the 10 percent significance level. The Dickey-Fuller unit-root tests for each return and volume series, with the critical value of the 1 percent significance level at -3.438, show that a unit root is easily rejected for each series.

Table 4 shows the market cap[6], annual revenue[7], average annual return, average daily trading volume, and average daily *FN* scores for each firm. The firms are sorted by the average *FN* scores from high to low. This provides an approximate examination of the relationship between negative sentiment and returns. Pfizer has the lowest average annual return, and its associated average *FN* score is the highest, indicating that it had the most negative words in its firm-specific news corpus throughout the 10-year period. Wal-mart and Merck also have relatively low annual returns with associated *FN* scores that are among the highest.

4 Main hypotheses

It is accepted within the textual finance literature that market-level sentiment (in particular negative words) is associated with market-level trading volumes and returns. It is interesting to examine the extent to which these relationships also hold for firm-specific news sentiment, firm-level returns and firm-level trading volumes. In addition, it is interesting to examine whether firm-specific textual sentiment acts as a potential source of information that drives firm-level returns by first working through trading volumes. We therefore examine the following six hypotheses:

$\mathrm{H}_1(Null)$: Firm-specific sentiment does not cause firm-level equity returns.
$\mathrm{H}_1(Alternative)$: Firm-specific sentiment does cause firm-level equity returns.

$\mathrm{H}_2(Null)$: Firm-level equity returns do not cause firm-specific sentiment.
$\mathrm{H}_2(Alternative)$: Firm-level equity returns cause firm-specific sentiment.

$\mathrm{H}_3(Null)$: Firm-specific sentiment does not cause trading volumes.
$\mathrm{H}_3(Alternative)$: Firm-specific sentiment causes trading volumes.

$\mathrm{H}_4(Null)$: Firm-level trading volumes do not cause firm-specific sentiment.
$\mathrm{H}_4(Alternative)$: Firm-level trading volumes cause firm-specific sentiment.

$\mathrm{H}_5(Null)$: Firm-level trading volumes do not cause firm-level equity returns.
$\mathrm{H}_5(Alternative)$: Firm-level trading volumes cause firm-level equity returns.

$\mathrm{H}_6(Null)$: Firm-level equity returns do not cause trading volumes.
$\mathrm{H}_6(Alternative)$: Firm-level equity returns causes trading volumes.

Tetlock (2007) has tested, at the market level, whether negative sentiment causes equity returns, whether equity returns cause negative sentiment, and whether negative sentiment causes trading volumes (corresponding to H_1, H_2, and H_3). Some other researches (e.g. Antweiler and Frank (2004), Das and Chen (2007), Tetlock et al. (2008), Garcia (2012), Ferguson et al. (2012), Chen et al. (2013)) have also examined versions of these three hypotheses. The corporation-expressed sentiment[8] literature (e.g. Engelberg (2008), Doran et al. (2010), Davis et al. (2011), Demers and Vega (2011), Jegadeesh and Wu (2012), Price et al. (2012)) has tested hypotheses similar to H_1 by investigating whether the tone of corporate disclosures or changes in the tone from the recent past are significantly correlated with short window contemporaneous returns around the date that the disclosures are made, or drift excess returns[9]. We examine H_4, H_5, and H_6 in addition to H_1, H_2, and H_3, and we consider a potential mechanism: sentiment indirectly causes returns by working through trading volumes.

5 Empirical Testing on Panel Data

One of the challenging issues in firm-specific sentiment analysis is that it can be difficult to collect sufficient numbers of news stories for a large number of firms. Although computer programs can scan very expansive news sources, time-series analysis at the daily frequency remains difficult if there are many missing sentiment data points for individual firms due to lack of news stories every day. In order to minimize the numbers of missing values for firm-level sentiment in this research, our sample focuses on large MNCs that usually attract large volumes of news. Combining our firm-level data for large MNCs with panel estimations provides a useful approach to exploring the relationship between textual sentiment and firm-level returns.

To facilitate the construction of a strongly balanced panel, only firms with 10 years of news data are incorporated in the dataset, resulting in a total of 17 firms and 2,515 observations per firm. This is the largest balanced panel that can be obtained from the whole dataset, yielding 42,704 observations. Besides returns and sentiment, several new variables are employed in the panel estimations. Firstly, volume is measured by turnover. Lo and Wang (2000) define turnover of stock *j* at time *t* as:

$$Turnover_{jt} = \frac{X_{jt}}{N_j} \tag{1}$$

where X_{jt} is the share volume of firm *j* that is traded at time *t*, and N_j is the total number of shares outstanding of firm *j*.

Three fundamental variables for each firm are also incorporated: the standardized unexpected earnings (SUE), the book-to-market ratio (B/M) and the market value (MV). Following Tetlock et al (2008), the SUE is transformed from each firm's quarterly earnings as follows:

$$SUE_t = \frac{UE_t - \mu_{UE_t}}{\sigma_{UE_t}} \tag{2}$$

$$UE_t = E_t - E_{t-4} \tag{3}$$

where E_t is the firm's earnings in quarter t, and μ_{UE_t} and σ_{UE_t} are the mean and standard deviation of the firm's previous 20 quarters of unexpected earnings data, respectively.

In order to ensure that the series are stationary, B/M and MV[10], which are daily variables, are detrended[11]. Three panel unit-root tests, the Levin-Lin-Chu (2002) (LLC) test, the Breitung (2000) test, and the Harris-Tsavalis (1999) (HT) test, are performed on *FN*, Turnover, SUE, B/M and MV. Each test has its own advantages and disadvantages to consider and there is no dominant performance of one particular test. In our panel dataset, *N* is moderate (*N*=17), *T* is large (*T*=2,515), and $N/T \to 0$. Under these conditions, the LLC test and the Breitung test work best. Table 5 reports the statistics and their significance levels (1 percent ***). The null hypotheses that the panels contain unit roots are rejected in all cases except one, the LLC test for SUE. Based on the overall results, we consider that all variables are appropriate for modelling.

Three groups of models are tested in order to examine the relations between firm-specific sentiment, firm-level returns and trading volumes.

Do sentiment and volumes cause returns?

We begin by conducting pooled ordinary least squares (OLS) regressions using standard errors clustered by calendar quarter. This model is written as:

$$R_{i,t} = \beta_{10} + \sum_{k=1}^{2} \beta_{1k} R_{i,t-\mathrm{k}} \,(\text{or } AR_{i,t-\mathrm{k}}) + \beta_{13} S_i + \beta_{14} V_{i,t-1} + \beta_{15}\, SUE_{i,t} + \beta_{16} (B/M)_{i,t}$$
$$+\beta_{17}\, MV_{i,t} + \beta_{18} \cdot Exog_{t-1} + \varepsilon_{i,t} \tag{4}$$

where i = 1, 2, …, 17, β_{10} is the constant, R_i is the firm-level stock returns, S_i is the sentiment measure, AR_i is the abnormal returns, and V_i is the firm-level trading volumes. Firm characteristic variables SUE[12], $\mathrm{B/M}$ and MV (described previously) are employed as control variables. $Exog$ includes three exogenous variables: volatility measure proxied by CBOE's volatility index (VIX)[13] and dummy variables for the Monday and January effects.

Using the first lag of *FN* as the sentiment measure, the results show that *FN* negatively and significantly predicts returns on the following day at the 5 percent significance level in both the first and second regressions (Table 6 column (1) and (2)). The second regression replaces the lags of returns in column (1) by the lags of abnormal returns, which is the return adjusted for the three Fama-French (1993) factors. The impact of a 10 percent increase in the percentage of negative words on the next day's stock return is approximately -0.31 or -0.36 basis points. Volumes only marginally significantly predict returns on the following day in regression (2), and higher volumes are associated with higher returns on the following day.

We perform the following robustness tests. In our first robustness check, another panel estimation method, the random effects model[14], is employed for the same regressions. The random effects model is the same as equation (4) except that the innovations contain a random unobservable individual-specific effect besides the conventional white noise error terms. In regression (3), *FN* still negatively and significantly predicts returns on the following day at the 5 percent level (Table 6 column (3)). Yet in regression (4), where the lags of abnormal returns are used instead of the raw returns, sentiment's predictability becomes marginally significant. The magnitude of effects is the same as the pooled OLS regressions (Table 6 column (4)). Volumes' effects on next day's returns become strongly significant, at the 5 percent level in regression (3) and 1 percent level in regression (4).

In our second robustness check, we use the change in *FN* (first difference) as the sentiment measure, and we repeat regressions (1) to (4). In all regressions, the differential of today's and yesterday's *FN* score has a significantly negative impact on today's return at approximately 0.65 to 0.66 basis points, at the 1 percent level of significance. Higher volumes predict higher returns on the following day, at least at the 10 percent level. Table 7 reports the results.

Our third robustness analysis is completed by winsorizing *FN*, returns/abnormal returns, and trading volumes at the 1 percent level to avoid the impact of outliers, and re-do regressions (1) to (4). The estimated coefficients and t-statistics (not reported) of *FN(-1),* no matter whether the pooled OLS or random effects model are used, are qualitatively the same as in Table 6.

Do returns and volumes cause sentiment?

To examine the effects of firm-level returns and trading volumes on firm-specific sentiment, the following model is tested:

$$S_{i,t} = \beta_{20} + \sum_{k=1}^{2} \beta_{2k} S_{i,t-\mathrm{k}} + \beta_{23} R_{i,t-1} + \beta_{24} V_{i,t-1} + \beta_{25}\, SUE_{i,t} + \beta_{26} (B/M)_{i,t}$$
$$+ \beta_{27}\, MV_{i,t} + \beta_{28} \cdot Exog_{t-1} + \varepsilon_{i,t} \qquad (5)$$

where all variables are defined in the same way as in equation (4) Similarly, this model is first estimated using pooled OLS with standard errors clustered by calendar quarter, followed by estimation using the fixed effects model[15] with Huber–White robust standard errors as a robustness check. The fixed effects model is the same as equation (5) except that the innovations contain a fixed unobservable individual-specific effect besides the conventional white noise error terms. The results show that higher returns predict less negative words on the following day at the 1 percent level of significance, after controlling for past sentiment, firm characteristics and exogenous variables (Table 8). A 1.0 percent increase in returns leads to a 0.6 percent decrease in negative sentiment the following day. Trading volumes do not show any significant impact on next day's sentiment. We also winsorize *FN*, returns/abnormal returns, and trading volumes at the 1 percent level, and re-do the two regressions. The results (not reported) are qualitatively similar.

Do sentiment and returns cause volumes?

To examine the effects of firm-specific sentiment and firm-level returns on trading volumes, the following model is tested:

$$V_{i,t} = \beta_{30} + \sum_{k=1}^{2} \beta_{3k} V_{i,t-\mathrm{k}} + \beta_{33} R_{i,t-1} + \beta_{34} S_{i,t-1} + \beta_{35}\, SUE_{i,t} + \beta_{36} (B/M)_{i,t}$$
$$+ \beta_{37}\, MV_{i,t} + \beta_{38} \cdot Exog_{t-1} + \varepsilon_{i,t} \qquad (6)$$

As before, we first estimate this model using pooled OLS with standard errors clustered by calendar quarter. We then estimate it using the fixed effects model[16] with Huber–White robust standard errors as a first robustness check. The results show that higher returns predict lower trading volumes the following day at the 1 percent level of significance, whatever estimation method is used (Table 9). In the pooled OLS regression, negative sentiment is negatively associated with next day's trading volumes at the 1 percent significance level. In the fixed effects estimation, however, the impacts of negative sentiment become marginally significant. Our second robustness check is completed by winsorizing *FN*, returns/abnormal returns, and trading volumes at the 1 percent level, and re-doing the two regressions (results not reported). This time, in the fixed effects estimation, the negative sentiment significantly affects trading volumes at the 5 percent significance level and the other results remain qualitatively similar.

Overall, using the panel data we find strong evidence of interaction between sentiment, returns and trading volumes using our novel dataset of firm-specific textual sentiment related to individual firms. We reject the null hypotheses of H_1 to H_6 except H_4. Higher negative sentiment predicts lower next-day returns, and that higher returns predict lower next-day negative sentiment. Higher returns predict lower next-day trading volumes, and higher trading volumes predict higher next-day returns. Higher negative sentiment causes lower trading volumes on the following day. The effects of trading volumes on next day's sentiment are not significant.

6 Empirical tests on individual firms

We now test the six hypotheses presented in Section 4 by examining each of the 20 firms in turn, using VAR models and rolling-window linear regressions together with the diagnostic tests associated with these models.

Testing over full data period

An important factor to consider when using VAR model is to choose the right lag length. For this research it is assumed that the ideal lag length is no more than 5 trading days as news articles published over a week ago are not expected to have significant impact on market activities today. The results of the lag length tests (not reported) demonstrate that with the exception of Chevron, the optimal lag length for all the other 19 stocks is 5 at the 1 percent level of significance. Chevron's optimal lag length is 4 at the same significance level.

The specific Equations in the VAR(5)[17] model are presented as below:

$$R_t = \alpha_1 + \beta_1 \cdot L5(R_t) + \gamma_1 \cdot L5(V_t) + \delta_1 \cdot L5(S_t) + Exog_{t-1} + \varepsilon_{1t} \tag{7}$$

$$V_t = \alpha_2 + \beta_2 \cdot L5(V_t) + \gamma_2 \cdot L5(R_t) + \delta_2 \cdot L5(S_t) + Exog_{t-1} + \varepsilon_{2t} \tag{8}$$

$$S_t = \alpha_3 + \beta_3 \cdot L5(S_t) + \gamma_3 \cdot L5(R_t) + \delta_3 \cdot L5(V_t) + Exog_{t-1} + \varepsilon_{3t} \tag{9}$$

Here, R, V and S represent firm-level equity returns, firm-level trading volumes and firm-specific sentiment. $L5$ is defined as the lag operator that transforms any variable x_t into a row vector $[x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}, x_{t-5}]$. $Exog$ includes three exogenous variables: volatility measure proxied by the CBOE's volatility index (VIX)[18] and dummy variables for the Monday and January effects.

Table 10 displays the results of estimating the VAR models, focusing on the F-statistics (with their significance levels in brackets). The column headed 'Usable obs' provides the number of usable observations for each firm. The three columns headed 'Return', 'Volume' and 'Fin Neg' denote the dependent variable in the vector of endogenous variables, and the three columns beneath are the explanatory variables in these equations. The F-statistics with their marginal significance levels indicate the joint significance of all lags of each explanatory variable in each equation. The most evident relations are that returns cause volumes (16 out of 20 cases are significant at the 5 percent level), and that volumes cause sentiment (15 cases are significant at the 5 percent level). The results are also relatively supportive for 'Sentiment causes volumes', with 8 cases being significant at the 5 percent level. The other relations are not very evident. Table 11 summarizes the number of significant cases in the causality tests.

It is important to note that although only 4 firms: Dell, GE, Verizon and Exxon Mobil, show that sentiment directly causes return, 3 firms: Ford Motor, GE and Home Depot, demonstrate indirect causality from sentiment to returns; that is to say sentiment causes volumes whilst volumes cause return (Table 12). A total of 6 firms or 30 percent, show that sentiment causes stock returns either directly or indirectly over the full sample period. Among them, GE reveals both a direct and indirect relationship. Overall, therefore, approximately 75 percent of the results indicate that both H_4 and H_6 can be rejected at the 5 percent level of significance. Half of the results show that sentiment causes trading volumes at the 10 percent level of significance. Therefore, we tend to reject H_3 at the individual firm level. Based on the other results, we cannot reject H_1, H_2 and H_5. Overall, six firms (30 percent) show that sentiment causes stock returns either directly or indirectly (through trading volumes) over the full sample period. This suggests the important contribution of our paper. It is intuitive that firm-level sentiment should not be continually significant, because negative news and negative sentiment is more powerful than positive news. This motivates our final set of tests aimed at uncovering the time-varying effects of negative firm-specific sentiment.

Empirical tests over rolling-window periods

The previous two groups of models (i.e. panel models and VARs) were employed to test hypotheses H_1 to H_6, from the perspectives of both the pooled sample and individual firms. We now examine H_1, and further explore the indirect relationship between sentiment and returns - sentiment causes volumes while volumes cause return (H_3, H_5) - by implementing regressions over 1-year (252-day) rolling windows. We therefore propose a further hypothesis:

$H_7(Null)$: Firm-specific sentiment does not cause firm-level equity returns in any periods.
$H_7(Alternative)$: Firm-specific sentiment causes firm-level equity returns in some periods.

We assume that the error terms ε_t in equation (7) to (9) are independent, and this allows us to estimate each equation using the OLS techniques separately. We first focus on equation (7) to examine the time-varying direct effects of the five lags of *FN* on firm-level equity returns, and together with equation (8) to examine the indirect effects from sentiment to stock returns.

Figure 2 displays the results of rolling regressions (equation (7)) for each firm, specifically whether the five lags of *FN* significantly forecast stock returns. The horizontal axis in each graph illustrates the date at which the individual 252-day sliding window ends. The vertical axis indicates whether the five lags of *FN* significantly forecast returns in the individual regression. A value of 1 on the vertical axis indicates significance at the 10 percent level, while a value of 2 indicates significance at the 5 percent level. From the graphs it is clear that with the exception of Chevron, sentiment predicts stock returns directly for at least some of the data period, although there is no fixed pattern of periods where predictability is concentrated.

Further analysis is performed to examine whether sentiment indirectly affects stock returns during other periods, namely, whether the lags of sentiment cause volumes and volumes cause returns. The results demonstrate that on the whole, *FN* is more likely to have direct effects on returns, although this happens less than 10 percent (9.56 percent) of the time on average (Table 13 panel (a)). The indirect effects are negligible or completely absent for several firms, such as Apple, AT&T, Boeing, Chevron, ConocoPhillips, Dell, and Pfize. On average, either or both of the direct and indirect effects appear 11.32 percent of time. Panel (a) of Table 13 also shows that the two effects do not usually overlap. For example, for HP, IBM, Intel, Johnson & Johnson, Merck and Verizon, the proportion of either direct or indirect effects is equal to or almost equal to the sum of the two respective proportions. Panel (b) further summarizes the descriptive statistics of the results, including the mean, standard deviation, minimum, first quartile, median, third quartile and maximum. The null hypothesis that the mean equals zero is rejected as the T-statistics are all greater than the critical value 2.86 at the

1 percent level of significance (last column of panel (b)).

We perform the following robustness analysis. Firstly, the firm-level returns are replaced by firm-level abnormal returns, and the interrelations among textual sentiment, volumes and abnormal returns are examined. Abnormal returns are the firms' raw returns minus the return of a value-weighted portfolio with similar size/book-to-market-characteristics[19]. We then run the 252-day rolling-window regressions as before to examine the time-varying patterns, except that now the dependent variable in equation (7) is replaced by the firm-level abnormal returns. Compared with the raw returns, the direct effects of sentiment on the abnormal returns decrease slightly, but the standard deviation is significantly smaller and the minimum, median and maximum values are greater (Table 14 panel (a)-(b)). The direct effects increase greatly for Chevron and Pfizer. The two firms' sentiment has exposed little or no effect on raw returns. However, the overall indirect effects become weaker. By and large, the effects on abnormal returns and raw returns are similar. Since there is no major difference between sentiment's effects on raw returns and abnormal returns, only raw returns are employed as the dependent variable in the remaining robustness analysis.

Our second robustness analysis limits the effects of outliers by winsorizing the time series of returns, trading volumes and sentiment at the 1 percent level. Three exogenous variables are still included in the model to control for volatility and potential return anomalies, and only direct effects are examined. The results reveal that wisorizing the data does not lead to any major differences (Table 15). On average, the direct effects with the winsorized data increase slightly, from 9.56 percent to 9.98 percent of time. It is noteworthy, however, that the direct effects have risen for 16 of the 20 firms, while IBM has the largest increase by 66.7 percent.

Our third robustness analysis tests another sentiment measure: the count of positive words minus the count of negative words, divided by the sum of positive and negative word counts. The daily sentiment is relatively positive if the measure is greater than 0, or relatively negative if less than 0. This measure replaces *FN* in equation (7), and the direct effects of sentiment on returns are examined. According to the results (not reported), this measure is no better than *FN*.

Overall, therefore, by employing 1-year rolling-window regressions, we find that with the exception of Chevron, sentiment predicts stock returns directly at least for some data periods (9.56 percent on average), although there seems to be no fixed pattern of where the predictability is concentrated. Similar effects are observed when returns in the VAR system are replaced by abnormal returns. Therefore, H_7 is rejected. By and large, the indirect effects of sentiment on return are negligible for most firms. On average, either of the two effects emerge 11 percent of the time, although they do not often coexist. This, we believe, constitutes perhaps our most significant finding. It suggests strongly and intuitively that the search for significant impact of firm-specific textual sentiment on firm-level performance should recognise this effect will necessarily be time-varying insofar as most firms will not generate significant news on a continuing daily basis – and indeed many firms would presumably prefer that this is the case. No news is good news, and the strongest finding to emerge thus far from the textual sentiment analysis is that the most significant impact of news sentiment on market-level performance is driven by negative sentiment. We confirm this at the level of the firm.

7 Summary and Conclusions

Recent studies in the textual sentiment literature draw attention to the statistically significant interactions between market-level textual sentiment and market returns. It is generally agreed that market returns predict textual sentiment, and that sentiment predicts market-level trading volumes. In this paper, six hypotheses regarding the relations between firm-specific sentiment, firm-level equity returns and trading volumes are examined. We employ panel data regressions, VAR models and rolling regressions on individual firm data in sequence. We use Loughran and McDonald (2011a)'s 'finance negative' words to proxy for sentiment.

Using almost 43,000 observations in our panel data of over 2,500 observations from 17 large firms over 10 years, we have seen that higher negative firm-specific sentiment predicts lower next-day firm-level returns, that higher firm-level returns predict lower next-day firm-specific negative sentiment, and that higher negative firm-specific sentiment causes lower firm-level trading volumes the following day. Using VAR models for each firm individually over the full data period, we show that firm-level trading volumes drive firm-specific sentiment, and that firm-level returns drive firm-level trading volumes. Around 75 percent of the results indicate that both H_4 and H_6 could be rejected at the 5 percent level of significance. Half of the results show that sentiment causes trading volumes at the 10 percent level of significance. Therefore, we tend to reject H_3 at the individual firm level. Based on the other results, we cannot reject H_1, H_2 and H_5. Six firms (30 percent) show that firm-specific sentiment impacts significantly on firm-level stock returns either directly or indirectly through trading volumes over the full sample period. Aggregating the results, we conclude that the interrelations between firm-specific sentiment, firm-level equity returns and trading volumes are most evident in the pooled sample. The results regarding the role of textual sentiment on equity returns and trading volumes are consistent with previous studies (e.g. Tetlock (2007), Tetlock et al. (2008), Garcia (2012)). Negative words are found to have an immediate negative impact on equity returns, while returns forecast negative words; higher returns predict lower next-day trading volumes.

We conclude that there is strong evidence of the indirect effects of firm-specific sentiment on firm-level equity returns. Firm-specific sentiment causes firm-level trading volumes, and the latter impacts on firm-level returns. This is most evident in our panel data. We have also examined the time-series pattern of how firm-specific sentiment impacts of firm-level performance, and our findings confirm that trading volumes cause sentiment, and *vice versa*. We also conclude that firm-specific sentiment does not cause firm-level returns continuously. Rather, it does so with time varying impacts. The discrete periods where the predictability is concentrated are likely to be associated with important firm-specific news and events. This should be a promising direction for future research. Overall, our results suggest that firm-specific textual sentiment is a potentially important time-varying factor in equity pricing models.

Table 1: Average number of articles and number of words per day (Firm-specific news)

Company	Number of observations	Average Number of Articles/ day	Average Number of Words/day
Apple	2515	20.01	10714.35
AT&T	2515	16.29	9309.99
Boeing	2515	42.68	21030.80
Chevron	1259	13.64	6730.83
Cisco	2515	20.38	12368.96
ConocoPhillips	1259	10.37	6173.93
Dell	2515	22.19	11279.08
ExxonMobil	1511	10.04	5701.69
Ford Motor	2515	11.26	7079.89
General Electric	2515	19.81	9734.83
Home Depot	2515	11.00	6570.31
HP	2515	12.67	7791.52
IBM	2515	37.41	19678.86
Intel	2515	17.76	9694.44
Johnson & Johnson	2515	10.72	5515.98
Merck	2515	13.22	9035.28
Microsoft	2515	46.25	24590.28
Pfizer	2515	17.46	9948.85
Verizon	2515	28.05	16166.98
Walmart	2515	27.85	14352.54

Notes: This table presents the average number of articles and number of words per day for each firm.

Table 2: Descriptive statistics of negative textual sentiment

Company	Mean	Variance	Skewness	Kurtosis	J-B P-val	Q10 P-val	DF t-stat
Apple	1.05	0.30	1.70	6.03	0.00	0.00	-34.37
AT&T	1.04	0.37	1.98	8.60	0.00	0.00	-35.89
Boeing	1.35	0.22	1.11	2.52	0.00	0.00	-30.37
Chevron	1.40	0.48	1.16	2.93	0.00	0.00	-25.38
Cisco	0.85	0.23	2.22	9.65	0.00	0.00	-35.99
ConocoPhillips	1.13	0.29	2.39	18.93	0.00	0.00	-40.00
Dell	1.04	0.22	1.45	3.89	0.00	0.00	-35.91
ExxonMobil	1.49	0.77	1.47	4.20	0.00	0.00	-28.46
Ford Motor	1.27	0.53	1.30	3.03	0.00	0.00	-37.92
GE	1.02	0.22	1.19	2.87	0.00	0.00	-40.25
Home Depot	1.19	0.37	1.29	3.41	0.00	0.00	-42.03
HP	0.93	0.40	2.22	7.88	0.00	0.00	-31.77
IBM	0.85	0.10	1.49	3.96	0.00	0.00	-35.07
Intel	0.92	0.37	2.19	7.61	0.00	0.00	-33.91
Johnson & Johnson	1.41	0.59	1.29	4.21	0.00	0.000	-38.57
Merck	1.50	0.62	1.03	2.94	0.00	0.00	-35.24
Microsoft	1.21	0.32	1.41	2.12	0.00	0.00	-27.41
Pfizer	1.52	0.39	1.43	4.88	0.00	0.00	-39.25
Verizon	1.26	0.21	1.66	7.10	0.00	0.00	-37.58
Walmart	1.51	0.22	1.12	3.62	0.00	0.00	-40.27

Notes: This table summarizes the descriptive statistics of *FN* series, including mean, variance, skewness, excess kurtosis, the Jarque-Bera (J-B) test of normality, the Ljung-Box Q test for autocorrelation and the Dickey-Fuller unit-root test.

Table 3: Summary statistics of stock return and volume

Company	Obs	Variable	Skewness	Kurtosis	J-B P-val	Q10 P-val	DF t-stat
Apple	2515	Return	-0.13	4.10	0.00	0.07	-51.06
		Volume	1.74	4.52	0.00	0.00	-18.12
AT&T	2515	Return	0.20	5.33	0.00	0.00	-51.45
		Volume	1.44	4.28	0.00	0.00	-15.94
Boeing	2515	Return	-0.31	6.10	0.00	0.03	-49.95
		Volume	2.15	7.76	0.00	0.00	-23.40
Chevron	1259	Return	0.20	13.25	0.00	0.00	-40.88
		Volume	1.78	6.36	0.00	0.00	-14.11
Cisco	2515	Return	0.18	7.40	0.00	0.03	-52.21
		Volume	3.92	41.93	0.00	0.00	-26.97
ConocoPhillips	1259	Return	-0.38	6.66	0.00	0.00	-38.61
		Volume	1.09	2.09	0.00	0.00	-15.49
Dell	2515	Return	0.00	4.73	0.00	0.00	-51.28
		Volume	2.44	11.16	0.00	0.00	-27.46
ExxonMobil	1511	Return	0.07	12.72	0.00	0.00	-46.09
		Volume	2.30	9.12	0.00	0.00	-15.43
Ford Motor	2515	Return	0.01	12.33	0.00	0.00	-48.42
		Volume	3.02	16.00	0.00	0.00	-16.84
GE	2515	Return	0.08	8.13	0.00	0.01	-50.80
		Volume	4.52	38.03	0.00	0.00	-14.97
Home Depot	2515	Return	0.13	5.02	0.00	0.08	-50.31
		Volume	2.28	10.61	0.00	0.00	-19.44
HP	2515	Return	0.01	7.69	0.00	0.04	-51.18
		Volume	6.62	100.35	0.00	0.00	-27.55
IBM	2515	Return	0.31	6.13	0.00	0.08	-51.14
		Volume	2.11	8.78	0.00	0.00	-23.85
Intel	2515	Return	-0.22	6.09	0.00	0.05	-52.81
		Volume	2.49	14.04	0.00	0.00	-28.14
Johnson & Johnson	2515	Return	-0.63	19.87	0.00	0.00	-52.27
		Volume	2.50	13.01	0.00	0.00	-22.15
Merck	2515	Return	-1.92	30.46	0.00	0.49	-50.11
		Volume	4.20	37.80	0.00	0.00	-23.38
Microsoft	2515	Return	0.21	6.50	0.00	0.00	-54.87
		Volume	3.80	42.50	0.00	0.00	-27.80
Pfizer	2515	Return	-0.33	5.43	0.00	0.00	-51.28
		Volume	2.58	17.32	0.00	0.00	-18.47
Verizon	2515	Return	0.13	5.56	0.00	0.00	-52.51
		Volume	1.83	6.40	0.00	0.00	-19.40
Walmart	2515	Return	0.26	4.25	0.00	0.00	-54.37
		Volume	2.64	15.78	0.00	0.00	-22.08

Notes: This table provides descriptive statistics of daily stock returns and volume, including skewness, excess kurtosis, the Jarque-Bera (J-B) test of normality, the Ljung-Box Q test for autocorrelation and the Dickey-Fuller unit-root test.

Table 4: Stock data and summary statistics

Company	Size (billion)	Revenue (million)	Return (%)	Volume (thousand)	Avg *FN*
Pfizer	152.3	67,809	-5.1	33,254	1.52
Walmart	197.7	421,849	1.8	13,566	1.51
Merck	108.0	45,987	-0.6	11,546	1.50
ExxonMobil	376.9	354,674	10.4	25,541	1.49
Johnson & Johnson	176.4	61,587	4.9	10,046	1.41
Chevron	211.0	196,337	14.3	11,387	1.40
Boeing	49.9	64,306	7.8	4,845	1.35
Ford Motor	41.3	128,954	28.4	36,995	1.27
Verizon	104.5	106,565	3.5	12,288	1.26
Microsoft	222.9	62,484	9.4	68,595	1.21
Home Depot	59.3	67,997	3.9	12,885	1.19
ConocoPhillips	95.0	184,966	9.8	12,065	1.13
Apple	357.3	65,225	68.3	22,572	1.05
AT&T	172.2	124,629	2.1	17,552	1.04
Dell	28.2	61,494	3.5	23,699	1.04
General Electric	169.8	151,628	-1.3	44,335	1.02
HP	54.6	126,033	8.9	14,027	0.93
Intel	127.5	43,623	6.4	62,793	0.92
Cisco	101.6	40,040	3.2	60,549	0.85
IBM	220.0	99,870	10.7	7,461	0.85

Notes: This table presents the firms' market capitalization on 15/11/2011, annual revenue (provided by the 2011 Fortune 500 list), average annual return (simple return), average daily trading volume, and average daily *FN* scores of each firm. The firms are sorted by the average *FN* scores, from high to low, for rough examination of the relationship between negative sentiment and returns.

Table 5: Panel Unit Root Tests

	LLC	Breitung	HT
FN	-120.00***	-82.15***	0.32***
Turnover	-65.48***	-64.07***	0.74***
SUE	1.24	-5.64***	0.99***
B/M	-8.59***	-16.92***	0.95***
MV	-10.12***	-2.78***	0.96***

Notes: This table reports the statistics and the significance level (1 percent ***) of panel unit root tests on each variables. Levin–Lin–Chu (LLC) test, Breitung test, and Harris–Tzavalis

Table 6: Panel estimation: do sentiment and volumes predict returns?
(Sentiment measure: First lag of *FN*)

	Dependent Variable: Returns (*R*)			
	(1)	(2)	(3)	(4)
FN(-1)	-3.567E-04	-3.101E-04	-3.567E-04	-3.101E-04
	(-2.38**)	(-2.01**)	(-2.12**)	(-1.75*)
R(-1)	-0.013		-0.013	
	(-1.10)		(-1.81*)	
R(-2)	-0.031		-0.031	
	(-1.86*)		(-2.34**)	
AR(-1)		-0.017		-0.017
		(-1.26)		(-4.34***)
AR(-2)		0.010		0.010
		(0.84)		(2.46***)
V(-1)	0.040	0.042	0.040	0.042
	(1.64)	(1.75*)	(2.17**)	(2.50***)
SUE	4.380E-05	4.360E-05	4.380E-05	4.360E-05
	(0.35)	(0.36)	(0.93)	(0.96)
B/M	-0.004	-0.003	-0.004	-0.003
	(-3.32***)	(-3.45***)	(-12.79***)	(-14.95***)
MV	1.360E-05	1.280E-05	1.360E-05	1.280E-05
	(0.42)	(0.40)	(0.54)	(0.53)
VIX(-1)	1.270E-05	1.350E-05	1.270E-05	1.350E-05
	(6.74***)	(7.42***)	(12.54***)	(15.44***)
Monday	5.718E-04	5.186E-04	5.718E-04	5.186E-04
	(0.76)	(0.68)	(2.54***)	(2.34**)
January	-6.613E-04	-5.991E-04	-6.613E-04	-5.991E-04
	(-0.79)	(-0.74)	(-2.68***)	(-2.43**)
Constant	5.690E-05	6.810E-06	5.690E-05	6.810E-06
	(0.11)	(0.01)	(0.25)	(0.03)
Estimation method	Pooled OLS	Pooled OLS	Random effects	Random effects
R-squared	0.01	0.01	0.01	0.01
Observations	42704	42704	42704	42704

Notes: This table reports the estimated coefficients and the corresponding t-statistics (in brackets) for each of the regressions in the four columns. The symbols ***, ** and * indicate t-stats significance at 1 percent, 5 percent and 10 percent level, respectively. The dependent variable is returns, and the first lag of *FN* (*FN(-1)*) is the sentiment measure. Regressions (1) and (2) are estimated by pooled OLS with standard errors clustered by calendar quarter. Regression (3) and (4) are estimated using random-effects model with Huber–White robust standard errors. Besides *FN(-1)*, other independent variables in column (1) and (3) include the first and second lag of returns (*R*), the first lag of trading volumes (*V*), standardized unexpected earnings (*SUE)* (use its value at the end of the preceding quarter), book-to-market ratio (*B/M),* market value (*MV*)*,* past volatility proxied by the first lag of VIX index, dummies for the Monday and January effects. In columns (2) and (4), the lags of return are replaced by lags of abnormal return (AR), which is the return adjusted for Fama-French (1993) three factors.

Table 7: Panel estimation: do sentiment and volumes predict returns?
(Sentiment measure: Change in *FN*)

	Dependent Variable: Returns (R)			
	(1)	(2)	(3)	(4)
D(FN)	-6.465E-04	-6.573E-04	-6.465E-04	-6.573E-04
	(-3.57***)	(-3.57***)	(-2.89***)	(-2.90***)
R(-1)	-0.013		-0.013	
	(-1.09)		(-1.78*)	
R(-2)	-0.030		-0.030	
	(-1.81*)		(-2.26**)	
AR(-1)		-0.017		-0.017
		(-1.25)		(-4.27***)
AR(-2)		0.010		0.010
		(0.82)		(2.42**)
V(-1)	0.041	0.043	0.041	0.043
	(1.68*)	(1.79*)	(2.21**)	(2.53***)
SUE	4.870E-05	4.780E-05	4.870E-05	4.780E-05
	(0.39)	(0.40)	(0.99)	(1.01)
B/M	-0.004	-0.003	-0.004	-0.003
	(-3.33***)	(-3.45***)	(-12.78***)	(-14.95***)
MV	1.340E-05	1.260E-05	1.340E-05	1.260E-05
	(0.41)	(0.40)	(0.53)	(0.52)
VIX(-1)	1.270E-05	1.350E-05	1.27E-05	1.35E-05
	(6.73***)	(7.38***)	(12.53***)	(15.48***)
Monday	4.550E-04	4.059E-04	4.550E-04	4.060E-04
	(0.60)	(0.53)	(2.08**)	(1.90*)
January	-6.716E-04	-6.096E-04	-6.716E-04	-6.096E-04
	(-0.80)	(-0.76)	(-2.70***)	(-2.45**)
Constant	-3.443E-04	-3.396E-04	-3.443E-04	-3.396E-04
	(-0.88)	(-0.82)	(-1.79*)	(-1.92*)
Estimation method	Pooled OLS	Pooled OLS	Random effects	Random effects
R-squared	0.01	0.01	0.01	0.01
Observations	42704	42704	42704	42704

Notes: This table reports the estimated coefficients and the corresponding t-statistics (in brackets) for each of the regressions in the four columns. The symbols ***, ** and * indicate t-stats significance at 1 percent, 5 percent and 10 percent level, respectively. The dependent variable is returns, and the change in *FN* (*D*(*FN*)) is the sentiment measure. Regressions (1) and (2) are estimated by pooled OLS with standard errors clustered by calendar quarter. Regression (3) and (4) are estimated using random-effects model with Huber–White robust standard errors. Besides *D*(*FN*), other independent variables in column (1) and (3) include the first and second lag of returns (*R*), the first lag of trading volumes (*V*), standardized unexpected earnings (*SUE)* (use its value at the end of the preceding quarter), book-to-market ratio (*B/M),* market value (*MV)*, past volatility proxied by the first lag of VIX index, dummies for the Monday and January effects. In columns (2) and (4), the lags of return are replaced by lags of abnormal return (AR), which is the return adjusted for Fama-French (1993) three factors.

Table 8: Panel estimation: do returns and volumes cause sentiment?

Dependent Variable: Sentiment (*FN)*		
	(1)	(2)
FN(-1)	0.344	0.284
	34.59***	13.67***
FN(-2)	0.157	0.099
	17.88***	8.92***
R(-1)	-0.611	-0.641
	-4.04***	-4.10***
V(-1)	-0.567	2.618
	-1.06	1.27
SUE	-0.008	-1.248E-02
	-1.92*	-2.13**
B/M	0.008	0.009
	3.41***	4.94***
MV	6.620E-05	-1.407E-04
	0.34	-0.53
VIX(-1)	1.340E-05	9.250E-06
	0.83	0.59
Monday	-0.050	-0.043
	-5.42***	-2.95***
January	0.002	0.003
	0.18	0.23
Constant	0.598	0.712
	32.98***	24.56***
Estimation method	Pooled OLS	Fixed effects
R-squared	0.19	0.11
Observations	42721	42721

Notes: This table reports the estimated coefficients and the corresponding t-statistics (in brackets) for each of the regressions in the two columns. The symbols ***, ** and * indicate t-stats significance at 1 percent, 5 percent and 10 percent level, respectively. The dependent variable is the sentiment measure, *FN*. Regressions (1) is estimated by pooled OLS with standard errors clustered by calendar quarter. Regression (2) is estimated using fixed-effects model with Huber–White robust standard errors. Independent variables include the first two lags of *FN*, the first lag of returns (*R*), the first lag of trading volumes (*V*), standardized unexpected earnings (*SUE)* (use its value at the end of the preceding quarter), book-to-market ratio (*B/M)*, market value (*MV)*, past volatility proxied by the first lag of VIX index, dummies for the Monday and January effects.

Table 9: Panel estimation: do sentiment and returns cause volumes?

Dependent Variable: Volumes (*V*)		
	(1)	(2)
V(-1)	0.634	0.603
	23.74***	35.30***
V(-2)	0.210	0.179
	6.94***	44.48***
R(-1)	-0.008	-0.008
	-2.00**	-3.03***
FN(-1)	-2.462E-04	-1.333E-04
	-6.60***	-1.80*
SUE	2.210E-05	7.640E-06
	1.22	0.22
B/M	2.454E-04	2.524E-04
	1.01	16.87***
MV	5.870E-06	6.110E-06
	1.92*	1.90*
VIX(-1)	2.810E-07	4.220E-07
	1.38	1.62
Monday	-0.001	-0.001
	-7.40***	-5.92***
January	2.657E-04	2.883E-04
	1.55	5.67***
Constant	0.002	0.002
	11.24***	12.38***
Estimation method	Pooled OLS	Fixed effects
R-squared	0.67	0.56
Observations	42721	42721

Notes: This table reports the estimated coefficients and the corresponding t-statistics (in brackets) for each of the regressions in the two columns. The symbols ***, ** and * indicate t-stats significance at 1 percent, 5 percent and 10 percent level, respectively. The dependent variable is trading volumes (*V*). Regressions (1) is estimated by pooled OLS with standard errors clustered by calendar quarter. Regression (2) is estimated using fixed-effects model with Huber–White robust standard errors. Independent variables include the first two lags of *V*, the first lag of returns (*R*), the first lag of sentiment measure(*FN*), standardized unexpected earnings (*SUE)* (use its value at the end of the preceding quarter), book-to-market ratio (*B/M)*, market value (*MV)*, past volatility proxied by the first lag of VIX index, dummies for the Monday and January effects.

Table 10: VAR modeling over full sample period

	Usable Obs	Return			Volume			Fin Neg		
Company		**Return**	**Volume**	**Fin Neg**	**Return**	**Volume**	**Fin Neg**	**Return**	**Volume**	**Fin Neg**
Apple	2509	2.85	1.32	0.67	3.62	797.40	2.69	1.45	3.85	79.35
		(0.01)	(0.25)	(0.65)	(***0.00***)	(0.00)	(***0.02***)	(0.17)	(***0.00***)	(0.00)
AT&T	2509	2.71	0.35	1.02	5.12	894.65	5.80	0.22	14.73	44.01
		(0.02)	(0.88)	(0.40)	(***0.00***)	(0.00)	(***0.00***)	(0.95)	(***0.00***)	(0.00)
Boeing	2509	2.66	1.08	1.72	8.50	366.84	2.65	0.62	7.48	141.60
		(0.02)	(0.37)	(0.13)	(***0.00***)	(0.00)	(***0.02***)	(0.69)	(***0.00***)	(0.00)
Cisco	2509	2.42	0.74	0.37	2.13	230.40	1.07	1.22	18.66	47.95
		(0.03)	(0.59)	(0.87)	(**0.06**)	(0.00)	(0.37)	(0.30)	(***0.00***)	(0.00)
Dell	2509	4.25	1.07	2.55	0.72	213.67	1.12	2.82	6.29	56.17
		(0.00)	(0.37)	(***0.03***)	(0.61)	(0.00)	(0.35)	(***0.02***)	(***0.00***)	(0.00)
Ford Motor	2509	5.64	2.36	1.10	5.47	884.16	4.99	1.45	8.06	44.55
		(0.00)	(***0.04***)	(0.36)	(***0.00***)	(0.00)	(***0.00***)	(0.20)	(***0.00***)	(0.00)
GE	2509	1.21	5.69	1.94	15.35	1354.63	2.13	3.16	4.42	37.81
		(0.30)	(***0.00***)	(**0.08**)	(***0.00***)	(0.00)	(**0.06**)	(***0.01***)	(***0.00***)	(0.00)
Home Depot	2509	2.32	1.79	0.44	3.82	581.86	2.49	1.51	13.36	12.40
		(0.06)	(**0.08**)	(0.82)	(***0.00***)	(0.00)	(***0.03***)	(0.18)	(***0.00***)	(0.00)
HP	2509	1.04	0.87	1.56	1.63	221.59	0.57	0.45	4.62	142.83
		(0.39)	(0.50)	(0.17)	(0.15)	(0.00)	(0.73)	(0.81)	(***0.00***)	(0.00)
IBM	2509	1.50	2.85	0.52	5.47	368.84	0.53	0.71	4.69	69.62
		(0.19)	(***0.01***)	(0.76)	(***0.00***)	(0.00)	(0.76)	(0.61)	(***0.00***)	(0.00)
Intel	2509	3.36	0.74	0.45	0.82	207.85	3.46	0.35	1.48	79.89
		(0.01)	(0.60)	(0.82)	(0.54)	(0.00)	(***0.00***)	(0.88)	(0.19)	(0.00)
Johnson & Johnson	2509	5.08	1.48	1.09	6.96	478.26	3.07	1.02	2.44	46.22
		(0.00)	(0.19)	(0.31)	(***0.00***)	(0.00)	(***0.01***)	(0.41)	(***0.03***)	(0.00)
Merck	2509	0.62	0.61	0.51	2.39	382.85	0.75	2.53	1.34	105.25
		(0.68)	(0.69)	(0.77)	(***0.04***)	(0.00)	(0.59)	(***0.03***)	(0.24)	(0.00)

Table 10 (continued from previous page)

	Usable Obs	**Return**			**Volume**			**Fin Neg**		
Company		**Return**	**Volume**	**Fin Neg**	**Return**	**Volume**	**Fin Neg**	**Return**	**Volume**	**Fin Neg**
Microsoft	2509	6.74	0.88	1.24	3.16	207.52	3.05	1.05	1.11	236.44
		(0.00)	(0.50)	(0.29)	(***0.01***)	(0.00)	(***0.01***)	(0.39)	(0.35)	(0.00)
Pfizer	2509	6.49	1.55	0.62	1.26	810.47	0.33	2.07	0.18	48.29
		(0.00)	(0.17)	(0.68)	(0.28)	(0.00)	(0.89)	(**0.06**)	(0.97)	(0.00)
Verizon	2509	3.50	0.34	2.11	3.29	653.52	1.92	1.66	5.14	46.05
		(0.00)	(0.89)	(**0.06**)	(***0.01***)	(0.00)	(**0.09**)	(0.14)	(***0.00***)	(0.00)
Walmart	2509	5.99	0.92	0.98	2.22	538.44	1.44	1.02	2.31	28.62
		(0.00)	(0.47)	(0.43)	(***0.05***)	(0.00)	(0.21)	(0.41)	(***0.04***)	(0.00)
Exxon Mobil	1505	16.90	1.07	2.06	10.76	377.14	1.59	0.38	3.52	35.24
		(0.00)	(0.37)	(**0.07**)	(***0.00***)	(0.00)	(0.16)	(0.86)	(***0.00***)	(0.00)
Chevron	1253	9.72	1.78	0.57	11.54	291.91	0.45	1.10	1.95	30.95
		(0.00)	(0.11)	(0.72)	(***0.00***)	(0.00)	(0.81)	(0.36)	(**0.08**)	(0.00)
ConocoPhillips	1253	5.18	1.33	1.08	14.26	217.67	0.39	0.75	3.31	6.75
		(0.00)	(0.24)	(0.37)	(***0.00***)	(0.00)	(0.85)	(0.59)	(***0.01***)	(0.00)

Notes: This table presents the results of estimating VAR(5) model (VAR(4) for Chevron) over the full sample period, focusing on the F-statistics (with their p-values in brackets). Except the own lags of the dependent variable in each equation, p-values for the other two variables that are significant at the 5 percent level are marked in bold and italic, and 10 percent significance levels are marked in bold only. The column headed 'Usable obs' provides the number of usable observations for respective companies. The three columns headed 'Return' 'Volume' and 'Fin Neg' denote the dependent variable in the vector of endogenous variables, and the three columns beneath these headings are the explanatory variables in these equations. The F-statistics with their marginal significance levels indicate the joint significance of all lags of each explanatory variable in each equation.

Table 11: Summary of causality tests

	P-values $\leq$ 0.05	0.05 $<$ P-values $\leq$ 0.10
Sentiment causes returns	1	3
Returns cause sentiment	3	1
Sentiment causes volumes	8	2
Volumes cause sentiment	15	1
Volumes cause returns	3	1
Returns cause volumes	16	1

Notes: This table summarizes the results of testing H_1 to H_6, employing VAR models on individual firm data (whole period). The column headed 'P-values $\leq$ 0.05' presents the number of significant cases at the 5 percent level, and the column headed '0.05 $<$ P-values $\leq$ 0.10' presents the number of marginally significant cases.

Table 12: The direct and indirect effects of *FN* on returns

Apple	None
AT&T	None
Boeing	None
Chevron	None
Cisco	None
ConocoPhillips	None
Dell	S → R
Exxon Mobil	S → R
Ford Motor	S → V → R
GE	S → R, S→V→R
Home Depot	S → V → R
HP	None
IBM	None
Intel	None
Johnson & Johnson	None
Merck	None
Microsoft	None
Pfizer	None
Verizon	S → R
Walmart	None

Notes: This table summarizes the direct and indirect effects of *FN* on returns, at the 10 percent level of significance.

Table 13: Firm-specific sentiment and firm-level returns rolling regressions

(a)

Company	Direct (%)	Indirect (%)	Either (%)	Total number of regressions
Apple	5.80	0.71	6.46	1255
AT&T	5.36	0.00	5.36	1255
Boeing	4.69	0.00	4.69	1255
Chevron	0.00	0.00	0.00	751
Cisco	11.47	0.84	12.31	1255
ConocoPhillips	4.19	0.00	4.19	751
Dell	24.52	0.04	24.57	1255
ExxonMobil	31.08	1.99	31.24	1003
Ford Motor	11.91	0.58	12.48	1255
GE	10.36	3.94	12.57	1255
Home Depot	3.45	4.96	5.93	1255
HP	3.32	7.35	10.67	1255
IBM	6.91	6.86	13.77	1255
Intel	3.19	3.05	6.24	1255
Johnson & Johnson	12.88	4.65	17.31	1255
Merck	12.04	1.90	13.94	1255
Microsoft	5.00	0.44	5.36	1255
Pfizer	0.89	0.13	1.02	1255
Verizon	15.10	4.47	19.08	1255
Walmart	19.12	0.18	19.21	1255

(b)

	Mean	Standard Deviation	Minimum	First Quartile	Median	Third Quartile	Maxi -mum	T-stats (mean=0)
Direct	9.56	8.05	0.00	3.82	6.35	12.46	31.08	**5.31**
Indirect	2.10	2.44	0.00	0.09	0.77	4.21	7.35	**3.86**
Either	11.32	8.03	0.00	5.36	11.49	15.36	31.24	**6.30**

Notes: Panel (a) displays the proportion of significant cases among all the 252-day rolling-window regressions. It shows at the 10 percent significance level, the percentage of the time that the five lags of sentiment measure (*FN*) have direct, indirect or either effect on stock returns. The 'indirect effect' indicates that sentiment cause volumes, whilst volumes cause returns. Panel (b) displays the descriptive statistics.

Table 14: Robustness analysis: firm-specific sentiment and firm-level abnormal returns rolling regressions

(a)

Company	Direct (%)	Indirect (%)	Either (%)	Total number of regressions
Apple	7.30	13.55	20.81	1255
AT&T	15.18	0.00	15.18	1255
Boeing	1.95	0.13	2.08	1255
Chevron	13.46	0.00	13.46	751
Cisco	9.47	0.00	9.47	1255
ConocoPhillips	13.56	0.00	13.56	751
Dell	11.55	0.80	11.69	1255
ExxonMobil	5.02	0.00	5.02	1003
Ford Motor	6.64	0.27	6.91	1255
GE	9.52	12.13	19.61	1255
Home Depot	6.37	1.28	7.26	1255
HP	7.75	1.73	9.47	1255
IBM	9.12	1.28	10.40	1255
Intel	4.12	0.00	4.12	1255
Johnson & Johnson	3.63	4.43	8.01	1255
Merck	10.71	2.39	13.10	1255
Microsoft	5.40	0.00	5.40	1255
Pfizer	9.07	0.00	9.07	1255
Verizon	9.83	0.00	9.83	1255
Walmart	13.37	4.03	13.46	1255

(b)

	Mean	Standard Deviation	Mini mum	First Quartile	Median	Third Quart ile	Maxi-mum	T-stats (mean=0)
Direct	8.65	3.66	1.95	5.89	9.10	11.13	15.18	**10.57**
Indirect	2.10	3.91	0.00	0.00	0.20	2.06	13.55	**2.40**
Either	10.40	4.85	2.08	7.08	9.65	13.46	20.81	**9.58**

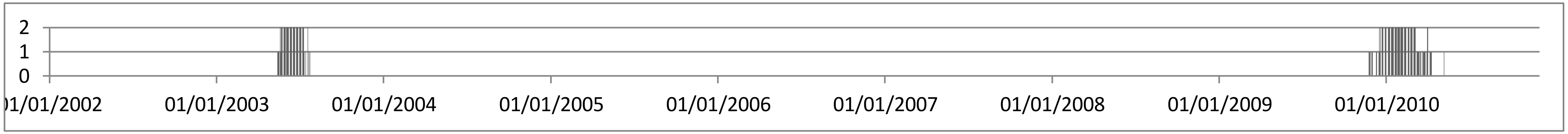
Notes: Panel (a) displays the percentage of significant cases in all the 252-day rolling-window regressions. It shows at the 10 percent significance level, the percentage of the time that the five lags of sentiment measure (*FN*) have direct, indirect or either effect on stock abnormal returns. Abnormal returns are raw returns minus the returns of a value-weighted portfolio with similar size/book-to-market-characteristics. The ‘indirect effect’ indicates that sentiment cause volumes, whilst volume causes abnormal returns. Panel (b) displays the descriptive statistics.

Table 4.15: Robustness Analysis: Winsorizing returns, volumes and sentiment data

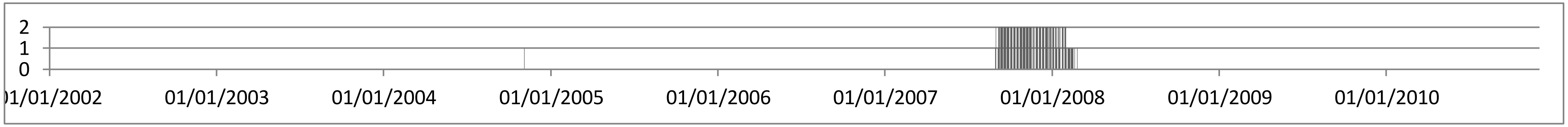
Company	Original Data (%)	Winsorized Data (%)
Apple	5.80	6.11
AT&T	5.36	5.49
Boeing	4.69	4.96
Chevron	0.00	0.20
Cisco	11.47	12.62
ConocoPhillips	4.19	2.79
Dell	24.52	23.42
ExxonMobil	31.08	33.55
Ford Motor	11.91	12.97
GE	10.36	7.70
Home Depot	3.45	3.59
HP	3.32	4.29
IBM	6.91	11.51
Intel	3.19	4.34
Johnson & Johnson	12.88	13.72
Merck	12.04	14.34
Microsoft	5.00	5.31
Pfizer	0.89	1.28
Verizon	15.10	15.23
Walmart	19.12	16.11
Average	9.56	9.98

Notes: This table compares the results of the modified model to the original model. The time series of return, volume and sentiment are all winsorized at the 1 percent level. Three exogenous variables (i.e. volatility measure proxied by VIX index and dummy variables for Monday effect and January effect) are still included in the model to control for volatility and potential return anomalies. Both columns present the percentage of significant cases in all the rolling-window regressions.

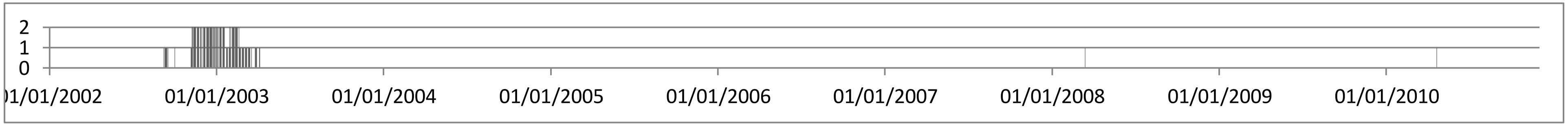
Figure 1: Predictability of sentiment on return (1-year sliding windows)



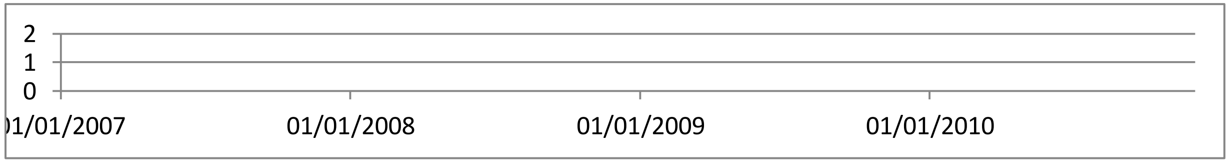
(a) Apple



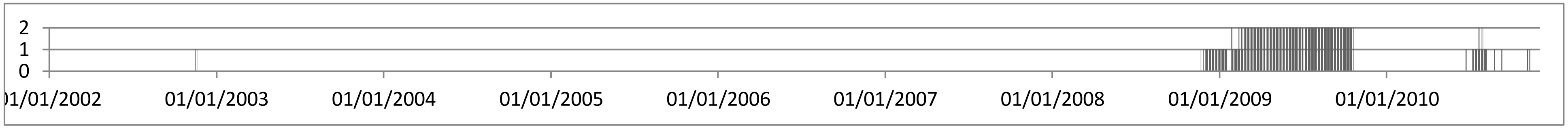
(b) AT&T



(c) Boeing

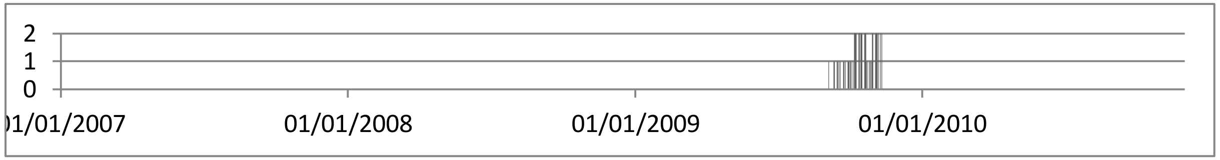


(d) Chevron

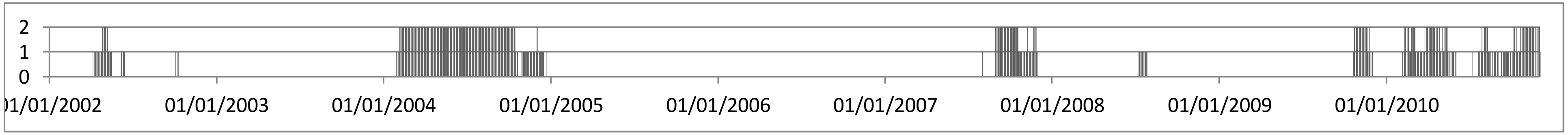


(e) Cisco

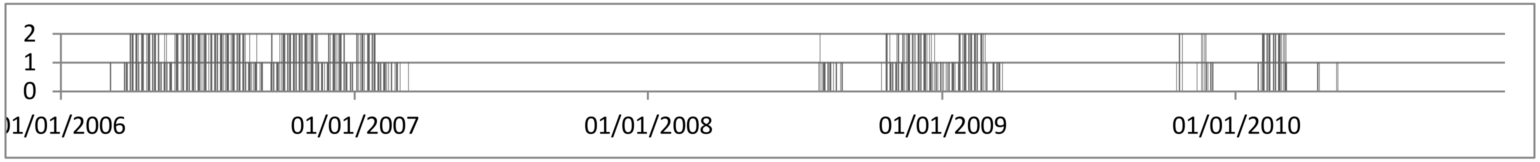
Figure 1 (continued from previous page)



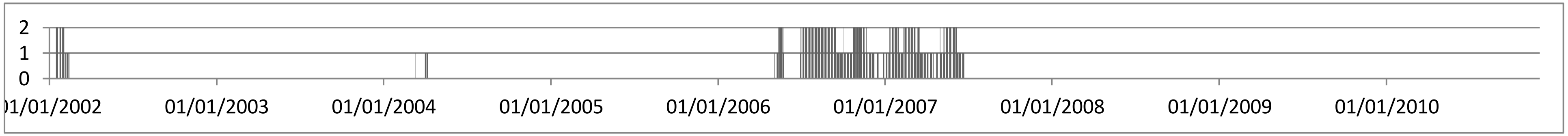
(f) ConocoPhillips



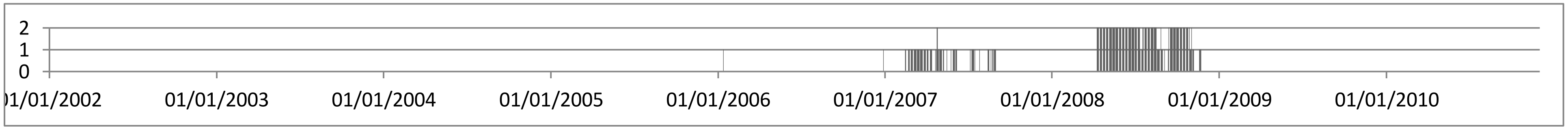
(g) Dell



(h) Exxon Mobil

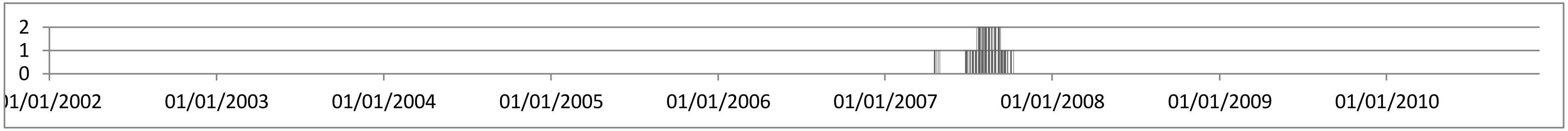


(i) Ford Motor

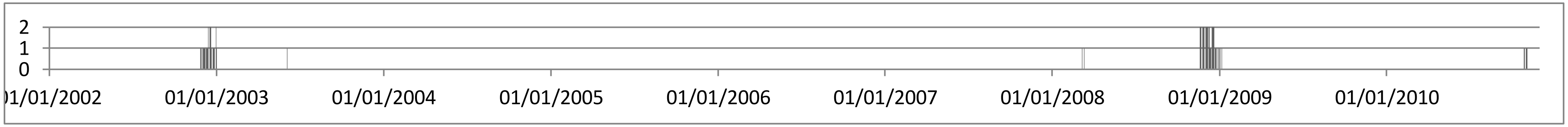


(j) General Electric

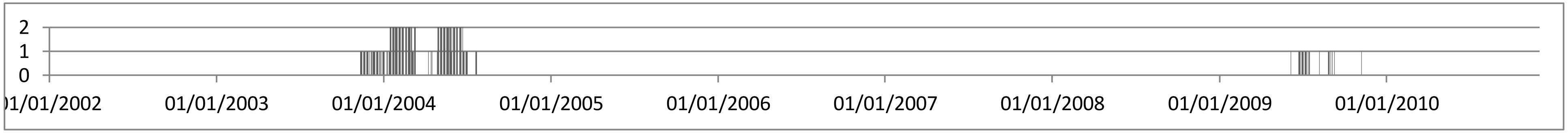
Figure 1 (continued from previous page)



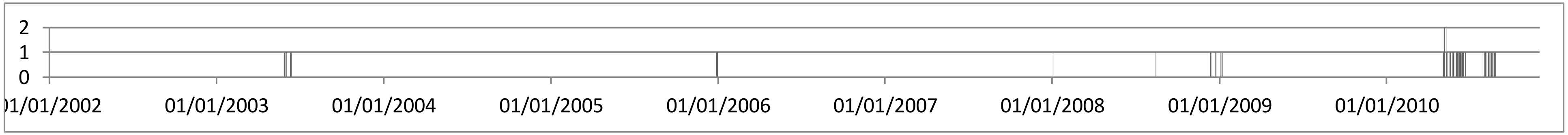
(k) Home Depot



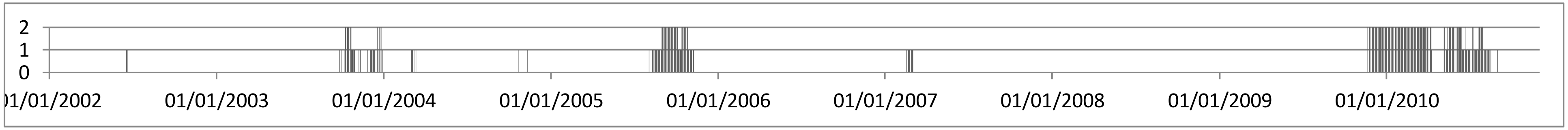
(l) HP



(m) IBM



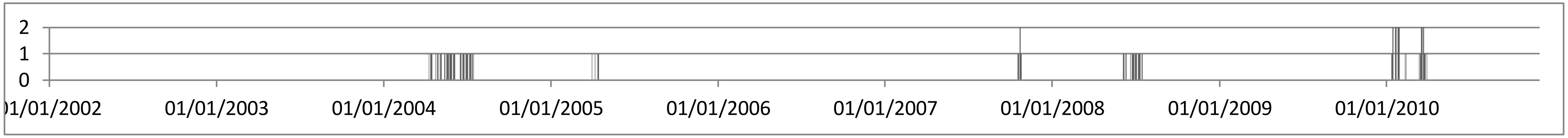
(n) Intel



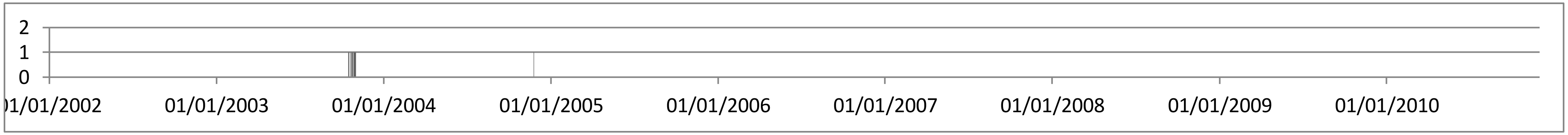
(o) Johnson & Johnson

Figure 1 (continued from previous page)

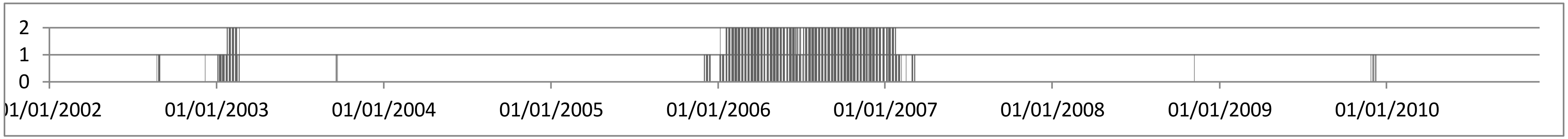
(p) Merck



(q) Microsoft

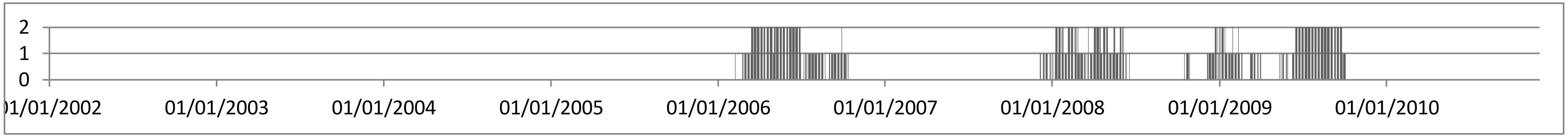


(r) Pfizer



(s) Verizon

Figure 1 (continued from previous page)



(t) Wal-mart

Notes: Graph (a) to (t) display the results of rolling regressions for all firms, specifically whether the five lags of *FN* significantly forecast stock return. In each graph, the horizontal axis in each graph illustrates the date at which the individual 252-day sliding window ends. The vertical axis indicates whether the five lags of FN significantly forecast returns in the individual regression. A value of 1 on the vertical axis indicates significance at the 10 percent level, while a value of 2 indicates significance at the 5 percent level.

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Endnotes

[1] The finance negative word list is available at http://nd.edu/~mcdonald/Word_Lists.html.

[2] http://money.cnn.com/magazines/fortune/fortune500/2011/full_list.

[3] Although for some companies there are a few days, usually less than 10 days throughout the 10-year period, having no articles.

[4] The retrieved articles are at least of 80% relevance, indicated by the relevance score.

[5] Treocht Ltd.,(www.treocht.com) is an Ireland-based company developing a web-based system that uses fusion analytics to deliver instant, accurate financial predictions.

[6] As on 15/11/2011.

[7] Data shown on 2011 *Fortune 500* list.

[8] Sentiment extracted from corporate disclosures

[9] Excess returns in a long period (e.g. 80 days) following the event.

[10] MV was divided by 10,000.

[11] The variable is demeaned to obtain a residual, square this residual, and subtract the past 60-day moving average of the squared residual.

[12] the value at the end of the preceding quarter.

[13] Obtained from Datastream. The VIX index is detrended in the following way: we demean the variable to obtain a residual, square this residual, and then subtract the past 30-day moving average of the squared residual.

[14] The random effects model was selected in preference to the fixed effects model, according to the result of Hausman's specification test (1978) .

[15] The fixed effects model was selected in preference to the random effects model, according to the result of Hausman's specification test.

[16] The fixed effects model was selected in preference to the random effects model, according to the result of Hausman's specification test.

[17] The model is VAR(4) for Chevron.

[18] Obtained from Datastream. The VIX index is detrended in the following way: we demean the variable to obtain a residual, square this residual, and then subtract the past 30-day moving average of the squared residual.

[19] The time series of the benchmark portfolios' (2×3) returns are obtained from Kenneth R. French's data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.