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Media-expressed negative tone and firm-level stock returns

Khurshid Ahmad[a], JingGuang Han[b], Elaine Hutson[c*], Colm Kearney[d], and Sha Liu[e]

Abstract

We build a corpus of over 5½ million news articles on 20 large US firms over the 10-year period from January 2001 to December 2010, and use it to study the time-varying nature of the relation between media-expressed firm-specific tone and firm-level returns. By estimating a series of separate rolling window vector autoregressive (VAR) models for each firm, we show how media-expressed negative tone impacts firm-level returns episodically in ways that vary across firms and over time. We find that firms experience prolonged periods during which media-expressed tone has no effect on returns, and occasional episodes when it has a significant impact. During the significant episodes, its impacts are sometimes quickly reversed and at other times they endure – implying that media comment and analysis can sometimes be *sentiment* (or noise), but it can also contain value-relevant information or *news*. Our findings are in general consistent with efficiently functioning markets in which the media assists with the processing of complex information.

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1. Introduction

A key question in the literature on the textual analysis of media content and how it relates to financial market outcomes is whether its 'tone' significantly affects stock returns, and if so whether the effects are transitory or persistent. Using a variety of text corpuses, content analysis methods, model specifications and estimation techniques, most studies find that negative media-expressed tone leads to significantly negative next-day returns that are partially reversed (Tetlock, 2007; Groß-Klußmann and Hautsch, 2011; Loughran and McDonald, 2011; Boudoukh et al., 2013; Dzielinski and Hasseltoft, 2013; Ferguson et al., 2013; Garcia, 2013; Chen et al., 2014; Heston and Sinha, 2014). Drawing on the 'noise trader risk' theory of DeLong et al., (1990a), Tetlock (2007) argues that persistent or enduring effects imply that media-expressed tone contains new information about fundamental value, whereas transitory effects that are quickly reversed suggest that media-expressed tone is *sentiment* – defined as the level of noise traders' beliefs relative to Bayesian beliefs about the effect of information on stock prices.[1]

Few studies have examined the media-expressed tone-return relation at the level of the firm. This constitutes a gap in the literature to the extent that the aggregation of media tone and returns data in prior studies may conceal potentially illuminating firm-level effects. For example, time-varying effects of media tone on returns are possible; Garcia (2013) finds that media pessimism affects the Dow Jones index three times more strongly in recessions than in economic expansions. One reason why firm-level studies are scarce is that most firms appear infrequently in the media, and this has stymied the ability of researchers to construct reliable measures of firm-specific tone – particularly at short data intervals. A common response of researchers to this constraint has been to aggregate firm-level media tone into a single proxy

[1] Baker and Wurgler (2007) define investor sentiment as '…a belief about future cash flows and investment risks that is not justified by the facts at hand.' (p. 129). More recent reviews of the literature are provided by Kearney and Liu (2014) and Tetlock (2014).

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measure, or by extracting firm-specific tone for each firm and combining these in a panel regression framework.[2] The former creates a single representative 'firm', and implicitly assumes that media tone is identical across firms. The panel regression approach allows for different measures of firm-level tone, but its default specification constrains the estimated effects on returns to be similar across firms and over time.[3]

In this paper, we ask whether these aggregate and market-level findings hold at the level of the firm. We conduct a time-varying analysis of the relation between media-expressed firm-specific negative tone and firm-level returns. To do this, we use daily data over the 10-year period 2001-2010 for 20 large non-financial US firms. Our corpus comprises more than 5½ million articles from newspapers, industry and trade magazines, newswires, financial blogs and other web-based publications, providing us with between 59,000 and 1.1 million articles for each firm. By focussing on a small number of large firms for which there are ample news stories, we are able to derive daily measures of firm-specific tone for each firm from a media corpus in which there are few days with no articles.

In addition to enabling a more detailed analysis of the firm-specific tone-return relation, our sample of large firms offers several advantages over studies that use firms of all sizes. *First*, our firms are unlikely to suffer from a lack of investor recognition or a scarcity of information that is associated with mispricing. An information-poor environment is associated with a slower speed of information diffusion that is more commonly observed among small firms (Hong and Stein, 1999; Hong, Lim and Stein, 2000). *Second*, our sample firms are not 'extreme growth' or 'high uncertainty' stocks that are difficult to value, so they should not be particularly vulnerable to sentiment (Zhang, 2006; Baker and Wurgler, 2007; Hillert, Jacobs

[2] See, for example, Engelberg (2008), Sinha (2010), Boudoukh et al., (2013), Dzielinski and Hasseltoft (2013), Sinha (2013) and Chen et al., (2014).

[3] See Holtz-Eakin, Newey and Rozen (1988); Canova and Ciccarelli (2013), and Lütkepohl (2014).

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and Müller, 2014). *Third*, our sample firms are unlikely to have binding constraints on arbitrage. The persistence of return autocorrelation is often explained by high trading costs and restrictions on short selling (Jegadeesh and Titman, 1993, 2001; Chan, 2003; Antoniou et al., 2013), and such barriers to arbitrage are more likely among small stocks (Baker and Wurgler, 2007). Our sample of large, liquid and information-rich firms allows us to draw conclusions about the effects of media-expressed tone on firm-level returns with confidence that our findings are not artifacts of information paucity or constraints on trading.

We begin by using a panel approach, and find that a rise in firm-specific negative media tone leads to a significant reduction in next-day firm-level returns. In contrast to prior studies, however, we find no evidence of return reversal – which suggests that the negative tone in media articles might contain new fundamental information about firm value. In the news arrival and volatility clustering literature, information events are considered to arrive sporadically – in short bursts followed by periods of relative quiet (Andersen, 1996; Andersen et al., 2010). Further, different types of news events can have dissimilar effects on returns (Engle, Hansen and Lunde, 2012; Boudoukh et al., 2013; Neuhierl, Scherbina and Schlusche; 2013)[4]. Using rolling VAR regressions with a one-year window moving forward a day at a time, we observe how media-expressed tone impacts returns in ways that differ for each firm and vary over time. We find that the negative tone-return relation is indeed episodic, with long interludes during which media tone has no effect on returns, interspersed by bursts of significance. Some of these episodes are transitory, and others are enduring or persistent. Our transitory episodes – involving initial overreaction followed by reversal – suggest that, consistent with the prior literature conducted at the market or aggregate level, media-

[4] Boudoukh et al., (2013) delineate ‘unidentified news’ from ‘identified news’, and find that ‘identified news’ days are associated with partial return continuation. Neuhierl, Scherbina and Schlusche (2013) classify corporate press releases into topic categories and show that some topics, such as corporate restructurings and FDA rejections, are associated with greater return and volatility impacts than others. Engle, Hansen and Lunde (2012) classify news events into different types and show that the categorizations help explain return and volatility dynamics.

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expressed tone is *sentiment*. Our novel result that media-expressed negative tone can sometimes lead to persistently lower returns suggests, however, that negative media tone can sometimes contain *news* about fundamental firm value.

In order to further test our argument that the enduring episodes are indicative of news, we construct a corpus of newswire articles;[5] we call this the *newswire corpus*, and we refer to our main collection of media articles as the *full corpus*. Newswires are likely to be the best measure of genuine news available (Fang and Peress, 2009; Kelley and Tetlock, 2013; Hillert, Jacobs and Müller, 2014); they are widely disseminated electronically, and their systems are designed to get news out as fast as possible.[6] If tone extracted from our newswire corpus contains new information about firm value, its effects on firm-level returns should be immediate, unbiased and enduring. Prior research findings, however, are not consistent with this insofar as newswire tone has been shown to impact returns with short and longer-term delays (Tetlock et al., 2008; Heston and Sinha, 2012; Sinha, 2012; Boudoukh et al., 2013). When we repeat our panel analysis, we find that negative newswire tone leads to significantly negative next-day returns that persist more strongly than for the full corpus. Replicating our firm-level rolling VAR regressions with the newswire corpus, we find that the relation is similarly episodic. Consistent with the notion that negative newswire tone reflects *news*, we find that in all but one of the episodes the effect of negative newswire tone on returns endures.

These findings prompt us to ask whether a related trading strategy yields positive excess returns. We conduct a zero-investment long-short portfolio analysis in which we sort our 20 firms each day from highest to lowest negative tone[7]. We short the 10 stocks with the highest negative tone and take a long position in the remainder. For the full corpus, we find a large

[5] It is drawn from the 421 newswire services available on *LexisNexis*. The full corpus is likewise drawn from *LexisNexis*.

[6] For good descriptions of the newswire dissemination process, see Engle, Hansen and Lunde (2012), and Sinha (2012).

[7] A similar approach is used by Sinha (2012).

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and significantly positive next-day return to the long-short portfolio of more than 17 percent annualised, and this is driven equally by the long and the short legs. It is also robust to the Fama-French (1993) and Carhart (1997) risk factors. This is a strong result given that our long-short portfolio comprises all of the sample stocks – in contrast to the standard approach to long-short portfolio construction that comprises only the extreme performers. A key finding from our portfolio analysis is that the full corpus tone is associated with a short-term overreaction that is fully reversed on day +2. For the newswire corpus, we find that the long-short portfolio earns positive but insignificant next-day returns – suggesting that there is little delay in the impounding of news into stock prices. Further, we find no evidence of longer-term 'drift' in returns using either the full or the newswire corpus. What we do find using both corpuses is that the long-short portfolios yield significant holding period returns (HPRs) of around 2 percent for holding periods of up to 250 days post-formation, and that these effects are driven by short positions in the high-negative tone stocks. This suggests that the combined effects of negative firm-specific news (in the form of media-expressed tone) across firms and over time is permanently reflected in aggregated returns.

Many studies of the media's effect on stock returns use 'media coverage'; that is, the count of articles or simply the existence of a news article, rather than tone (Chan, 2003; Vega, 2006; Barber and Odean 2008, Fang and Peress, 2009; Engelberg and Parsons, 2011, Hillert, Jacobs and Müller, 2014). We re-run our long-short analyses using the daily count (or 'coverage') of articles, this time taking a long position in the 'low coverage' and a short position in 'high-coverage' stocks. We find no evidence that media coverage affects next-day returns. The longer-term effect, however, is very similar to our findings using negative tone: the long-short portfolio HPR converges to about 2 percent, and this is driven by the short leg containing the high-coverage stocks. This suggests that the count of media articles might be a proxy for negative tone. We confirm that the general media, as represented by our full corpus,

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is significantly biased toward negative news stories. Furthermore, this bias cannot be traced to newswires or to news releases by the firm in the form of 8-Ks. It follows that the news media is more likely to pick up and run with bad news stories.[8] This finding may provide a partial explanation for the findings of studies such as Chan (2003) and Fang and Peress (2009) – that high media coverage stocks underperform low or no-coverage stocks.

The literature on the arrival and processing of market-relevant information has sharpened our understanding of what occurs during the time between information becoming available and its being impounded into stock prices (Campbell and Hentschel, 1992; Andersen, 1996; Engelberg, 2008; Engle, Hansen and Lunde, 2012; Demers and Vega, 2014; Heston and Sinha, 2014). A potential explanation for return persistence in our enduring episodes is that some bad news events are sufficiently complex or ambiguous that some 'processing' is needed before investors get a full understanding of their implications for firm value (Engle, Hansen and Lunde, 2012), or that 'soft' information (as opposed to 'hard' information such as financial statements) takes longer to be impounded into prices because it is more costly to process (Engelberg, 2008; Demers and Vega, 2014). Several recent studies suggest that the media can play a role in this process (Dougal et al., 2012; Engle, Hansen and Lunde, 2012; Boudoukh et al., 2013), and our paper shows how this occurs at the firm level.

The remainder of our paper is structured as follows. In the next section we describe the data and present summary statistics. In section 3, we present our initial panel analysis, followed by our more detailed rolling regression VAR models for each firm. In section 4, we further test our findings by running our tests on the newswire corpus. In section 5 we conduct our long-short portfolio analyses, and in section 6 we present our 'count' portfolio analysis. Section 7 summarises and draws together our main conclusions.

[8] This is well understood in the media and politics literature; see, for example, Trussler and Soroka (2014).

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2. Data

In order to construct the best possible dataset of firm-specific media-expressed tone at the daily frequency, we need to select firms for which news and commentary articles are likely to be available most days. Our sample comprises the 20 largest non-financial US companies on the 2011 *Fortune 500* list that have a sizeable daily news flow over the 10-year period from 1 January 2001 to 31 December 2010. The firms are Apple, AT&T, Boeing, Chevron, Cisco Systems, ConocoPhillips, Dell, ExxonMobil, Ford, General Electric (GE), Hewlett Packard (HP), Home Depot, IBM, Intel, Johnson & Johnson (J&J), Merck, Microsoft, Pfizer, Verizon Communications, and Walmart.[9] We obtain daily closing prices and trading volumes for each firm from Thomson Reuters Datastream. Stock prices are adjusted for dividends and splits. The CRSP NYSE/AMEX/NASDAQ value-weighted return is our proxy for the return on the market.

2.1 The media corpuses

Given that most of our sample firms are highly multinational and their 'corporate brands' are well-known throughout the world, they are potentially of interest to investors everywhere. Our full text corpus (the *full corpus*) is drawn from the *LexisNexis News and Business* electronic news database's 'all English language news,' which includes articles from newspapers, newswires, industry and trade magazines, financial blogs and other web-based publications around the world. Our *newswire corpus* is drawn from the 421 newswire services in the LexisNexis database.

A news item about a particular firm often refers to other firms in the same or related sectors, such as customers, suppliers or competitors, so it is important to select news items

[9] Three firms do not have sufficient news stories early in our data period. For ExxonMobil, the start date is 1 Jan 2005, and for ConocoPhillips and Chevron it is 1 Jan 2006. Because the data sets are truncated for these firms, we use a reduced sample of 17 firms for the panel analysis in section 3.

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whose primary content is the particular firm. Techniques for retrieving texts using keywords often include statistical methods to measure the overall relevance of the text to the keywords based on their frequency in the document (Manning, Raghavan and Schütze, 2008). Another method identifies the location of the keyword in a text; for example, if a word or term appears in the title of an article, the article will be more relevant to the keyword than if it appears in the body of the text. In compiling our corpus, we searched for articles that contained the firm's name in the headline as well as at least five additional mentions in the text. To further ensure that the retrieved articles were written specifically about the particular firm, we chose the *LexisNexis* option 'strong references only'. Lastly, we removed articles with a high similarity to previously published content.[10] This is essential because articles are duplicated as a result of media syndication, and because websites often repeat newspaper and other articles and commentaries. By doing this we remove a potential source of media-expressed tone identified by Tetlock (2011) as 'stale' news that is contained in news articles with a high degree of similarity to previously published articles.

Table 1 provides media article information by firm for the full corpus and the newswire corpus. Our search of *LexisNexis News and Business* yielded 5,673,793 articles for the full corpus, or on average 20 articles per day for each firm. The firms with most articles are Microsoft, Boeing and IBM, with an average of 46, 43 and 37 each day respectively. The column headed 'Days with no articles' shows that we have chosen our sample of firms effectively to ensure that there are very few days without articles. For Microsoft and Verizon, there are articles every day, and no firm has more than 30 days without an article[11]. In the newswire corpus, there are on average 4 articles per day for each firm, ranging from 13.4 for Microsoft to 0.6 for HP. For many firms there is a high proportion of days on which no

[10] This is accomplished using the program *Rocksteady,* which will be described in section 2.2.

[11] Tetlock (2007) and Ferguson et al., (2013) exclude days with no news articles.

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newswire article appears – an average of 23 percent of days.[12] Twenty percent of the full corpus comprises newswire articles, with 18 percent of total words coming from newswires.

~ Table 1 about here ~

2.2 Media-expressed tone

There is a burgeoning literature on textual news analytics in financial economics. Mitra and Mitra (2011) survey the many recent sources of news analytic data, algorithms, metrics and studies of their applications. We use the tone analysis program *Rocksteady*[13] (Ahmad, 2014), which is designed to be used with generalist or specialist word lists or dictionaries. Amongst the most popular word lists are the dictionaries within the General Inquirer (GI) software, most of which come from the Harvard IV-4 dictionaries; these have been used by Tetlock (2007), Tetlock et al., (2008), Engelberg (2008), Feldman et al., (2010), Kothari, Li and Short (2009), and Rees and Twedt (2012). General-use dictionaries like the Harvard IV-4 are not ideal for use in finance research. Loughran and McDonald (2011) find that almost three-quarters of the negative word counts using the GI software are attributable to words that are typically not negative in a financial context, and Heston and Sinha (2014) show that sentiment measures extracted from the Harvard IV dictionaries and Loughran and McDonald's (2011) word list are in fact negatively correlated. We use the Loughran and

[12] Our firms are undoubtedly high-coverage firms. Heston and Sinha (2014) show that for the largest decile of their sample firms, the average number of news stories per week is 7.63, and over 90 percent of firms in their smallest three deciles have zero news items per week. Similarly, amongst Fang and Peress's (2009) sample firms, more than a quarter do not feature in the 4 US national newspapers in a typical year; for those with media coverage the median number of articles per year is 5. Using the same set of newspapers as Fang and Peress (2009), each firm in Hillert, Jacobs and Müller's (2014) sample has an average of 16 articles (and a median of 3) per year. Using the Dow Jones newswire service, Boudoukh et al., (2013) find that 57 percent of their stock-day observations contain no news article.

[13] *Rocksteady* can aggregate the frequency of words in a document according to word categories and aggregate frequency over time-scales. It also has facilities for sophisticated terminology management. Computational linguists have in the past half century developed approaches to identifying the grammatical categories of words within text to a high degree of accuracy. Modern systems understand, for example, that *rose*, *rise*, *risen*, and *rising* are the morphological variants of the same root *rise*. These systems can also automatically identify that the word *share*, when used in financial texts, is a noun rather than a verb – so-called *automatic syntactic* analysis. *Rocksteady* performs this automatic morphological and syntactic analysis.

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McDonald (2011) dictionary.[14] Specifically, we use Loughran and McDonald's (2011) 'finance negative' list of 2,349 words that are typically negative in finance and business contexts. We construct daily measures of negative media tone for each firm with reference to the date and time stamp on each news item, adjusting for time zone differences. We express the frequency of the 'finance negative' words as a proportion of the total words in the day's articles pertaining to each firm, and setting the score to zero on days when there are no articles, we obtain our negative tone (*NT*) measure for each firm. A rise in the *NT* series indicates greater negative sentiment.

2.3 Summary statistics

Table 2 presents summary information for the characteristics of our sample firms and the negative tone for each derived from the full and newswire corpuses. Columns (1) to (4) show respectively firm size by market capitalization (as at November 2011), annual revenue (from the 2011 *Fortune 500* list), annualized average return, and the average daily number of shares traded (in millions). These figures confirm that our sample firms are large and their stocks are highly liquid. Our largest firm by market cap is ExxonMobil at $377 billion, and the smallest is Dell ($28.2bn). Despite their difference in size, these two firms have similar daily trading volumes of 25.5 and 23.7 million shares respectively. Columns (5) to (9) present descriptive statistics for the full corpus *NT* series, and (10) to (14) for the newswire series. The negative tone scores extracted from the newswire corpus have a lower average than for the full corpus, 1.03 versus 1.20, but the variance of the newswire tone is almost three times greater than that of the full corpus. We will consider this further in section 4.

~ Table 2 about here ~

[14] See http://nd.edu/~mcdonald/Word_Lists.html. The L&M finance dictionary has also been used by Doran et al., (2010), Rees and Twedt (2012), Heston and Sinha (2014), Garcia (2013), Jegadeesh and Wu (2013), and Chen et al., (2014), among others.

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Comparison of the firm-level returns (column 3 of Table 2) with the means of the *NT* series provides an initial glimpse at the relation between each firm's average negative tone score and stock return. As might be expected, high negative tone is associated with weak firm-level returns. For example, the pharmaceutical firms Pfizer and Merck have the highest full corpus *NT* scores (and the third and fourth-highest newswire *NT* scores), as well as amongst the lowest average annualised returns over the period: -5.1 and -0.6 percent respectively.

Our sample provides clear evidence of the extent to which firm-specific tone (drawn from the full corpus) varies across firms and over time. Column (5) of Table 2 shows that the average of the three most negative tone scores (Pfizer, Exxon Mobil and Walmart) is 1.52, which is almost double that of the three least negative scores (Cisco, IBM and Intel) at 0.87. Column (8) shows that differences in the variance of *NT* over time is even more pronounced than in their means. The average of the three most volatile firm-specific tone scores (Exxon Mobil, J & J and Merck) at 0.66 is more than three times that of the three least variable scores (IBM, Verizon and either Boeing, Dell, GE or Walmart) at 0.18.

2.4 Correlations and autocorrelations

Panel A of Table 3 presents the correlations for our sample firms' firm-specific negative tone (*NT*) scores derived from the full corpus. One-half (95) of the correlations are significant at the 5 percent level, of which three quarters (71) are positive and the remaining 24 are negative. The largest positive *NT* score cross correlations can again be seen amongst the oil companies – Chevron-ConocoPhillips (0.72), ConocoPhillips-ExxonMobil (0.56), and ExxonMobil-Chevron (0.53). Amongst the largest negative correlations are AT&T-Chevron (-0.28), AT&T-ConocoPhillips (-0.27), Chevron-Microsoft (-0.27), and ConocoPhillips-Microsoft (-0.25). Although there are three times as many significantly positive correlations

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as negative, they are mostly small in magnitude, indicating that our firm-specific tone scores are essentially idiosyncratic.

Panel B of Table 3 presents the autocorrelations for our firm-specific *NT* scores derived from the full and newswire corpuses. Fig. 1, which depicts mean autocorrelations at each lag, shows that the autocorrelations of *NT* for the full corpus are on average double those of the newswire corpus. It is clear that the full corpus tone has the greater temporal dependency – as commentators, analysts and bloggers in the broad media contribute analysis and opinion and come up with new angles on the news, until the story eventually becomes stale. The fact that the newswire corpus has lower temporal dependency is consistent with the idea that it is a purer source of news. Looking closely at the individual autocorrelations in Panel B of Table 3, two observations are noteworthy. *First*, our finding that the newswire tone has less temporal dependency than the full corpus tone applies not just to the average, but to each individual firm. *Second*, the temporal dependence in firm-specific tone differs considerably across firms. For example, the average of the largest three lag 1 autocorrelations of firm-specific tone for the full corpus (for Microsoft, Boeing and HP) at 0.48 is more than three times the average of the smallest three lag 1 autocorrelations (for ConocoPhillips, Home Depot and Walmart) at 0.17. This lends weight to the main argument of our paper: that focussing on the time-varying nature of the relation between firm-specific tone and firm-level returns *at the level of the individual firm* is illuminating because each firm's experience is quite unlike any other. These differences cannot be observed when using the aggregative approach common in prior studies.

~ Table 3 and Fig.1 about here ~

3. Panel and VAR analyses: full corpus

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We earlier alluded to the data limitations in constructing useful time-series of firm-specific tone. Researchers such as Engelberg (2008), Tetlock et al., (2008), Sinha (2012), Dougal et al., (2012), Ferguson et al., (2013)[15], Boudoukh et al., (2013), Dzielinski and Hasseltoft (2013), Sinha (2012) and Chen et al., (2014) have either combined a series of firm-specific media news stories into a single measure of 'firm-level' tone and regressed this on a market index return, or alternatively have formed a corpus of 'firm-specific' tone and combined these within a panel regression framework to examine its impact on firm-level returns[16]. No study that we are aware of has yet constructed a set of firm-specific corpuses of media-expressed tone for individual firms and separately modelled the time-varying interaction between each firm's negative tone and its stock returns. It is appropriate, however, that we begin by putting our firm-specific corpuses to work using a combined panel approach to see if they predict next-day returns in a manner consistent with the prior literature.

3.1 Panel

To facilitate the construction of a balanced panel, we include the 17 firms for which the full 10 years of the *NT* series is available. This yields a panel with 2,515 observations per firm and 42,755 observations in total. We estimate two models as follows:

$$R_{i,t} = \alpha_{1,i} + \sum_{k=1}^{5} \beta_{1k} R_{i,t-\mathrm{k}} + \sum_{k=1}^{5} \delta_{1k}\, NT_{i,t-k} + \theta_1 DMon_t + \tau_1 DJan_t + \varepsilon_{i,t}^{R} \quad (1)$$

$$NT_{i,t} = \alpha_{2,i} + \sum_{k=1}^{5} \beta_{2k} R_{i,t-\mathrm{k}} + \sum_{k=1}^{5} \delta_{2k}\, NT_{i,t-k} + \theta_2 DMon_t + \tau_2 DJan_t + \varepsilon_{i,t}^{NT} \quad (2)$$

[15] Like Tetlock et al., (2008), Ferguson et al., (2013) also exclude all dates on which there are no news articles for each firm. We do not do this. Leaving the zero news dates in the data set tends to bias our coefficients to zero, so in our analysis finding significant effects is harder. However, by focussing on large, well-known stocks, we have very few non-news days.

[16] We refer to *firm-level* tone as being a single aggregate measure of tone that is obtained from news media stories relating to identified firms that are combined before tone is extracted. In contrast, we refer to *firm-specific* tone as a measure of tone for each firm that is obtained from news media stories specific to each firm, and that is not aggregated across firms. This results in a measure of 'firm-specific' tone for each firm.

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In these models, $R_{i,t}$ is firm *i*'s stock return on day *t*, and $NT_{i,t}$ is firm *i*'s full corpus negative tone on day *t*. In Eq. (1) we regress firm-level returns on five own lags, five lags of *NT*, and two dummy variables controlling for Monday and January effects – *DMon* and *DJan*. In Eq. (2), negative tone (*NT*) is the dependent variable. The parameters are estimated using the dynamic panel estimation technique with firm fixed effects. In choosing the lag length, we experimented with a range of selection criteria including the Akaike information criterion (AIC), the Schwarz Bayesian (SBC) criterion, and the general-to-specific chi-squared (GTOS) test, starting with a maximum lag length of 5. This resulted in optimal lag lengths of between 1 and 5 lags, with the SBC yielding the shortest on average and the others tending towards 5.

The results from estimating the panels in Eq. (1) and Eq. (2) with Huber-White standard errors are presented in Table 4. In this specification, $R_{i,t}$ is firm *i*'s market-adjusted return on day *t*. Columns (1) and (2) present our estimates with *NT* as the dependent variable (Eq. (2)), and in columns (3) and (4) return is the dependent variable (Eq. (1)). The coefficients have been multiplied by 100. We expect to find a negative sign on the coefficient for the first lag of *NT* in Eq. (1), indicating that a rise in *NT* is associated with lower next-day returns. Column (4) in Table 4 shows that this is indeed the case, with the coefficient on the first lag of *NT* in the return equation being -0.046 and statistically significant at the 1 percent level. This is consistent with previous research examining media-expressed tone using aggregated or market-level data – that greater negative tone predicts lower next-day returns. In contrast to prior findings (Tetlock, 2007; Garcia, 2013; Ferguson et al., 2013), however, we find little evidence that this initial effect dissipates over subsequent days. Rather, we find evidence of persistence insofar as the sum of the coefficients on lags 1 to 5 of *NT* in the return equation at

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-0.101 (column 4 of Table 4) is significant at the 5 percent level and reinforces the initial effect. The sum of lags 2 to 5 is negative but insignificant at standard levels. [17]

~ Table 4 about here ~

In the negative tone equation, we find that lower firm-level returns lead to greater next-day firm-specific negative tone (column 1 of Table 4); the coefficient on the first lag of returns at -106.6 is highly significant (p = .00). Like Tetlock (2007) and others, therefore, we find that the causal link between negative tone and returns goes both ways: greater negative tone causes lower next-day returns *and* lower returns predict greater next-day negative tone. In robustness tests using unadjusted returns, abnormal returns calculated using the Fama-French 3-factor model, including trading volumes as an additional explanatory variable to capture the information transmission effects associated with the mixture of distributions hypothesis[18], and winsorising variables at the 1 percent level to eliminate the effects of extreme observations, the panel estimates of the relation between negative tone and returns are similar to those reported in Table 4.[19]

3.2 VAR analysis of each firm

Canova and Ciccarelli (2013) review the specifications and applications of panel VAR models used in economics and finance, and note their capacity to capture both static and dynamic interdependencies such as the links across units at each point in time and over time as they respond to shocks. We have seen how variations of these models have been used to study the relation between media-expressed tone and firm-level returns, and how data

[17] Note that our findings cannot be explained by an 'echo' effect of news articles – that is, investors overreacting to news that is 'stale' (Tetlock, 2011) – because we remove articles with similar content to prior articles.

[18] See, for example, Gallant, Rossi and Tauchen (1992), Richardson and Smith (1994), Lo and Wang (2000) and Hill (2010).

[19] The results from these robustness tests are available from the authors on request.

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limitations on the number of news articles available at the level of the firm have necessitated compromise in model specification and testing. This is nothing new, and is known as the 'curse of dimensionality,' whereby allowing for cross-sectional heterogeneity along with static and dynamic interdependencies leads to rapid explosion in the number of parameters to be estimated relative to the availability of data. Combining firm-specific news stories into an aggregate 'firm-level' news corpus prior to extracting its tone ameliorates the dimensionality problem by creating a general measure of corporate sector tone that is not specific to individual firms. Alternatively, pooling a series of individual firm-specific tone scores within a cross-section or time series panel to estimate how they relate to firm-level returns makes the implicit assumption that the underlying relation is the same for each firm and constant over time (see Holtz-Eakin, Newey and Rosen, 1988). Introducing fixed effects into the panel allows the constant term, and thus the levels of media-expressed tone and firm-level returns to differ across firms, and allowing heteroscedasticity in the errors allows differences in the variability of each firm's tone and stock returns. Neither, however, permits unconstrained variations in the correlations between these variables across different firms and over time. As Canova and Ciccarelli (2013) point out, optimal model selection depends on the context, and having constructed a sufficiently large corpus for each firm, we can overcome the 'curse of dimensionality' by estimating separate VAR models for each firm. In doing so, we make differences in how firms respond to media-expressed tone the prime focus of our paper, rather than the static and dynamic interdependencies.

The vector autoregressive (VAR) model introduced by Simms (1980) has been widely applied across many topics in finance, and surveys of its structures and applications in inference, forecasting and simulation are provided by Tsay (2010), Lütkepohl (2014) and

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Pesaran (2015)[20]. In the news and tone literature, Da, Engelberg and Gao (2011) use weekly data from the *Dow Jones News Service* and the *Wall Street Journal* on Russell 3000 firms from January 2004 to June 2008 to model the relation between media attention, trading volumes and returns. Groß-Klußmann and Hautsch (2011) estimate high-frequency VAR models for 39 stocks traded on the London Stock Exchange to study the relation between news and trading activity. Dzielinski and Hasseltoft (2013) use a VAR model to study how the dispersion in aggregate firm-level news tone (derived from combining firm-specific news for *Fortune 500* firms from the *Thomson Reuters News Analytics* database) relates to alternative measures of analyst disagreement. Wisniewski and Lambe (2013) derive a measure of media pessimism about banking crises from news articles in *LexisNexis* containing the phrases 'credit crunch', 'financial crisis' and 'bank failures', and use VAR models on monthly data from Canada, the United Kingdom and the United States to show how negative tone Granger causes banking stock returns rather than *vice versa*.

We conduct our time-varying, firm-level analysis by estimating a series of separate rolling regression 1-year window VAR models for each of the 20 large firms in our sample, over the 10-year sample period from January 2001 to December 2010. The VAR models take the familiar form:

$$A(L)x_t + By_t = u_t \tag{3}$$

with

$$A(L) = 1 - A_1 L - A_2 L^2 - \ldots\ldots - A_p L^p,$$

$$E(u_t) = 0, \quad E(u_t u'_t) = \Sigma, \quad E(u_t u'_s) = 0, \text{ for } t \neq s, \quad E(x_t u_t) = 0,$$

[20] Applications of VARs in finance have a pedigree; see, for example, Booth et al., (2002); Brandt and Kang (2004); Lee and Rui (2007); Booth and Gurun (2008); Joslin, Le and Singleton (2013); and Maio and Santa-Clara (2015). Applications of time-varying VARs include Serrano and Hoesli (2007); Benati and Goodhart (2008); and Koop and Tole (2013).

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$x_t = (R_t, NT_t)$, and $y_t = (Const, DMon, Djan_t)$

This is a standard VAR representation in which x is a (2×1) vector of endogenous variables, A is a (2×2) matrix of coefficients, u is a (2×1) vector of white noise disturbance terms, and L denotes the lag operator (for example, $L^i x_t = x_{t-i}$). The y vector contains the constant term, *Const*, and the controls *DMon* and *DJan*. These VAR models allow us to examine the interactions between firm-level returns (*R*) and firm-specific negative tone (*NT*) for each firm. In specifying our VAR models, it is necessary to first determine the orders of integration of the variables to be included. Intuitively, it is possible that the stock prices are cointegrated with the tone scores in a series of long-term relations. If this is the case, we should incorporate these long-term cointegrating relations in our VAR models for each firm – by specifying the associated error correction models. Our unit root analysis of the stock prices for each firm reveal that 12 are I(1) and the remaining 8 are I(0) at the 5 percent significance level. Further, all 20 of the negative tone (*NT*) series are I(0) at the 1 percent level. We conclude, therefore, that there is no long-run cointegrating relation between the level of stock prices and the negative tone score for any of our sample firms, and we therefore estimate the VAR models using the firm-level returns and firm-specific negative tone scores.

A convenient feature of the VAR representation in Eq. (3) is that it can be estimated by ordinary least squares, which provides consistent and asymptotically efficient estimates of the A matrix because the right-hand-side variables are predetermined and are the same in each equation of the model. The first step in the estimation process is to decide on the appropriate lag length (p). As with the panel estimates, we experimented with the AIC, SBC and GTOS tests, starting with a maximum lag length of 5. This resulted in optimal lag lengths of between 1 and 5 lags, with the SBC being the shortest on average and the others tending towards 5. We subjected this to a robustness test by using the same three selection criteria commencing with

10 lags. This led to a range of 3-10 lags for the AIC, 1-5 lags for the SBC, and 3-10 lags for the GTOS test, with average lags of 6, 2 and 7 respectively for the AIC, SBC and GTOS criteria across all our sample firms. Given that we are estimating firm-specific VAR models in which the optimal lag lengths will vary to some degree, we choose 5 lags as the pragmatic solution that captures the obvious richness in dynamics without exhausting the necessary degrees of freedom.

In a first step, we estimate Eq. (3) for the full period for each firm.[21] Our findings are inconclusive. Negative tone has a jointly significant effect on returns for only two firms, and *NT* has a significantly negative impact on next-day returns for only one firm. It is clear that our panel and full-period VAR analyses of the negative tone-return relation conceals a more complex story at the level of the firm. A potential explanation might be found in Das and Chen (2007), who similarly find a significant relation at the market level between investor sentiment (derived from postings on Yahoo's stock message board) and stock returns, but not at the firm level. They argue that this is because at the market level the idiosyncratic element of firm-specific tone is washed out. We advance an alternative explanation: the relation between firm-specific tone and firm-level returns is time-varying in nature, and occurs episodically rather than continuously.

3.3 Rolling window estimates

To examine the possibility that the relation between firm-specific tone and firm-level returns is time-varying and episodic, we estimate a series of rolling VAR models as described in Eq. (3) for each firm using a 1-year (250-day) window that is rolled forward a day at a time. Table 5 presents our findings. Fifteen firms have at least one episode during which negative tone leads to a significant reduction in next-day returns. For these firms, the table details the

[21] For the sake of brevity we do not provide tabulated results; they are available from the authors on request.

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periods during which this occurred (the column headed 'Lag 1 significant'), and the periods in which the initial decline in returns either persists ('enduring') or reverses ('transitory'). We detail for each firm the number of significant episodes, the proportion of the 10-year sample period in which the significant episodes occur, and the associated dates. (Given that we are using one-year windows, each period is at least a year long.) We find 20 episodes of significantly negative first-lag effects of negative tone on returns, and on average the firms encountered these episodes for 18 percent of the sample period, or almost two years. This is a key finding of our paper, and it is consistent with the notion that firm-specific media-expressed tone impacts next-day firm-level returns episodically.

~ Table 5 about here ~

A major objective of our rolling regression analysis is to distinguish periods during which firm-specific tone has enduring effects on firm-level returns from periods where the effect is transitory. We identify each of these periods as follows. An *enduring* episode is a period during which (at the 5 percent level) the first lag of tone is significantly negative, *and* the sum of lags 1 to 5 is significant and negative; in these cases the initial negative shock to returns persists. A *transitory* episode is when the first lag of tone is significantly negative, *and* the sum of lags 2 to 5 is significant and positive.[22]

We find 5 enduring and 5 transitory episodes. Fig. 2 depicts the rolling regression coefficients for the firms with transitory periods (Panel A), and enduring periods (Panel B) – demonstrating the time-varying nature of the relation between media-expressed tone and lagged returns. As well as the coefficient on lag 1 of *NT* in the return equation, Panel A shows the sums of the coefficients of lags 2 to 5 and Panel B show the sums of the coefficients on

[22] For those firms for which lag 1 is significant and negative but there are no enduring or transitory effects are reported, neither the sum of lags 1 to 5 nor lags 2 to 5 are significant at the 5 percent level. It is therefore not possible to definitively identify the direction of returns vis-à-vis *NT* after the first lag.

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lags 1 to 5. Both figures also include 'significance markers' which mark the significant episodes. As seen in Panel A, the transitory episodes arise when the coefficient on lag 1 and the sum of lags 2 to 5 move in the opposite direction, and in Panel B the enduring episodes occur when the first lag and the sum of lags 2 to 5 move together. When we appropriately allow for time-varying effects of media-expressed firm-specific tone on firm-level returns, we find a richer set of outcomes than has been reported to date insofar as tone can have both permanent and transitory effects on subsequent returns. This suggests that media-expressed tone drawn from a large corpus can be pure *sentiment* (DeLong et al., 1990; Tetlock, 2007), and it can also be *news*. We discuss the implications of the latter in the next section.

~ Fig. 2 about here ~

4. Analysing the newswire corpus

If newswire articles contain 'news' in the sense that they are conduits for the dissemination of new information to the market, an efficient markets perspective would suggest that stock prices react quickly and unbiasedly to newswire tone. A few recent studies that have examined the effect of newswire tone on returns show that this is not the case. Tetlock et al., (2008) find that newswire tone is impounded in stock prices with a 1-day delay. Sinha (2012) finds that stock prices underreact to newswire tone, showing return drift over 13 weeks, and Heston and Sinha (2014) show return reversals after 1 or two 2 days as well as longer-term drift effects. Boudoukh et al., (2013) show that the speed of incorporation of news into stock prices declines with its complexity.

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Table 6 presents our panel analysis results using firm-specific tone extracted from the newswire corpus. Consistent with the panel results for the full corpus, we find a significant next-day decline in returns, and persistence in the effect of negative tone on returns (column 4). Unlike the full corpus, however, we find that the sum of lags 2 to 5 is negative and statistically significant ($p = 0.05$). Further, the coefficient on lag 1 (-0.021) is less than half the size of the equivalent coefficient in the full corpus panel (-0.046). In sum, we find that negative tone extracted from the newswire corpus is associated with a weaker next-day return reaction but with stronger persistence over time.

~ Table 6 about here ~

If newswire articles are 'pure' news, returns should not affect subsequent newswire tone. While we find no significant effects of returns on newswire tone at lags 1 to 4 inclusive (column 1 of Table 6), the coefficient on lag 5 is highly significant and negative; a reduction in returns leads to greater negative newswire tone five days later. A possible explanation for this can be found in Dougal et al., (2012), who suggest that as well as providing interpretation and commentary related to news events, journalists sometimes create new content. Particularly value-relevant bad news may inspire investigative journalists to dig further and uncover additional elements of the story, or possibly related news. It is not uncommon for this journalist-generated news to be picked up and reported by the newswire services. An example from our data set relates to Verizon Communications. Following a run of bad news involving poor performance, layoffs and calls for corporate governance reform through 2001 and into 2002, the *New York Times* broke a story about a new round of redundancies. This was picked up and reported by the newswire services.[23]

[23] "Verizon Wireless Plans To Lay Off 1,000 Workers – NYT", *Dow Jones International News*, 15th February, 2002.

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When we repeat our firm-specific full-period VAR analysis with negative tone from the newswire corpus, we again find little in the way of significant effects. Negative tone has a jointly significant effect on returns for three firms, and we no evidence at all of significant negative next-day effects on returns.[24] Table 7 presents our findings for the rolling VAR analysis. For 15 firms we find 21 episodes during which negative newswire tone leads to a reduction in returns the next day. Consistent with our findings using the full corpus, therefore, the negative tone extracted from newswires impacts next-day returns episodically. If newswire tone reflects genuine news, it should have permanent effects on returns. This is essentially what we find: there are 7 enduring episodes and only 1 transitory episode, and this is consistent with the view that firm-specific tone extracted from our newswire corpuses contains new fundamental information about the firms. Note that all eight of these episodes occur at different times to the enduring and transitory episodes that we find using the full media corpus.

~ Table 7 about here ~

A novel finding of our paper is that enduring or persistent episodes occur for both the full and the newswire corpuses. This phenomenon fits with two theoretical ideas. The *first* is underreaction to news due to slow diffusion of information (Hong and Stein, 1999), or due to behavioural biases (Barberis et al., 1998; Daniel et al., 1998). The *second* is that certain types of information need close analysis or 'processing', which can take time. Engelberg (2008) argues that information is not homogeneous, and that 'soft' information (as opposed to 'hard' information such as financial statements) takes longer to be impounded into prices because it is more costly to process. Engle, Hansen and Lunde (2012) similarly suggest that following the arrival of public news, private information is generated over time by the processing of

[24] In the interest of brevity, these results are not tabulated. Full results are available from the authors on request.

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public information; they call this the 'information processing hypothesis.' An implication of our full corpus finding that some episodes are enduring is that, consistent with Engle, Hansen and Lunde (2012), Dougal et al., (2012) and Boudoukh et al., (2013), journalists and other expert commentators may play a role in interpreting or processing complex or 'soft' information.

5. Portfolio analysis

The strength of our findings about the impact of firm-specific tone on next-day firm-level returns suggests the possibility of a successful trading strategy. In our long-short analysis, we use the overlapping holding period approach of Jegadeesh and Titman (1993) with a daily formation period. On each day, we sort our 20 stocks from highest to lowest negative tone. We take a long position in an equally-weighted portfolio of the 10 stocks with the lowest negative tone, and we short the 10 stocks with the greatest negative tone. We calculate two sets of average return metrics for the long-short portfolio and for each leg of the strategy: *first*, mean post-formation holding period returns (HPRs) of 1 to 250 days,[25] and *second*, mean daily returns for each of the 10 post-formation days. The latter allows us to focus on the length of time that any return effects persist. Fig. 3 depicts these HPRs and returns in annualised percentage form; Panel A for the full corpus and Panel B for the newswire corpus.

~ Fig. 3 about here ~

Short-term effects. For the full corpus (Panel A), there is substantial overreaction to negative media-expressed tone on day +1 post-formation. The long-short strategy yields a highly significant (p = 0.00) annualised return of 17.4 percent, and this is driven by symmetric

[25] We use this approach rather than the standard cumulative return method, because we believe it yields a more illuminating picture of average portfolio returns – enabling us to observe both short-run and longer-run effects.

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effects on each leg of the strategy: a next-day return of 8.1 percent for the low negative tone portfolio and -8.0 percent for the high negative tone portfolio. This strong day +1 HPR subsequently drops dramatically to 7.6 percent for the two-day holding period, and for the three-day period the HPR is 5 percent. The day +1 return is in fact completely reversed on day +2. This can be seen in the graph depicting annualised daily returns in the 10 days post-formation; from day +2, the post-formation returns are near-zero and are insignificant at standard levels. For the newswire corpus (Panel B) the next-day return to the long-short portfolio of 6.1 percent is about one-third the size of the full corpus day +1 return, and it is not significant ($p = .16$), as are the days +2 to +10 daily post-formation returns.

If the next-day return on the long-short strategy can be explained by known risk factors, the alphas generated using the Fama-French (1993) 3-factor and the Carhart (1997) 4-factor models should not be significant. Table 8 presents results on the returns to the long-short portfolio, and each leg of the strategy separately, using both the full corpus and the newswire corpus. For the full corpus, the long-short portfolio return loads negatively on UMD, indicating a negative correlation with the momentum factor, and this can be traced to a highly negative loading for the low negative tone (long) leg offsetting a much smaller negative loading on the high negative tone (short) leg. The long-short portfolio alpha is highly significant, as are the alphas for the each leg separately. Consistent with the day +1 returns depicted in Panel A of Fig. 3, both the long and short legs contribute more or less equally to this.[26] In contrast, the alphas for the newswire tone long-short portfolio are not significant,

[26] We are confident that this effect is short-term. We have conducted several alternative analyses with various formation and holding periods. We have also investigated the possibility that media-expressed negative tone is associated with longer-term momentum: one month, three month and six month formation periods, and for each,

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and the loading on UMD is positive – which is purely driven by a strongly negative loading for the short leg.[27] Our findings for the full corpus are impressive given that our long-short portfolio comprises *all* our sample stocks – rather than extremes of the formation period sorts as in standard long-short analysis as well as in prior studies that create long-short portfolios on the basis of media-expressed tone (Tetlock et al., 2008; Sinha, 2012).[28] Further, our data period includes the 'momentum crash' of 2009 (Barroso and Santa-Clara, 2015).

~ Table 8 about here ~

The spike in returns followed by reversion might be explained at least partly by short selling activity. Engelberg, Reed and Ringgenberg (2012) find that shorting on negative news days earns short-sellers four times the mean return to short selling, suggesting that short-sellers have a superior ability to process the 'soft' information in news announcements (Engelberg, 2008; Demers and Vega, 2014). Short-sellers may contribute to the day +2 reversal for the long leg (the low negative tone stocks), as they observe and then act on the excessively positive next-day reaction to 'good news' (low levels of negative tone). It is also

1,3,6,9 and 12 month holding periods. In every case, for both the full and newswire corpuses, the alphas are far from significant.

[27] As shown in Table 1, there is no firm for which a newswire appears every day. In the approach that we use, the 10 firms with the highest negative tone are the "high negative tone" stocks (and we take a short position in these), and the remainder are considered the low negative tone stocks (and we take a long position in these). Using this approach, many "low negative tone" stocks in fact had no newswire article that day. Further, an analysis across all firms shows that on a small minority of days – 4.3 percent of the time – half or more of our firms have no news article. On these days, therefore, it is not possible to extract a tone measure for the low-negative tone portfolio; tone is therefore zero for this portfolio. We therefore use an additional approach to sorting the stocks. During the portfolio formation period, we remove firms that had no newswire article that day. We sort the remainder into low negative tone and high negative tone groups. Our findings using this approach yields a day +1 return of 10.3 percent, but as in our main findings this is not significantly different from zero at standard levels, and neither does it yield a significant alpha using Fama-French (1993) and Carhart (1997) risk factors. These findings are available from the authors on request.

[28] After demonstrating that their high negative tone portfolio leads to negative returns the next day, Tetlock et al., (2008) go on to show that transactions costs may eliminate any positive alpha. While we acknowledge that this may arise in our long-short analysis, it is likely to be less of an issue than in Tetlock et al., (2008) because the daily portfolio rebalancing involves a small number of stocks, and those stocks are highly liquid.

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possible that the day +1 return on the short leg (the high negative tone stocks) is due to short-selling in response to bad news, in which case short-sellers may be contributing to the overreaction to negative media-expressed tone.

Our long-short portfolio finding of short-term overreaction that is quickly traded away is consistent with the notion that negative media-expressed tone has a substantial element of sentiment. This is despite the fact that our sample of stocks are not expected to be particularly vulnerable to sentiment. Comparing the long-short portfolio short-term returns, the mean next-day return for the full-corpus portfolio is nearly three times the magnitude of that of the newswire portfolio – which is not significantly different from zero. These findings suggest that investors overreact to negative media-expressed sentiment, but not to bad news.

The evidence of initial overreaction followed by rapid reversion that we find is similar in spirit to studies of sentiment in other settings. Dougal et al., (2012) find some evidence of reversion within one day as a result of the pessimism and optimism biases of individual journalists, and Antweiler and Frank (2004) find that the number of messages posted on Yahoo's message board has a small but significantly negative effect on next-day returns that reverses on day +2.

Long-term effects. For the full corpus long-short portfolio (whose returns are depicted in Panel A of Fig. 3) the HPRs for the 3-day to 10-day holding periods are insignificant. At holding periods of 11 days and longer, however, they are significant.[29] With some initial volatility, the strategy settles down to a HPR of around 2 percent for holding periods greater than 60 days. It is clear that in the longer term, the return to the long-short portfolio of -2

[29] Given that there is much greater variance in HPRs for short holding periods versus long due to the averaging effect of returns over time, short holding period returns must jump a much higher hurdle.

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percent is driven by the short leg – whose HPR is significant at standard levels for holding periods of more than 20 days. In contrast, the low negative tone portfolio HPR hovers around zero, and is not significant at any holding period. This longer-term positive performance of the long-short portfolio suggests that highly negative media-expressed tone – drawn from a large media corpus – has a persistent longer-term effect on returns.

We find a similar pattern in post-formation HPRs using the newswire corpus. The newswire long-short portfolio HPRs are significant for the three-day and longer holding periods, and this again is driven by a HPR to the short leg of about -2 percent – significant at holding periods of more than 21 days. None of the long leg HPRs are significant. This similarity between the long-short portfolio HPRs is confirmed by a t-test of difference between the full and newswire corpus HPRs: for all holding periods from 2 to 250 days, there is no significant difference between the two. The fact that the longer-term performance of the long-short portfolios using the newswire and full corpus is so similar implies that this longer-term effect is driven by bad *news* rather than negative media sentiment. Once the initial overreaction to media-expressed sentiment is traded away, stock prices rationally reflect investors' revised beliefs about future returns to stockholders associated with negative news.

The prevailing theories of momentum in stock returns (Barberis, Shleifer and Vishny, 1998; Daniel, Hirshleifer and Subrahmanyam, 1998; Hong and Stein, 1999; Antoniou, Doukas and Subrahmanyam, 2013[30]) tend to imply that underreaction or overreaction to news

[30] Hong and Stein (1999) explain under- and overreaction in stock prices on the basis of the gradual diffusion of private information to the market, leading to underreaction in the short-run. Drawing on Griffin and Tversky (1992), Barberis, Shleifer and Vishny (1998) use representative heuristic and conservatism biases to explain underreaction and reversion. A series of good news leads to overoptimism because investors pay too much attention to the strength of a news signal, leading to overreaction, and subsequent news that contradicts this optimism leads to reversion. Daniel, Hirshleifer and Subrahmanyam (1998) draw on psychological theories of

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occurs over months rather than days. We find no evidence of longer-term over- or underreaction. However, they are relevant to our findings for two main reasons. *First*, although Hong and Stein's (1999) analysis focuses on longer-term underreaction, they argue that short-term underreaction to public news could be explained by the fact that information needs 'processing' – a similar idea to Engelberg (2008), Engle, Hansen and Lunde (2012), and Demers and Vega (2014). Although we cannot draw definitive conclusions as to whether our 'enduring episode' findings are best explained by irrational reactions to news by noise traders or by 'information processing', we argue that the latter provides the more plausible explanation. One of Hong and Stein's (1999) core propositions is that information is likely to diffuse more slowly for small firms, and this was demonstrated empirically by Hong, Lim and Stein (2000). For our large sample firms, therefore, 'information processing' should occur relatively quickly, and this may explain why we find no evidence of longer-term 'drift' (as found by Sinha, 2012 and Heston and Sinha, 2014). Rather, we find that the high negative tone portfolio earns a significantly negative 2 percent HPY over the year following portfolio formation, which suggests that negative tone drawn from both the full and newswire corpuses cause investors to rationally revise downward their estimates of fundamental firm value.

Second, the model of Daniel, Hirshleifer and Subrahmanyam (1998) differs from the other momentum theories in that it suggests initial overreaction rather than underreaction. Although this theory (along with the other momentum theories) seeks to explain longer-term rather than short-term swings away from fundamentals, it provides a potential explanation for our full corpus findings that negative media tone triggers a short-term return overreaction. Daniel, Hirshleifer and Subrahmanyam (1998) suggest that the psychological biases behind their theory – that investors are overconfident and exhibit biased self-attribution – are likely to

overconfidence and biased self-attribution, resulting in overreaction and long-run reversion. Antoniou, Doukas and Subrahmanyam (2013) describe how sentiment can influence the profitability of momentum strategies when news contradicts investors' prior sentiment – causing cognitive dissonance that slows down the rate of diffusion of the story.

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better explain momentum in securities with high barriers to arbitrage. Our findings are consistent with the spirit of this idea; overconfidence and biased self-attribution may contribute to the next-day spike in returns, and because our sample firms are highly liquid and are unlikely to be short-sales constrained this overreaction is immediately traded away by rational arbitrageurs.

6. Portfolio analysis using article count

Studies examining how news media impacts stock returns often use a 'count' approach, whereby media attention or news is proxied by whether an article has appeared (Chan, 2003; Barber and Odean, 2007), or how many have appeared during a given period (Fang and Peress, 2009; Hillert, Jacobs and Müller, 2014). In this section, we repeat our long-short analysis, this time sorting on the daily count of articles. Because prior studies have found that low- and no-media coverage stocks are associated with outperformance vis-à-vis high coverage stocks (Fang and Peress, 2009), we take a long position in the 10 stocks with the lowest count of articles, and a short position in the 10 highest count stocks. As described in section 2.1, newswire articles do not appear every day. For the newswire corpus, therefore, in addition to the approach used for the full corpus ('strategy 1'), we sort as follows. For each portfolio formation day, we define firms as those *with coverage* (firms with at least 1 newswire article that day) and those without – the *no-coverage* portfolio. The long-short strategy ('strategy 2') involves taking a long position in the *no-coverage* firms and a short position in the *coverage* firms. This is similar to the approach of Fang and Peress (2009), except that they use *high-coverage* firms rather than *coverage* firms, and omit from their long-short analysis the 'low-coverage' stocks. Fig. 4 replicates the graphs of Fig. 3 with the

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portfolio sorts conducted using count rather than negative tone. Panel A depicts the long-short HPRs full corpus and Panel B the newswire corpus.

Short-term effects. In stark contrast to the negative tone long-short analysis, for the full corpus (Panel A of Fig. 4) there appears to be very little short-term overreaction to the count of articles in the days post-portfolio formation. The 1-day return for the long-short portfolio is 3.7 percent, and this is not significant ($p = 0.81$). At first sight there appears to be a much greater return reaction to newswire count; the day +1 returns are 7.3 and 7.6 percent for strategies 1 and 2 respectively. However, these are also insignificant (p-values are 0.29 and 0.15 respectively). We find no evidence that the number of firm-specific media articles predicts firm-level returns in the short term. Our findings for the full corpus show that investors react to the qualitative information conveyed in media articles, rather than to media attention *per se*.

~ Fig. 4 about here ~

Longer-term effects. As we saw in section 5, long-short portfolios formed on the basis of negative tone tend to converge to a HPR of about 2 percent. This is also the case when the portfolios are formed on the basis of count; the return to the long-short strategy is significant at the 1 percent level for all holding periods greater than 12 and 4 days for the full and newswire corpus portfolios respectively. When we conduct paired t-tests of difference between full corpus HPRs calculated using negative tone versus count, we find that beyond day +1 the HPRs are not significantly different from each other at any holding period. We find essentially the same for the newswire corpus, except that the insignificant difference also

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holds for the day +1 return. The fact that a highly significant persistent 2 percent longer-term return is observed in both the count and negative tone portfolio analysis suggests that the count of media articles may be a proxy for negative tone. This suggests the possibility that – to adapt Campbell and Hentschel's (1992) term 'no news is good news' – *news is bad news*.

6.1 Is news bad news?

If the news media are even-handed in the sense that they are equally likely to publish positive and negative news articles, there should be no correlation between each firm's daily article count and negative tone. If, however, the media are more likely to run with bad news stories than good, there will be a positive correlation between count and negative tone. For the newswire corpus, most firms have insignificant correlations between negative tone and count, but of the three we find weakly significant ($p < 0.10$) are all positive. In newswire articles, therefore, there is a hint of bias toward the negative but no solid evidence. For the full corpus, in contrast, we find a strong negative bias. The mean correlation between article count and negative tone is 0.09 (for the newswires the average is 0.06), and 19 of our 20 firms show positive correlations, of which 13 are significant at the 1 percent level, with one other significant at the 10 percent level. The fact that newswires appear to report in a more-or-less even-handed manner while in the full corpus there is a strong bias toward the negative constitutes evidence that the non-newswire media are more likely to run with negative news than positive; that is, media attention as measured by the count of articles in our full corpus is a proxy for negative media tone.[31] Such a bias toward negative news stories is well-known in

[31] Our finding that 'news is bad news' contrasts with that of Boudoukh et al., (2013), who find that the tone score for 'identified' news events (that is, the most price-relevant news) is on average positive.

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the press and media literature (see, for example, Trussler and Soroka, 2014) and it has obvious implications for the relation between the count of media articles and stock returns. Chan (2003) finds that 'loser' stocks in the news experience negative return drift, while those without news experience return reversal. Fang and Peress (2009) find that stocks with a high count of newspaper articles underperform those with no articles, and that this 'no-media premium' is most apparent amongst loser stocks. Our findings suggest that these results may in part be explained by the fact that the news media are biased toward bad news. We further suggest that Chan's (2003) and Fang and Peress's (2009) findings may at least in part be due to the fact that *news is bad news*. The average correlation coefficient between the number of firm-specific news articles each day for the full corpus and the newswire corpus is 0.65, ranging from 0.81 for Apple to 0.27 for ExxonMobil. It is plausible, therefore, that the count of media articles is in fact a reliable proxy for the *arrival* of bad news.

6.2 8-Ks versus newswires

Form 8-K is the means by which the Securities and Exchange Commission (SEC) requires US firms to report information that is considered to be 'material'. In the early 2000s, the 8-K requirements were overhauled to include additional mandated information items as well as more timely disclosure; these became effective from August 23rd, 2004 (Lerman and Livnat, 2010). Because of this major regulatory change, we restrict our 8-K analysis to the period from August 23rd, 2004 to the end of 2010. Summary information for the 8-Ks can be seen in Table 9. There are relatively few 8-Ks for each firm – 17 per year on average – ranging from 5 for GE to 36 for Ford, or 1.8 percent of days for the former and 13 percent of days for the

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latter. Assuming that the content of an 8-K is potentially picked up by the newswires on the day it appears, we find that 8-Ks are sometimes not reported by the newswires. For three firms – Boeing, Ford and Microsoft – the 8-Ks are always picked up (they have a value of zero in the column headed ‘8-K, no newswire’), whereas for other firms, the newswires seem to have little interest in 8-K content. In the column headed ‘newswire, no 8-K’ it can be seen that the vast majority of newswires appear on days without an 8-K filing – on average 92.7 percent of days that newswires appear. With the proviso that newswires often follow quarterly or annual report filings (we do not include 10-Ks and 10-Qs), most breaking news for our sample firms is not sourced from official filings by the firm.

~ Table 9 about here ~

The last column in Table 9 reports the mean *NT* score for the 8-Ks.[32] In many cases, the 8-K form itself is devoid of information apart from reference to an attached press release from the firm. We therefore calculate our *NT* scores as follows. If there is no associated press release, the *NT* score is calculated from the text of the 8-K itself, but if the 8-K filing includes a press release, *NT* is extracted from the press release. The *NT* scores for the 8-Ks are much lower than for the newswires; in fact, for every one of our sample firms the mean newswire *NT* score exceeds the 8-K *NT* score. There are two potential explanations for this. *First,* firms are reluctant to report negative news via official filings. This is unlikely, given that filings are required and that there is a strong prospect of investor litigation if bad news is not reported accurately and promptly (Skinner, 1994; Baginski, Hassell and Kimbrough, 2002). Our

[32] Because it is very rare that firms file more than one 8-K on any day, we cannot calculate firm-specific correlations between 8-K count and negative tone.

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second explanation is more plausible: firms use carefully crafted language when reporting bad news, by using as few negative words as possible and avoiding words with strongly negative connotations. This conjecture receives some support from Davis and Tama-Sweet (2012), who find that there is less use of pessimistic language in earnings press releases than in the MD&A section of 10-Ks and 10-Qs. This, they argue, is because press releases appear before the official filings – so they are more likely to elicit a stock price reaction.

7. Summary and conclusions

In this paper, we have built a corpus of over 5½ million news articles on 20 large US firms over the 10-year period from January 2001 to December 2010, and used it to study the time-varying nature of the relation between firm-specific negative tone and firm-level returns. By focussing on a small number of large, well-known and widely traded firms for which there are many news stories, we have been able to construct separate series of firm-specific negative media-expressed tone for each firm with very few days on which there are no articles. This has allowed us to overcome a limitation in previous studies that has necessitated either the aggregation of firm-specific tone into an aggregate measure across all firms, or the combining of firm-specific tone scores within a panel regression framework – which constrains the extent to which the estimated parameters can vary across firms and over time. By estimating a series of separate rolling window VAR models for each firm, we have been able to study how media-expressed tone affects firm-level returns in a way that varies for each firm and over time.

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We have shown that when replicating prior studies using a panel approach, increases in firm-specific negative tone lead to lower next-day firm-level returns. In contrast to prior studies, however, we find no evidence of return reversal, implying that rather than being a source of sentiment or noise, media-expressed tone may contain fundamental information about firm value. When we implement separate rolling regression VARs for each firm, we find episodes during which the negative next-day effect of media-expressed tone endures and others when it reverses, suggesting that media comment and analysis is not always noise; it can sometimes be news. This is a novel finding, and it addresses an important question in the literature: does media-expressed negative tone contain value-relevant information, or is it simply a source of noise? We conclude that it can be both.

Consistent with the intuition that newswire articles are a relatively pure source of news, we find that negative tone extracted from newswires has time-varying effects on returns that when significant tend to endure rather than to reverse. Further, our long-short portfolio analysis corroborates the VAR findings that negative media-expressed tone can contain news. Shorting the stocks with the greatest negative tone and going long in those with low negative tone is associated with a significantly positive long-term holding period return that is driven by the short leg of the portfolio. The fact that we find a similar pattern using newswire tone confirms that this return persistence is likely to reflect a reduction in the fundamental value of firms that have received highly negative media attention.

Our findings are in general consistent with market efficiency. Firm-specific negative tone impacts on firm-level returns occasionally; and while we find a next-day spike in returns in response to negative media tone in our portfolio analysis, this overreaction is reversed

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immediately. Further, the lagged effect in enduring episodes is not necessarily evidence of inefficiency. Rather, the most plausible explanation for lagged return effects in our time-varying VARs is that it takes time for the market to process complex or 'soft' information (Engelberg, 2008; Boudoukh et al., 2012; Engle, Hansen and Lunde, 2012; Demers and Vega, 2014). Journalists and other content creators – in providing background, conducting in-depth analysis, and sometimes undertaking further investigations – provide the 'processing' that assists market participants to evaluate the implications of news stories for fundamental firm value. As Dougal et al., (2013) point out, journalists sometimes amplify news signals, but at other times they play an attenuating role when bad news arrives. In concluding, we believe that the time-varying VAR approach that we have used in this study provides opportunities for future researchers to exploit the increasing availability of big data sets to investigate the role of textual analytics and machine learning in many areas within and related to corporate finance.

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Table 1 Summary statistics – media articles

	Full corpus					Newswire corpus					
	Articles per day				Mean words per day	Articles per day					Mean words per day
	Mean	*Median*	*Max.*	*Days with no articles*		*Mean*	*Median*	*Max.*	*Days with no articles*	*% days with no articles*	
Apple	20	12	355	14	10,714	4.3	3	47	736	29.3	1,541
AT&T	16	13	180	4	9,310	5.1	4	74	221	8.8	3,052
Boeing	43	38	258	2	21,031	7.9	6	69	63	2.5	3,370
Chevron	14	12	89	8	6,731	3.2	2	16	243	19.3	1,155
Cisco	20	16	158	6	12,369	4.8	4	33	271	10.8	2,793
ConocoPhillips	10	8	79	5	6,174	2.2	2	20	240	19.1	618
Dell	22	18	175	2	11,280	2.7	2	27	845	33.6	851
ExxonMobil	10	7	101	19	5,702	1.2	1	9	746	49.4	587
Ford	11	9	128	4	7,080	5.5	4	71	140	5.6	2,746
General Electric	20	16	157	9	9,735	4.4	3	34	236	9.4	2,174
Home Depot	11	8	114	11	6,570	1.0	0	31	1,315	52.3	548
HP	13	9	154	15	7,792	0.6	0	18	1,600	63.6	327
IBM	37	33	206	6	19,679	4.7	4	42	224	8.9	2,736
Intel	18	14	114	8	9,694	5.2	4	54	224	8.9	3,021
J & J	11	8	95	30	5,516	1.0	1	19	1250	49.7	514
Merck	13	9	221	26	9,036	2.2	1	41	837	33.3	1,573
Microsoft	46	41	352	0	24,590	13.4	11	94	19	0.8	8,053
Pfizer	17	14	266	5	9,949	2.6	2	49	687	27.3	1,587
Verizon	28	24	192	0	16,167	4.5	4	31	215	8.5	2,665
Walmart	28	24	271	1	14,353	4.2	3	54	317	12.6	2,038
Average	**20**	**17**	**183**	**9**	**11,174**	**4**	**3**	**42**	**521**	**23**	**2,097**

Notes. This table presents summary information on the number of articles collected for each firm and the number of words per day extracted from each firm's full corpus and newswire corpus, over the period January 2001-December, 2010. The total number of days is 2,515 for all firms except for Chevron and ConocoPhillips (1,259 days for each) and ExxonMobil (1,511 days).

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Table 2 Summary statistics – firm characteristics and negative tone (*NT*) scores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
					***NT* series**									
					Full corpus					**Newswire corpus**				
	Size ($b)	**Revenue ($b)**	**Return (%)**	**Trading volume (millions)**	**Mean**	**Median**	**Max**	**Variance**	**Skew**	**Mean**	**Median**	**Max**	**Variance**	**Skew**
Apple	357.3	65.2	68.3	22.6	1.05	0.95	5.30	0.30	1.70	0.99	0.70	7.05	0.97	1.98
AT&T	172.2	124.6	2.1	17.6	1.05	0.94	6.02	0.37	1.98	0.84	0.62	10.87	0.64	3.14
Boeing	49.9	64.3	7.8	4.8	1.35	1.28	4.14	0.22	1.11	1.13	0.92	6.51	0.68	1.77
Chevron	211.0	196.3	14.3	11.4	1.40	1.30	5.28	0.48	1.16	1.41	1.05	8.79	1.70	1.51
Cisco	101.6	40.0	3.2	60.5	0.85	0.75	4.80	0.23	2.22	0.62	0.45	8.13	0.46	4.09
ConocoPhillips	95.0	185.0	9.8	12.1	1.14	1.08	7.48	0.29	2.39	0.85	0.68	6.14	0.65	1.74
Dell	28.2	61.5	3.5	23.7	1.04	0.95	4.30	0.22	1.45	0.96	0.71	9.45	0.88	2.43
ExxonMobil	376.9	354.7	10.4	25.5	1.51	1.35	6.41	0.77	1.47	0.79	0.47	10.22	1.11	3.54
Ford	41.3	129.0	28.4	37.0	1.27	1.14	6.25	0.53	1.30	1.20	0.96	8.56	1.10	2.13
General Electric	169.8	151.6	-1.3	44.3	1.03	0.95	3.68	0.22	1.19	0.80	0.64	7.20	0.47	2.73
Home Depot	59.3	68.0	3.9	12.9	1.20	1.10	4.70	0.37	1.29	1.19	0.68	9.48	1.96	2.38
HP	54.6	126.0	8.9	14.0	0.93	0.77	5.50	0.40	2.22	1.20	0.86	9.74	1.74	2.50
IBM	220.0	99.9	10.7	7.5	0.85	0.79	2.66	0.10	1.49	0.75	0.60	7.95	0.45	3.64
Intel	127.5	43.6	6.4	62.8	0.92	0.77	5.48	0.37	2.19	0.74	0.52	6.63	0.55	2.75
J&J	176.4	61.6	4.9	10.0	1.43	1.31	7.36	0.59	1.29	1.10	0.79	8.20	1.41	2.24
Merck	108.0	46.0	-0.6	11.5	1.51	1.41	6.99	0.62	1.03	1.35	1.03	7.54	1.31	1.66
Microsoft	222.9	62.5	9.4	68.6	1.22	1.07	3.70	0.32	1.41	1.02	0.78	6.91	0.57	1.89
Pfizer	152.3	67.8	-5.1	33.3	1.53	1.44	6.03	0.39	1.43	1.33	1.06	11.69	1.31	2.48
Verizon	104.5	106.6	3.5	12.3	1.26	1.20	5.27	0.21	1.66	0.80	0.62	7.50	0.61	2.56
Walmart	197.7	421.8	1.8	13.6	1.51	1.46	4.59	0.22	1.12	1.57	1.29	13.37	1.61	1.99
Average	**151.3**	**123.8**	**9.5**	**25.3**	**1.20**	**1.10**	**5.30**	**0.36**	**1.56**	**1.03**	**0.77**	**8.60**	**1.01**	**2.46**

Notes: This table provides descriptive statistics for firm variables size, revenue, return and trading volume (columns 1 to 4), and for the negative tone series (*NT*), which is the number of negative words each day expressed as a percentage of total words, for the full corpus (columns 5 to 9) and the newswire corpus (columns 10 to 14). *Size* is market capitalisation on 15th November, 2011, and *revenue* is drawn from the 2011 *Fortune 500* list. *Return* is average annualised return for the full 10-year period, and *trading volume* is average number of shares traded each day.

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Table 3 Correlations and autocorrelations

Panel A: Correlations – firm-specific negative tone for the full corpus

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*
1	Apple																				
2	AT&T	-0.03																			
3	Boeing	-0.01	0.04																		
4	Chevron	**0.18**	**-0.28**	-0.01																	
5	Cisco	0.00	**0.13**	0.00	**-0.18**																
6	ConocoPhillips	**0.20**	**-0.27**	-0.02	**0.72**	**-0.16**															
7	Dell	**0.04**	0.03	0.01	0.02	**0.08**	0.03														
8	ExxonMobil	**0.15**	**-0.24**	-0.03	**0.53**	**-0.15**	**0.56**	0.03													
9	Ford	-0.01	**0.09**	0.00	**-0.17**	**0.08**	**-0.14**	**0.06**	**-0.09**												
10	General Electric	-0.03	**0.05**	**0.06**	**-0.08**	**0.04**	**-0.09**	**0.06**	**-0.13**	**0.08**											
11	Home Depot	**0.05**	**-0.09**	-0.01	**0.18**	-0.03	**0.19**	**0.05**	**0.18**	-0.01	-0.02										
12	HP	0.03	0.00	-0.02	**0.04**	0.01	**0.05**	**0.11**	**0.05**	0.01	0.01	-0.03									
13	IBM	0.01	**0.06**	0.02	0.00	0.04	**0.04**	**0.04**	0.01	0.02	0.01	**0.04**	0.01								
14	Intel	0.02	0.00	0.01	0.03	**0.04**	**0.07**	**0.08**	**0.04**	0.00	0.01	0.04	-0.01	**0.1**							
15	J & J	0.04	**-0.05**	-0.02	**0.09**	-0.04	**0.10**	0.02	**0.14**	**-0.05**	-0.03	**0.06**	**0.04**	-0.02	-0.02						
16	Merck	**0.04**	0.03	-0.02	0.00	0.01	0.01	0.03	**0.13**	0.00	**-0.07**	0.01	0.03	**0.05**	0.02	0.01					
17	Microsoft	-0.04	**0.11**	0.00	**-0.27**	**0.11**	**-0.25**	**0.05**	**-0.24**	**0.12**	**0.08**	-0.04	**0.06**	**0.06**	**0.04**	**-0.04**	**-0.06**				
18	Pfizer	0.02	**0.04**	0.04	-0.03	0.01	0.00	0.04	**0.07**	0.03	-0.01	**0.06**	-0.01	**0.08**	**0.09**	0.02	**0.13**	-0.01			
19	Verizon	-0.03	**0.17**	**0.05**	**-0.18**	**0.09**	**-0.17**	**0.04**	**-0.16**	0.00	**0.09**	-0.03	-0.03	0.03	**0.05**	-0.01	-0.03	**0.1**	0.00		
20	Walmart	0.02	**0.04**	-0.02	-0.02	**0.05**	-0.01	0.02	**0.04**	0.03	-0.04	0.03	-0.01	**0.04**	0.02	0.02	**0.05**	0.03	**0.05**	**0.04**	

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Panel B: autocorrelations – full corpus and newswire corpus negative tone (*NT*)

	Full corpus										**Newswire corpus**									
Lags	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Apple	0.36	0.21	0.16	0.13	0.16	0.13	0.12	0.09	0.11	0.12	0.26	0.21	0.11	0.12	0.14	0.12	0.12	0.12	0.13	0.17
AT&T	0.32	0.16	0.18	0.20	0.20	0.20	0.18	0.15	0.15	0.16	0.13	0.04	0.05	0.04	0.05	0.07	0.05	0.03	0.03	0.01
Boeing	0.46	0.30	0.23	0.24	0.23	0.18	0.14	0.13	0.13	0.12	0.25	0.14	0.11	0.11	0.11	0.09	0.06	0.04	0.01	0.07
Chevron	0.32	0.20	0.17	0.13	0.07	0.05	0.04	0.01	0.03	0.08	0.16	0.10	0.13	0.02	0.07	0.04	0.03	0.00	0.01	0.06
Cisco	0.32	0.16	0.10	0.12	0.14	0.11	0.10	0.10	0.14	0.12	0.14	0.06	0.03	0.07	0.08	0.03	0.03	0.01	0.04	0.04
ConocoPhillips	0.13	0.06	0.09	0.01	0.06	0.06	0.01	0.02	0.03	0.02	0.11	0.02	-0.04	0.00	0.03	0.02	0.03	0.03	0.00	0.00
Dell	0.32	0.15	0.13	0.13	0.13	0.08	0.10	0.08	0.09	0.13	0.20	0.11	0.08	0.08	0.08	0.07	0.07	0.08	0.07	0.07
ExxonMobil	0.30	0.22	0.17	0.14	0.10	0.13	0.15	0.12	0.08	0.16	0.10	0.04	0.03	-0.01	0.00	0.08	-0.03	-0.01	-0.02	-0.01
Ford	0.27	0.19	0.15	0.17	0.16	0.16	0.12	0.12	0.11	0.10	0.14	0.09	0.07	0.05	0.10	0.10	0.07	0.08	0.06	0.04
General Electric	0.22	0.13	0.12	0.10	0.15	0.13	0.11	0.12	0.13	0.12	0.09	0.05	0.03	0.01	0.05	0.02	0.05	0.06	0.02	-0.01
Home Depot	0.17	0.09	0.09	0.08	0.10	0.09	0.09	0.15	0.12	0.07	0.14	0.06	0.04	0.06	0.07	0.04	0.02	0.04	0.01	0.05
HP	0.43	0.30	0.28	0.27	0.23	0.22	0.18	0.19	0.19	0.17	0.16	0.11	0.11	0.11	0.05	0.05	0.09	0.10	0.06	0.07
IBM	0.34	0.17	0.12	0.11	0.09	0.07	0.08	0.03	0.06	0.07	0.15	0.01	0.02	0.05	0.04	0.03	0.02	0.01	0.04	0.00
Intel	0.37	0.15	0.12	0.10	0.09	0.06	0.04	0.05	0.08	0.06	0.16	0.08	0.07	0.07	0.06	0.02	0.04	0.06	0.05	0.02
J & J	0.26	0.19	0.12	0.09	0.12	0.07	0.13	0.09	0.06	0.06	0.11	0.13	0.05	0.03	0.05	0.06	0.05	0.01	0.05	0.00
Merck	0.34	0.26	0.23	0.25	0.24	0.24	0.22	0.22	0.22	0.23	0.26	0.21	0.19	0.16	0.18	0.16	0.17	0.18	0.14	0.15
Microsoft	0.54	0.31	0.25	0.28	0.30	0.26	0.21	0.19	0.21	0.23	0.28	0.07	0.07	0.12	0.16	0.15	0.08	0.07	0.10	0.13
Pfizer	0.24	0.16	0.14	0.16	0.14	0.13	0.09	0.10	0.11	0.12	0.14	0.08	0.07	0.04	0.02	0.05	0.07	0.06	0.05	0.09
Verizon	0.28	0.13	0.13	0.13	0.15	0.14	0.15	0.08	0.13	0.12	0.03	0.02	0.03	0.08	0.02	0.11	0.05	0.03	0.06	0.06
Walmart	0.21	0.08	0.09	0.07	0.07	0.05	0.08	0.06	0.07	0.07	0.11	0.07	0.07	0.07	0.03	0.07	0.06	0.02	0.04	0.05
Average	0.31	0.18	0.15	0.15	0.15	0.13	0.12	0.11	0.11	0.12	0.16	0.08	0.07	0.06	0.07	0.07	0.06	0.05	0.05	0.05

Notes: Panel A of this this table presents correlations between the firm-specific negative tone (*NT*) scores for the full corpus. Correlations significant at the 5 percent level or better are in **bold.** Panel B presents the autocorrelations for the full corpus and the newswire corpus *NT* scores, each showing autocorrelations up to the 10th lag.

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Table 4 Panel analysis

	(1)	(2)	(3)	(4)
	Negative tone equation		**Return equation**	
	R	*NT*	*R*	*NT*
Lag 1	-106.618 **(0.00)**	26.165 **(0.00)**	9.713 **(0.00)**	-0.046 **(0.01)**
Lag 2	-14.959 (0.23)	6.362 **(0.00)**	7.100 **(0.00)**	0.020 (0.29)
Lag 3	-0.425 **(0.01)**	0.053 **(0.00)**	0.068 **(0.00)**	0.000 (0.43)
Lag 4	-35.114 **(0.02)**	6.101 **(0.00)**	8.793 **(0.00)**	-0.039 **(0.05)**
Lag 5	-37.105 (0.12)	8.090 **(0.00)**	7.607 **(0.00)**	-0.020 (0.22)
Sum of lags 1 to 5				-0.101 **(0.03)**
Sum of lags 2 to 5				-0.054 (0.16)

Notes. This table provides panel estimates (with fixed effects) of the relation between firm-specific negative media tone derived from the full corpus and firm-level market-adjusted returns, using 42,755 daily observations from 17 firms over the 10 year period from January 2001 to December 2010. Columns (1) and (2) present the results from estimating Eq. (2) (the negative tone equation), and columns (3) and (4) present the results from estimating Eq. (1) (the return equation). *R* denotes firm-level equity returns which are market adjusted against the *CRSP* NYSE/AMEX/NASDAQ value-weighted return. As well as 5 lags of *R* and *NT*, the equations include *Monday* and *January* dummies. Coefficients have been multiplied by 100. The figures in brackets under the coefficients are p-values, with **bold** indicating significance at the 5 percent level or better.

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Table 5 Individual firm rolling regression analysis

	Lag 1 significant			Enduring			Transitory		
	No. episodes	**% of time**	**Dates**	**No. episodes**	**% of time**	**Dates**	**No. episodes**	**% of time**	**Dates**
Apple	2	31.0	1 Mar 2002-28 Apr 2003 8 Apr 2008-15 Mar 2010				1	16.0	8 April, 2008-6 Nov 2009
Boeing	1	14.8	31 Jan 2002-23 Jul 2003						
Chevron	1	20.3	29 Dec 2009-31 Dec 2010						
Dell	1	10.1	12 Nov 2008-12 Nov 2009						
Ford	1	11.3	24 August 2007-7 Oct 2008						
General Electric	1	13.4	28 Sep 2007-28 Jan 2009						
Home Depot	1	11.0	21 Jul 2006-24 Aug 2007				1	11.0	21 Jul 2006-24 Aug 2007
Hewlett Packard	2	23.1	10 Feb 2003-10 Feb 2004 15 Sep 2009-31 Dec 2010	1	10.3	15 Sep 2009-24 Sep 2010			
IBM	1	30.5	29 Dec 2003-16 Jan 2007				1	17.7	9 Jul 2004-13 Apr 2006
Intel	1	11.8	10 Apr 2002-13 Jun 2003						
J & J	2	26.7	26 Oct 2004-3 May 2006 7 Jun 2007-29 Jul 2008	2	22.3	26 Oct 2004-18 Nov 2005 7 Jun 2007-29 Jul 2008			
Merck	1	13.1	17 Jul 2009-3 Nov 2010				1	10.2	17 Jul 2009-22 Jul 2010
Microsoft	1	14.1	30 Apr 2007-23 Sep 2008						
Pfizer	1	16.6	7 Jun 2007-30 Jan 2009				1	10.0	29 Oct 2007-27 Oct 2008
Verizon	2	28.3	15 Feb 2001-15 Aug 2002 5 May 2004- 6 Sep 2005	1	14.4	15 Feb 2001-30 Jul 2002			
Walmart	1	15.1	22 Mar 2005-20 Sep 2006	1	15.1	22 Mar 2005-20 Sep 2006			
Sum	**20**			**5**			**5**		
Mean		**18.2**			**15.5**			**13.0**	

Notes. In this table, we report the number of episodes and the percentage of time that the first lag of negative sentiment (*NT*) significantly and negatively (at the 5 percent level) impacts on returns (*R*) for each firm using rolling VAR regressions (Eq. (3)), whereby a 1-year window is rolled forward a day at a time. We also report the dates delineating the significant periods. The columns headed 'enduring' report the number of significant episodes and proportion of time when lag 1 of *NT* is significantly negative *and* the sum of lags 1 to 5 of *NT* are significant and negative. The columns headed 'transitory' report the number of significant episodes and proportion of time in which the lag of *NT* is significantly negative *and* the sum of lags 2 to 5 of *NT* are significant and positive. AT&T, Cisco, ConocoPhillips and ExxonMobil do not appear in this table because for these firms we found no periods during which the first lag of *NT* has a significantly negative impact on returns.

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Table 6 Panel analysis, newswire corpus

	(1)	(2)	(3)	(4)
	Negative tone equation		**Return equation**	
	R	*NT*	*R*	*NT*
Lag 1	-44.113 (0.20)	14.050 **(0.00)**	9.740 **(0.00)**	-0.021 **(0.01)**
Lag 2	-40.979 (0.17)	5.994 **(0.00)**	7.125 **(0.00)**	-0.001 (0.93)
Lag 3	-13.444 (0.58)	4.103 **(0.00)**	6.829 **(0.00)**	-0.014 (0.12)
Lag 4	-52.718 (0.10)	4.377 **(0.00)**	8.860 **(0.00)**	-0.009 (0.40)
Lag 5	-89.409 **(0.01)**	4.775 **(0.00)**	7.657 **(0.00)**	-0.024 **(0.05)**
Sum of lags 1 to 5				-0.069 **(0.02)**
Sum of lags 2 to 5				-0.048 **(0.05)**

Notes. This table provides panel estimates (with fixed effects) of the relation between market-adjusted returns and negative newswire tone (*NT*) derived from the newswire corpus, using 42,755 daily observations from 17 firms over the 10 year period from January 2001 to December 2010. Columns (1) and (2) present the results from estimating Eq. (2) (the negative tone equation), and columns (3) and (4) present the results from estimating Eq. (1) (the return equation). *R* denotes is firm-level equity returns, which are market adjusted against the *CRSP* NYSE/AMEX/NASDAQ value-weighted return. As well as 5 lags of *R* and *NT,* the equations include Monday and January dummies. Coefficients have been multiplied by 100. p-values appear under the coefficients in brackets; for coefficients significant at the 5 percent level or better the p-value is in **bold.**

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Table 7 Individual firm rolling regression analysis: newswire corpus

	Lag 1 significant			Enduring			Transitory		
	No. episodes	**% of time**	**Dates**	**No. episodes**	**% of time**	**Dates**	**No. episodes**	**% of time**	**Dates**
Apple	1	10.9	12 Feb 2002-14 Mar 2003						
AT&T	1	11.9	27 Jul 2007-2 Oct 2008	1	11.9	27 Jul 2007-2 Oct 2008			
Chevron	1	20.1	31 Dec 2009-31 Dec 2010						
Dell	1	10.1	22 Dec 2004-23 Dec 2005						
Ford	3	32.5	16 Oct 2002-23 Oct 2003 18 May 2004-4 Aug 2005 19 Sep 2007-18 Sep 2008						
General Electric	2	32.4	12 Jan 2004-14 Dec 2005 15 Oct 2007-30 Jan 2009	1	10.0	19 Feb 2004-16 Feb 2005	1	10.7	15 Oct 2007-4 Nov 2008
Home Depot	2	24.8	28 Sep 2001-30 Sep 2002 27 May 2004-11 Nov 2005	1	12.9	4 Aug 2004-11 Nov 2005			
Hewlett Packard	1	10.0	13 Jan 2009-12 Jan 2010						
IBM	1	10.2	25 Oct 2002-30 Oct 2003						
J & J	2	25.1	9 Jan 2001-1 May 2002 6 Apr 2005-20 Jun 2006	1	12.4	30 Jan 2001-1 May 2002			
Merck	2	21.7	14 May 2002-9 Jul 2003 16 Apr 2008-17 Apr 2009	1	11.6	14 May 2002-9 Jul 2003			
Microsoft	1	15.2	19 Jun 2007-22 Dec 2008	1	10.0	24 Dec 2007-22Dec 2008			
Pfizer	1	18.9	12 Feb 2009-31 Dec 2010						
Verizon	1	15.1	9 Jan 2001-19 Jul 2002	1	10.5	25 Jun 2001-19 Jul 2002			
Walmart	1	25.3	26 Mar 2007-30 Sep 2009						
Sum	**21**			**7**			**1**		
Mean		**18.9**			**11.3**			**10.7**	

Notes. In this table, we report the number of episodes and the percentage of time that the first lag of negative sentiment (*NT*) derived from the newswire corpus significantly and negatively (at the 5 percent level) impacts on returns (*R*) for each firm using rolling VAR regressions (Eq. (3)), whereby a 1-year window is rolled forward a day at a time. We also report the dates delineating the significant periods. The columns headed 'enduring' report the number of significant episodes and proportion of time when lag 1 of *NT* is significantly negative *and* the sum of lags 1 to 5 of *NT* are significant and negative. The columns headed 'transitory' report the number of significant episodes and proportion of time in which the lag of *NT* is significantly negative *and* the sum of lags 2 to 5 of *NT* are significant and positive.

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Table 8 Fama-French and Carhart model results

	Full corpus						Newswire corpus					
	Long low-negative, short high-negative		Low-negative		High-negative		Long low-negative, short high-negative		Low-negative		High-negative	
	FF Three-Factor	Carhart Four-Factor	FF Three-Factor	Carhart Four-Factor	FF Three-Factor	Carhart Four-Factor	FF Three-Factor	Carhart Four-Factor	FF Three-Factor	Carhart Four-Factor	FF Three-Factor	Carhart Four-Factor
Intercept (alpha)	0.055	0.055	0.027	0.028	-0.028	-0.027	0.022	0.021	0.010	0.010	-0.012	-0.011
	(0.00)	**(0.00)**	**(0.03)**	**(0.02)**	**(0.01)**	**(0.01)**	(0.17)	(0.18)	(0.34)	(0.34)	(0.34)	(0.36)
Mkt - Rf	0.071	0.049	1.061	1.029	0.990	0.980	0.015	0.050	1.032	1.028	1.016	0.978
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	(0.20)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
SMB	0.149	0.156	-0.109	-0.099	-0.258	-0.255	0.043	0.033	-0.165	-0.164	-0.209	-0.197
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	(0.10)	(0.21)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
HML	-0.093	-0.101	-0.328	-0.339	-0.234	-0.238	0.011	0.024	-0.273	-0.274	-0.284	-0.297
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	(0.64)	(0.33)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
UMD		-0.055		-0.079		-0.024		0.085		-0.008		-0.093
		(0.00)		**(0.00)**		**(0.03)**		**(0.00)**		(0.45)		**(0.00)**
Adj. R-square	0.029	0.033	0.840	0.843	0.857	0.857	0.015	0.027	0.864	0.864	0.838	0.842

Notes. This table presents our results for the Fama-French 3-factor model and the 4-factor Carhart (1997) model on long-short portfolios calculated using a daily holding period and daily returns, for portfolio sorts using the full corpus (Panel A) and the newswire corpus (Panel B). For each 1-day formation period, our 20 sample stocks are sorted from high to low negative tone. The top 10 are labelled the 'high-negative' tone, and the bottom 10 are the 'low-negative' tone. p-values appear below each coefficient; p-values denoting significance at the 5 percent level or better are in **bold**.

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Table 9 Summary information – 8-Ks

	8-K count		percentage of days			mean *NT*
	total	per year	with 8-Ks	newswire, no 8-k	8-K, no newswire	
Apple	57	9	3.5	96.1	3.6	0.30
AT&T	161	26	8.4	91.3	2.2	0.45
Boeing	101	16	6.1	93.9	0.0	0.80
Chevron	76	12	4.6	94.3	8.1	0.17
Cisco	99	16	5.7	94.1	2.2	0.42
ConocoPhillips	99	16	5.3	94.5	43.5	0.38
Dell	116	18	7.0	90.9	7.1	0.54
ExxonMobil	87	14	5.3	93.7	30.6	0.30
Ford Motor	224	36	13.0	87.0	0.0	0.35
General Electric	30	5	1.8	98.2	3.4	0.50
Home Depot	84	13	5.1	91.7	15.9	0.54
HP	117	19	6.5	88.2	24.0	0.63
IBM	167	27	10.2	89.6	2.5	0.44
Intel	120	19	7.0	92.6	0.9	0.71
JJ	88	14	5.3	91.8	12.9	0.35
Merck	93	15	5.6	94.1	14.6	0.73
Microsoft	94	15	5.6	94.4	0.0	0.71
Pfizer	97	15	5.7	93.3	4.3	0.64
Verizon	160	25	9.8	90.1	3.2	0.52
Walmart	93	15	5.5	94.3	3.4	0.56
Average	108	17	6.4	92.7	9.1	0.50

Notes. This table presents summary information for the 8-Ks of our 20 sample firms, for the period 23rd August, 2004 to 31st December, 2010. For each firm, we present the total number of 8-Ks during the period, the number per year, the percentage of days during the period in which newswires appear without 8-Ks appearing on the same day, and the percentage of days on which 8-Ks appear but no newswires. The column headed 'mean *NT*' is the average negative tone score extracted from the firm's 8-K or its companion press release.

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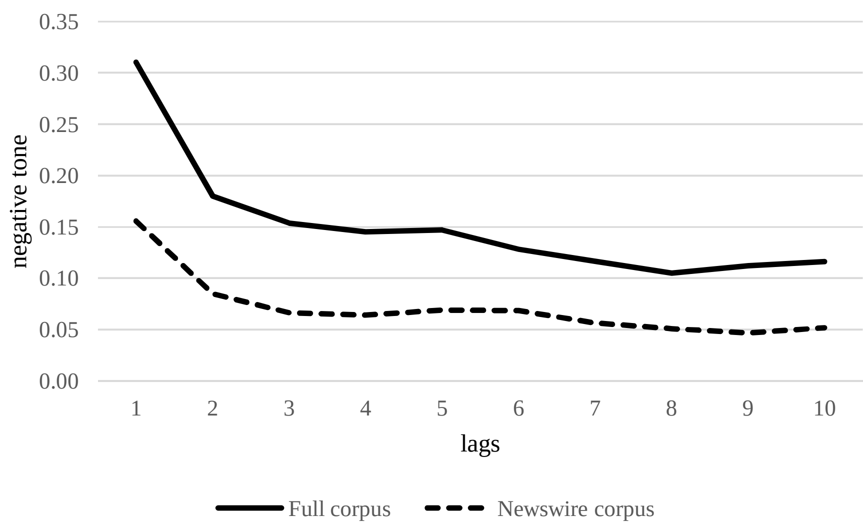
Fig. 1 Mean autocorrelations, full corpus and newswire negative tone (*NT*)



Notes: This figure plots the mean autocorrelations for the negative tone (*NT*) score for the full corpus and the newswire corpus, from the first to the 10 lag.

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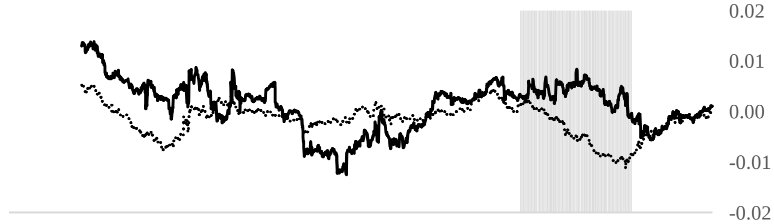
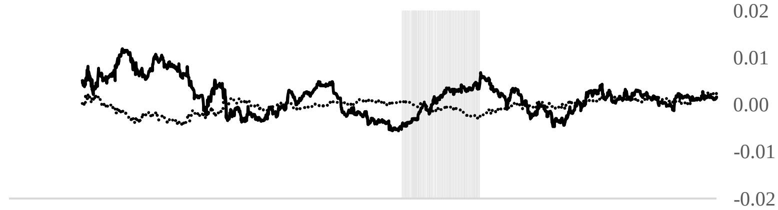
Fig. 2 Rolling regression coefficients

Panel A: firms with transitory periods

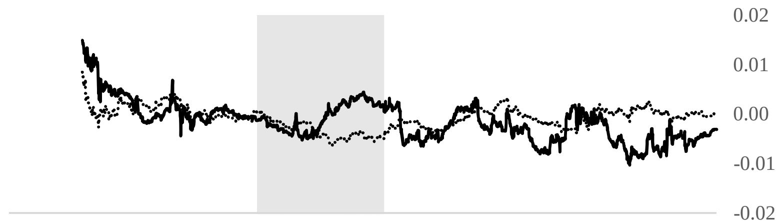
Apple



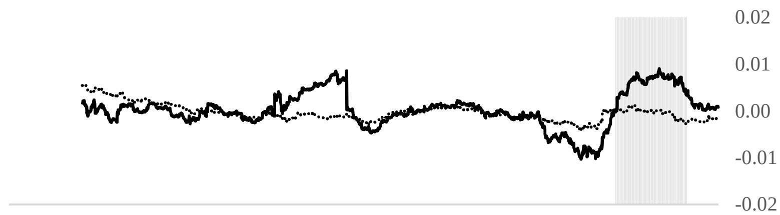
Home Depot



IBM



Merck



Pfizer

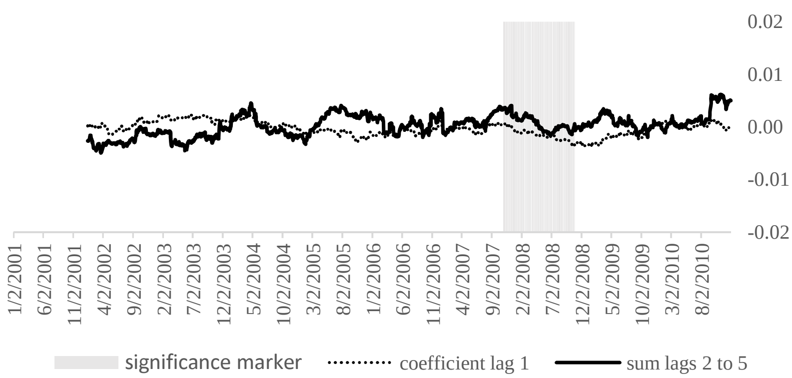


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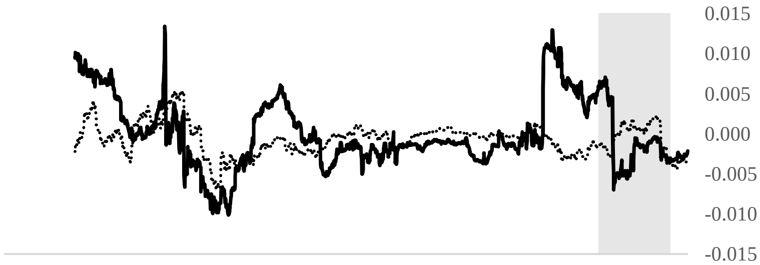
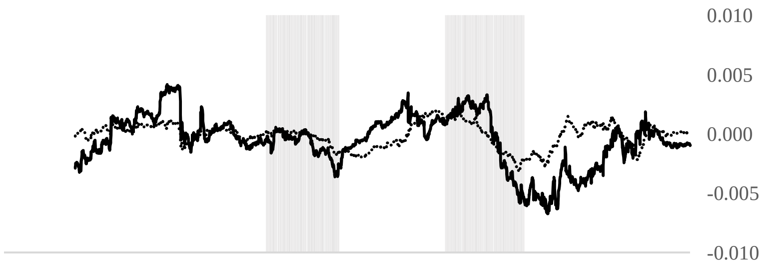
Fig. 2 Rolling regression coefficients (continued…)

Panel B: firms with enduring periods

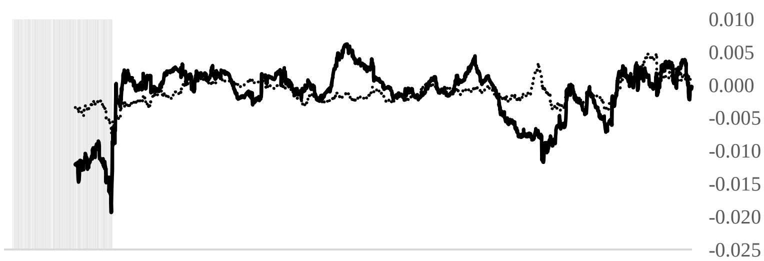
Hewlett-Packard



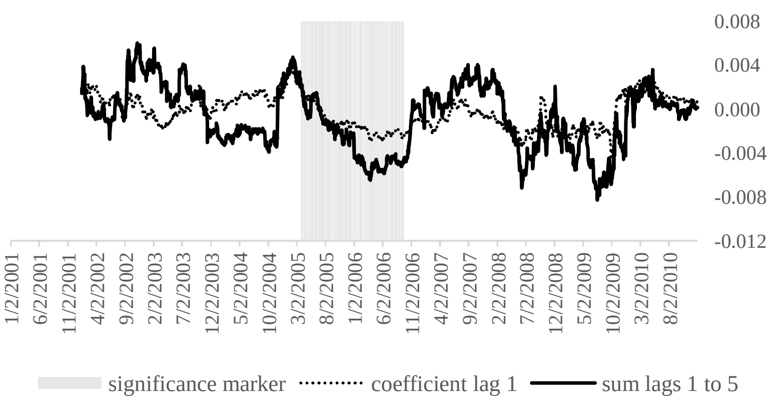
Johnson & Johnson



Verizon



Walmart



Notes. This figure depicts our rolling regression findings for the firms with *transitory* episodes (Panel A) and *enduring* episodes (Panel B). The significance markers mark significant transitory or enduring periods. Transitory periods are defined as those where there is a negative and significant effect of *NT* on returns the next day, and a positive and significant sum of the coefficients on lags 2 to 5. For enduring periods, as well as a negative and significant first lag effect, the sum of lags 1 to 5 must also be significant and negative.

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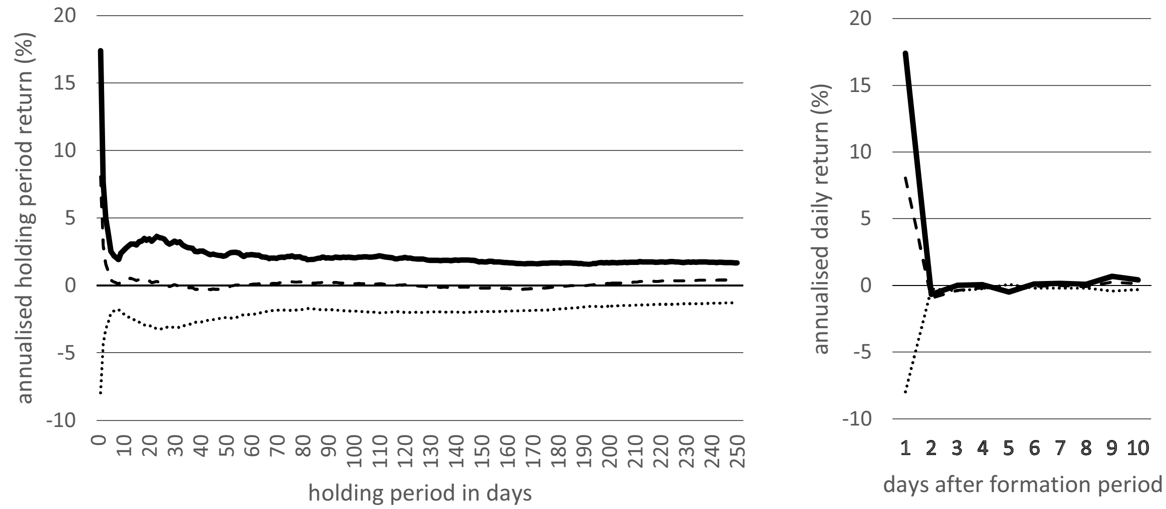
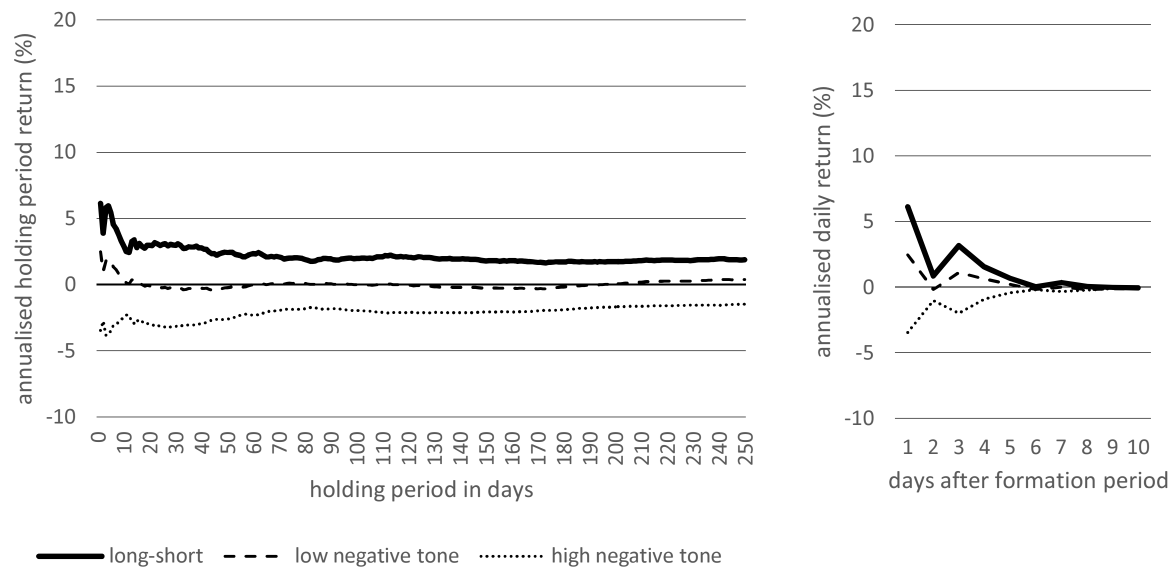
Fig. 3 Average returns to the long-short strategies

Annualised daily returns (%)

Panel A: full corpus



Panel B: newswire corpus



Notes. These figures depict for the full corpus (Panel A) and the newswire corpus (Panel B): annualised average returns for long-short portfolios as well as the short and long legs separately. The portfolios are formed as follows: on each 1-day formation period, our 20 sample stocks are sorted from high to low negative tone. The top 10 are labelled the 'high negative tone' portfolio and the bottom 10 the 'low negative tone' portfolio. To create the long-short portfolio, we take a long position in the low negative tone portfolio and a short position in the high negative tone portfolio. The left-hand-side graphs depict annualised holding period returns (HPRs) – from 1 to 250-day holding periods, and the right-hand-side graphs depict and annualised returns on each day for the first 10 days after the portfolio formation period.

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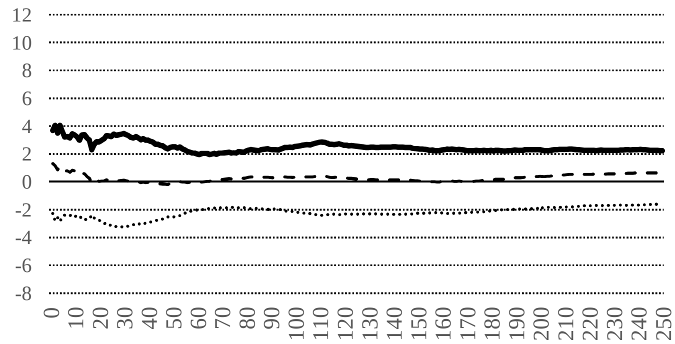
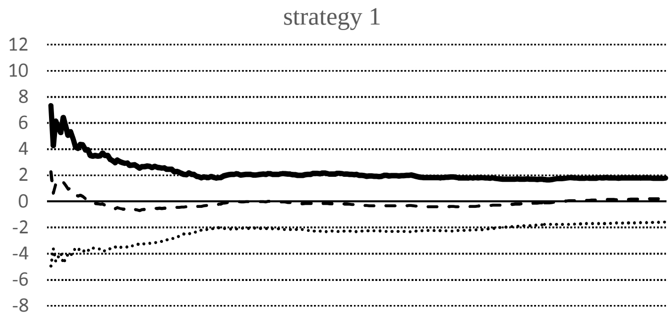
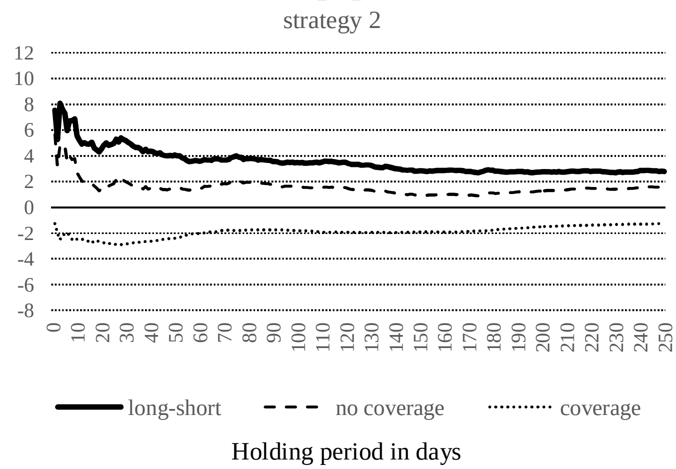
Fig. 4 Average HPRs to the long-short strategies – coverage

Panel A: Full corpus



Panel B: newswire corpus





Notes. These figures depict for the full corpus (Panel A) and the newswire corpus (Panel B) the average holding period return – from 1 day to 250 days – for the long-short portfolios, as well as the short and long legs separately. For the full corpus, and in 'strategy 1' for the newswire corpus, our 20 sample stocks are sorted daily from high to low coverage or count of articles and we take a long position in the low-coverage portfolio, and a short position in the high coverage portfolio. In 'strategy 2' the long-short portfolios are formed by defining the firms in each 1-day holding period as firms with 'coverage' (those with at least 1 newswire article) or 'no-coverage' (those with no newswire articles) firms. The long-short strategy takes a long position in the 'no-coverage' firms and a short position in the 'high-coverage' firms.

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Highlights

- We create a measure of firm-specific negative media tone from 5½ million articles for 20 large US firms.
- Using a panel approach, rising negative sentiment triggers permanently lower returns, but at the level of the firm, this relation occurs only intermittently – in short episodes.
- Some of these episodes are persistent, implying that media-expressed negative tone can sometimes contain fundamental information about firm value.
- Our findings are in general consistent with efficiently functioning markets in which the media assists with the processing of complex information.

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