News Media Content and UK Stock Returns

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Abstract

Previous studies have examined the separate effects of the tone and volume of news media on stock returns. We incorporate both these aspects into our study and examine their combined effect on stock returns using UK news media data over the period 1981–2010. We find that high media coverage predicts low stock returns and that both positive and negative words drive investor reaction to news. Investors tend to overreact to highly visible news, whether positive or negative, and this effect is more pronounced for larger stocks, indicating both visibility and tone are key factors that determine how investors respond to news.

JEL Classification: G1; G14; G17

Keywords: *newsmedia, stock returns, textual analysis, news-based trading strategy*

1. Introduction

The analysis of news media content in financial research is a relatively new field. Some of the most respected and credible news publications in the world are dedicated to financial and business news, which plays a key role in providing financial markets participants with information and aiding them in forming their views on the stock market. Stock prices are a function of the firm's fundamentals and are subject to the investors' information sets. Investors receive both private and public information concerning the underlying value of a stock. Contained in an investor's information set are also qualitative descriptions of the expectations of a firm's future performance, such as the quality of management, talk of a merger, lawsuits or legal action being taken against the firm, or new product announcements. Shiller (2005) suggests that the news media actively shape public opinion and play a large role in the propagation of speculative bubbles through feedback mechanisms and attention cascades whereby the media may exaggerate the relevance of past price movements, affectingfuture price movements.

The conundrum of explaining the movements in stock prices that cannot be accounted for by new fundamental or economic information is an interesting puzzle that has remained unresolved due to the difficulties of quantifying or measuring qualitative news media data (see Cutler *et al.*, 1989). However, in recent times researchers have begun to measure linguistic data contained in media articles using textual analysis in an attempt to capture hard to quantify information and the characteristics of news media data to determine their effect on stock prices (Tetlock, 2007; Tetlock *et al.*, 2008; Loughran and McDonald, 2011). By using a quantitative measure of the semantics in the language used in news articles, it is possible to measure the effects of investor reaction to such news events and identify common patterns concerning the way asset prices react to news in general, whether positive or negative.

Previous research shows the tone of news articles drives investor sentiment (Tetlock, 2007), captures information beyond fundamentals (Tetlock et. al., 2008), and shows that the tone of news can be improved by increasing local advertising spending and hiring investor relationship firms (Gurun and Butler, 2011; Solomon, 2011). Another branch of studies shows that the amount of news media coverage reduces firms' expected returns (Fang and Peress, 2009) and simulates local trading (Engelberg and Parsons, 2011). This paper attempts to combine the tone and volume of news media coverage in a unified framework to better understand the role of the media in financial markets.

We conjecture that if investors are shown to overreact to attention-grabbing stocks (Barber and Odean, 2008) and linguistic tone reflects investor sentiment (Tetlock, 2007; Tetlock et. al., 2008), then the combined effect of the tone and amount of news stories should magnify market reactions. We therefore examine the impact of (positive and negative) news media content and the volume of media coverage on a firm's stock returns. Since larger firms generally tend to receive much greater media attention than smaller ones, we split our firm-specific media article sample of FTSE 100 stocks by market capitalisation and study the differing effects of media attention on the firms' stock returns. We thus explore the notion of whether informational risk is a determinant of the cross-sectional dispersion of returns (Merton, 1987; Easley and O'Hara, 2004, Fang and Peress, 2009). Our approach substantiates the approach of Barber and Odean (2008), who proxy attention-grabbing stocks by stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one-day returns and study the effect of news attention on investor buying behaviour. Furthermore, we analyse whether market-level returns can be explained by aggregate measures of news media content. We build a news-based trading strategy using these aggregate measures of news media content to study the potential economic significance of our results.

Our sample consists of 304,105 firm-specific UK news media articles covering FTSE 100 firms over the 30-year period 1981–2010. Our sample period, to the best of our knowledge, is substantially longer than that of any other previous study, providing a comprehensive analysis of the effect of news media on stock returns. Most studies use news media articles from the US market, and therefore this study is the first to provide independent evidence of the effect of news media content on stock returns from the UK market. The UK, as a leading global financial centre, with some of the world's oldest and most respected news publications, is a key market for analysing the role of media in shaping public opinion and investor reaction. We source the news articles from national newspapers that are globally recognised, such as *Financial Times, Times, Guardian* and *Mirror,* and use Loughran and McDonald's (2011) financial news-specific word lists [1] to construct variables for both positive and negative news media content. Previous studies, such as that of Tetlock *et al.* (2008), only consider the effect of negative news on stock returns. By using both positive and negative measures of media content, this paper uses the overall distribution of news to gain insight into the frequency and possible biases inherent in news articles.

Our results show that the effect of semantics in news media content on stock returns varies according to firm size. First, we find large and medium firms stock returns have a negative relation with negative words the day after the news articles are published, which is consistent with Tetlock *et al.* (2008). Small and medium firms stock returns have positive relations with positive words the day news articles are published, and small firms stock returns have a

[1] Previous studies, such as those of Tetlock (2007) and Tetlock et al. (2008), use the Harvard psychosocial dictionary to identify words of different categories in news articles. However,Loughran and McDonald (2011) created a new word list of financial news-specific words that they showed to have greater explanatory power over stock returns than the Harvard psychosocial dictionary categories.

significant negative relation with negative words on the day news articles are published. This suggests that for small and medium firms, newspapers are a key source of new information for investors, who act upon it quickly.

Second, we show that media coverage, which we proxy for recognition or attention, predicts low returns and that this effect is driven by large firms. This is consistent with the informational risk hypothesis of Merton (1987) and the results of Fang and Peress (2009) and Barber and Odean (2008). More importantly, when considering the joint effect of media coverage and the tone of the media content, we find that the market overreacts to highly visible news, whether positive or negative, and there is a reversal the following trading day. Our findings thus show that the combination of the visibility and tone of news drives an overreaction from investors to firm-level information. Lastly, we construct a trading strategy using aggregate levels of news media content to demonstrate the application of these results to financial practice. We find that the strategy has an average daily return of 4.6 bps and during 2006–2010 the strategy earned significant risk-adjusted abnormal returns of 17 bps per day.

The outline of the remainder of this paper is as follows. Section 2 provides a brief review of related literature. Section 3 discusses the properties of the news media data. Section 4 presents the main results of this study, examining the effect of news media content and coverage on stock returns. Section 5 investigates the predictive ability at the market level of aggregate measures of news media content. Section 6 concludes this study.

2. Literature Review

One of the first empirical studies to explore the relation between news information and stock prices was that of Cutler *et al.* (1989). Their research expressed difficulty in explaining the variance in stock prices, finding that only around half of the asset price volatility could be explained by news about fundamentals. After accounting for significant macroeconomic news, the authors find that news about fundamentals can explain up to one-third of stock price movements and that significant world news about politics or natural disasters does have some effect on stock prices. The authors also note that some of the largest market movements occur on days with no significant news.

Tetlock (2007) uses daily content from a *Wall Street Journal* article to examine the effect media pessimism has on market prices. By using principal component analysis on words belonging to specific categories of the Harvard psychosocial dictionary, the author creates pessimism factors that intend to capture negative investor sentiments or risk aversion. Using this media pessimism factor to forecast patterns of market activity, he finds that high media pessimism predicts downward pressure on stock prices, which usually revert to fundamentals within five days, although this effect is much larger and noticeably slower to reverse itself in small stocks. This is consistent with models of investor sentiment and noise trading activity, such as that of DeLong *et al.* (1990). Tetlock (2007) also finds that unusually high or low media pessimism predicts a temporarily high trading volume and that pessimism weakly predicts increases in market volatility. However, the hypothesis that media pessimism can reflect negative fundamental information that has not been incorporated into stock prices does not receive much support from the data. This is especially true given the reversal of pessimism effects.

This work on linguistic tone and pessimism contained in news media articles was further extended to the firm level by Tetlock *et al.* (2008) to look specifically at whether quantitative measures of language contained in news articles are able to predict firm fundamentals and stock returns. As in Tetlock (2007), the paper uses the Harvard psychosocial dictionary to classify language present in news articles and finds that the fraction of negative words in the financial press can forecast low earnings and returns. This suggests that linguistic media content can capture otherwise hard to quantify aspects of firms fundamentals. The authors also find that there is return predictability contained in negative media sentiment on the day following the publication of the media articles. They note that there is a strong link between news stories containing the word *earn* and stock returns and that stories about fundamentals are a useful predictors of earnings and returns. Their results corroborate evidence from psychology (Baumeister*et al.*, 2001) that negative information in news stories has more impact, also finding that the market response to negative words is up to five times stronger when media coverage is earnings related.

Research has also shown the linguistic tone of news articles is influenced by the spin of investor relations firms (Solomon, 2011) generating greater media coverage of positive news than of negative news. There is also a local bias on media reporting, found by Gurun and Butler (2011), which, due to local advertising expenditure, creates a positive abnormal slant of news reporting that is strongly related to firm equity values.

The relation between media coverage and the cross section of expected stock returns is investigated by Fang and Peress (2009). Their main findings show that stocks not covered by the news media earn higher future returns than those that are highly covered. This return difference was found to be significant and over 0.2% per month, after accounting for other common risk factors. This effect was shown to be particularly strong in small stocks, revealing that media coverage improves the quality of information available about stocks and reduces their associated informational risks. Therefore stocks that are more intensively covered earn a lower return due to lower informational risks. Their findings support the informational risk hypothesis of Merton (1987) and Easley and O'Hara (2004), who posit that informational risk is a determinant of the cross-sectional dispersion of stock returns. Fang and Peress (2009) argue that media articles can be classified firmly as public information, which leads, they suggest, to the implication that a firm's media relations can affect its cost of capital. This is also consistent with Doukas*et al.* (2005), who find that excess analyst coverage is associated with overvaluation and low future returns, as well as with Barber and Odean (2008), who find that individual investors are net purchasers of attention-grabbing stocks or stocks in the news, which can temporarily inflate a stock's price and lead to disappointing returns.

In a further extension to the research investigating the effect media coverage has on stock returns, Carretta*et al.* (2011) examine news specifically concerned with corporate governance issues. Their research gives further insight into the characteristics of media reporting that influence stock price reactions. In particular, the authors show that news about ownership issues or changes in a board of directors has a negative effect on stock returns unless the firm covered was unprofitable at the time. Additionally, Cai*et al.* (2006) show that a firm's corporate governance characteristics also affect the market reaction to company-specific news. Engelberg and Parsons (2011) further demonstrate that local media coverage strongly predicts local trading.

Many media studies involving financial markets use the Harvard psychosocial dictionary to categorise the words featured in financial news articles. Loughran and McDonald (2011) argue, however, that many words that appear in negative categories in the Harvard psychosocial dictionary are not negative in a financial sense: They are merely descriptive terms. These are words such as *depreciation*, *liability*, *foreign*, and *mine*. Therefore, trying to model the effects on media sentiment on asset prices using the Harvard psychosocial dictionary can lead to the effect of media articles being overstated. Loughran and McDonald's (2011) research shows that in a sample of US firms, more than half of the words in the Harvard list are not negative sentiment words in the financial sense. To overcome this problem, the authors created a specialised list of words that carry a negative sentiment in the financial sense. This enabled them to more accurately account for negative sentiment when reviewing financial media. To test the effectiveness of each list to predict returns patterns from media data, the authors examined the 10-K financial reports from US companies. A strong relation is found with Loughran and McDonald's list of words and announcement returns. Firms with a high proportion of negative words in these filings had lower subsequent stock returns than those with a lower proportion of negative words. Using the negative word categories from the Harvard psychosocial dictionary, the authors find no return pattern in the data. Significant relations with returns are also highlighted in other word categories, such as *positive*, *litigious*, and *weak modal*.

3. News Media Data Characteristics and Variable Construction

News media articles specific to individual companies were obtained manually from LexisNexis UK. The sources of the LexisNexis UK data include the daily publications *Financial Times*, *Times*, *Guardian*, and *Mirror*. The data covered UK companies from the FTSE 100 Index from 1981 through 2010. A total of 304,105 media articles were used in our analysis over the sample period considered.

The content of the media articles is analysed to determine the number of positive and negative words they contain. The words in each article are compared to Loughran and McDonald's (2011) positive and negative financial word lists to identify the number of positive and negative words in a financial context.[2] The current versions of the positive and negative lists contain 353 and 2,337 words, respectively. The measures of positive and negative news media contentare determined for each individual news media article as follows:

$$Positive\ Content = \frac{Positive\ Words}{Total\ Words}$$

$$Negative\ Content = \frac{Negative\ Words}{Total\ Words}$$

We then average these measurements of positive and negative content for all news media articles written about each company i on each day t to construct the variables $Pos_{i,t}$ and $Neg_{i,t}$, which provide a daily company-specific quantitative measurement of semantic news media content.[3]

The news media articles are dated on the trading day on which they are published. This is appropriate, since all the news sources in our sample are daily publications. For instance, the *Financial Times*, which makes up the largest part of our sample (55%), goes to press around 1:00 a.m. on the day it is published. All deliveries are completed by 7 a.m., which is before the UK stock markets open. Hence it would be expected that investors would act upon the news media content on day t. Therefore we match each measure of $Pos_{i,t}$ and $Neg_{i,t}$to the associated company's daily excess stock returns on day t. For days when there is no media coverage about a specific firm, $Pos_{i,t}$ and $Neg_{i,t}$ have a value of zero. This approach is similar

[2]The positive and negative financial word lists can be obtained from McDonald's website at http://www.nd.edu/~1onald/Word_Lists.html.

[3]We also consider other measures of positive and negative news media content such as (#Positive words) / (#Positive words + #Negative words), (#Negative words) / (#Positive words + #Negative words), and Ln(1+ Pos) and Ln(1 + Neg) and find similar relations, consistent with the measures selected.

to that of Loughran and McDonald (2011), who evaluate the proportion of words from a specific word list appearing in a firm's 10-K report. Table 1 reports the raw news-specific statistics.

[Insert Table 1 around here]

From Table 1 we are able to draw some inferences regarding the characteristics of news media and their semantic content over the last 30 years. The volume of news has been generally increasing from 1981 to 2010. News media's fascination with financial markets appears to have peaked around the time of the dot-com bubble of 1996–2000, which has the lowest mean negative news media content, and the recent financial crisis of 2006–2010, which has the highest mean value for negative news media content.

Aggregate measures of positive and negative news media content, $AggPos_t$and $AggNeg_t$, are constructed that take the average of $Pos_{i,t}$ and $Neg_{i,t}$, respectively, across all companies with news articles published about them on day t. These measures are used to draw market-level inferences about news media content. Figure 1 shows a rolling average of 100 days of $AggPos_t$and $AggNeg_t$and we see that negative news media content has significantly more variation than positive news media content.

[Insert Figure 1 around here]

The first period of pronounced negative news media content occurs in early 1986, although we find no firm-specific or economic news to warrant the high content of negative words in news articles, world events such as the American bombing of Libya and the Chernobyl disaster may have contributed. Negative news media content then decreases for the rest of 1986 and reaches a minimum around the time of the 'Big Bang', so termed for the sudden deregulation of British financial markets on 27 October 1986. The next large market event in our sample is the crash of 1987. Shiller (2005) examines the news during the crash and finds no cause or consensus in US financial markets. In the UK, the FTSE 100 Index fell 11% on 19 October 1987, and 13% on 20 October 1987. Looking at our measures of aggregate news media content, we find that on 19 October it was below average, at 1.3% of words; however, positive news was well below average, at 0.4% of words. Given that the crash occurred on a Monday, looking back to the Friday before the crash, we notice no remarkable changes in the aggregate measures of news media content, with both measures around the long-term average. The next significant peak in negative news media content occurs in autumn 1992. This corresponds to the withdrawal of the UK from the European Exchange Rate Mechanism. The UK economy then turned around in early 1993 and produced a strong recovery, which also corresponds to the gradual fall in negative news media content to its lowest point in the sample period, in early 1997. The next notable spikes in negative news media content come in 2002 and 2003, as the UK economy faltered and global stock markets began to tumble and an impending war with Iraq weighed on the UK stock market. This then brings us to the financial crisis that began in 2007. The level of negative news media content rose sharply throughout 2008, especially after the Lehman Brothers bankruptcy in the US, reaching a hiatus in February and March 2009, when concerns about the strength of the UK's financial institutions were at their gravest. The steep rise and eventual high point in aggregate negative news media content was made more pronounced due to the unprecedented level of media coverage during the global financial crisis. In particular, the news surrounding financial institutions, which make up a large proportion of the FTSE 100 Index, heavily influence the aggregate measures of news media content.

From this cursory investigation, it appears that aggregate measures of negative news media content have a strong relation with market-level events, which will be formally investigated in the next section.

4. Using Semantic Measures of News Media Content to Predict Stock Returns

This section studies the empirical hypothesis that semantic measures of news media content can predict stock returns. We examine the reaction of investors to news media content, not only on the day news media articles are published but also on the days following the news publication, using lagged measures of news media content. We also investigate the role played by the volume of media coverage each newsworthy event receives.

The construction of daily company-specific positive and negative measures of news media content, $Pos_{i,t}$ and $Neg_{i,t}$, is detailed in Section 3. We match these measures to the daily stock excess returns over the FTSE 100 Index returns on day *t*. As previously explained, all news sources in our sample are daily publications, which are released before market opening on day *t.* So we measure the effect of the media content in such news articles on the closest next trading period where we would expect their effects to be realised.

Since larger firms tend to receive more media attention than smaller firms, we split our sample of FTSE 100 firms by market capitalisation and examine the variouseffects of news media content on the stock returns of large, medium, and small firms. Largefirms in our sample are in the top third of companies by market capitalisation, mediumfirms are in the second third, and small firms are the bottom third. There are 25 firms in each category.

To assess the impact of media attention on a firm's stock returns, we include a variable for media coverage ($MC_{i,t}$) in the regression specifications. We define this as the number of news media articles published about a specific company *i*on each day *t*. We thus explore the notion of whether informational risk is a determinant of the cross-sectional dispersion of returns (Merton, 1987; Easley and O'Hara, 2004; Fang and Peress, 2009), where the more heavily a firm is covered by the news media, the lower the informational risk they should have. We also examine the interaction between media attention and news media content; that is, for positive and negative news media content, we study whether higher visibility news events have a greater effect on stock returns. We include the variables $MC_{i,t}*Pos_{i,t}$, $MC_{i,t}*Neg_{i,t}$, and their lags to investigate this. These variables capture the effect of a firm's positive and negative news media coverage.

Our regressions include control variables capturing a firm's size, book-to-market ratio, and trading volume, as in Tetlock *et al.* (2008). We measure firm size as Ln*(Market Equity)*, book-to-market ratio as Ln*(Book/Market)*, and trading volume as Ln*(Share Turnover)*. We calculate all these measures on a daily basis. We also control for a firm's recent past returns using the lagged values of its excess stock returns.

Table 2 reports the results of the three ordinary least squares (OLS) regressions for small, medium, and large firms as measured by their market capitalisations, along with the regression for all the firms within the sample. The dependent variable is firm excess returns on day *t* regressed on positive and negative measures of news media content in firm-specific news stories, media coverage variables, and controls. Consistent across the regressions, we see an overall continuation and reversal effects of news media on firms' excess returns on days *t* and *t* - 1,respectively, which was also observed by Tetlock *et al.* (2008).

[Insert Table 2 around here]

The main results of Table 2 show that the effect of semantic measures of news media content on stock returns varies according to firm size. First, we find that large and medium firms stock returns have a significant negative coefficients for $Neg_{i,t-1}$. This means large and medium firms stock returns have a negative relation with negative words the day after the news articles are published, which is generally consistent with the full-sample results of Tetlock *et al.* (2008). However, the significance of the result of Tetlock *et al.* (2008) is driven by the proportion of the sample from the Dow Jones News Service, which releases intraday stories with extremely recent information. When using the proportion of the sample belonging to the *Wall Street Journal*, a daily news publication issued before market opening each day (similar to the characteristics of our own media data sample), Tetlock *et al.* (2008) find that negative words do not significantly predict lower stock returns on day $t + 1$. The authors note that the lack of significance of the *Wall Street Journal* stories is due to the recapitulations of the previous day's events. We find some support for this hypothesis, since we also see that on the day the news articles are published, large firms' stock returns have a negative relation with positive words, indicated by a significant negative coefficient for $Pos_{i,t}$, and a positive relation with negative words, indicated by a significant positive coefficient for $Neg_{i,t}$. This suggests that with highly visible firms, the information from a news article may have already been incorporated into the price or the news article is reporting on past events and we are seeing a reversal due to prior overreaction. The significant negative coefficient of $Neg_{i,t-1}$is then driven by a subset of investors who are slower to react, possibly due to some cognitive dishonesty or conservatism, as in Barberis *et al.* (1998), who find that investors are reluctant to change their beliefs in the face of new evidence. This reluctance to believe news is much more prominent in the case of bad news, since $Pos_{i,t-1}$ has no predictive power. This finding is supported by behavioural models that suggest investors tend to hold on to losing stocks longer than they should (Shefrin and Statman, 1985; Frazzini, 2006).

Furthermore, we find small and medium firms stock returns have positive relations with positive words the day news articles are published, and small firms stock returns have a significant negative relation with negative words on the day news articles are published. However, medium-sized firms have significant negative coefficients for $Neg_{i,t-1}$, again highlighting some reluctance to act quickly to a rise in negative news media content. This suggests that for more visible firms, where reaction to news media content is strongest, investors react slower to negative news media content and hence display more conservatism or cognitive dishonesty about their investment decisions regarding more visible stocks.

Additionally, we show that media coverage, $MC_{i,t}$, which we proxy for recognition or attention, predicts low returns and that this effect is driven by large firms, shown by the significant negative coefficient. This is consistent with the informational risk hypothesis of Merton (1987) and the results of Fang and Peress (2009).

Importantly, when the media coverage variable interacts with the news media content variables($MC_{i,t}*Pos_{i,t}$and $MC_{i,t}*Neg_{i,t}$), that is, when we consider the joint effect of the volume and tone of news media information, we find that stock prices overreact to highly visible news. We see an amplified effect of news events that receive higher levels of media coverage, whether positive or negative, and there is a reversal the following trading day. This is highlighted by the reversal of the sign of the coefficients between $MC_{i,t}*Pos_{i,t}$and $MC_{i,t-1}*Pos_{i,t-1}$and between $MC_{i,t}*Neg_{i,t}$and $MC_{i,t-1}*Neg_{i,t-1}$ and is consistent across all firm sizes, with the strongest effect, though, coming from large, highly visible firms. The initial overreaction is greater for highly visible news with a positive tone than it is for highly visible news with a negative tone; the reversal, however, is more significant for higher visible news with a negative tone. In each case the reversal in sign between $MC_{i,t}*Pos_{i,t}$and $MC_{i,t-1}*Pos_{i,t-1}$and between $MC_{i,t}*Neg_{i,t}$and $MC_{i,t-1}*Neg_{i,t-1}$is smaller and significant, showing that not all of the overreaction to news media content is corrected for. This result showing investor overreaction to the combination of volume and tone is consistent with the results of Barber and Odean (2008) finding attention-driven buying behaviour by investors.

[Insert Table 3 around here]

We also consider the alternative risk adjustment using the Fama–French three-factor model. Table 3 reports the results of the three OLS regressions for small, medium, and large firms as measured by their market capitalisations, along with the regression for all the firms within the sample. The dependent variable is abnormal return adjusted by the Fama–French three-factor model (*FFCAR*$_{i,t}$)estimated by a trading period between 252 and 31 days prior to the media article's publication day *t*. We also include two control variables of lagged abnormal returns (*FFCAR*$_{i,t-1}$and*FFCAR*$_{i,t-2}$). The rest of the control variables remain the same as in Table 2. The results of Fama–French abnormal returns in Table 3 are very similar to the excess returns in Table 2, reinforcing the fact that our previous findings of the relation between media tone, coverage, and stock returns are robust to alternative risk measurements.

5. Market-Level Return Predictability of Aggregate News Media Content

When describing the evolution of measures of aggregate news media content over time in Section 3, it appeared that they were negatively correlated with market-level events. We now formally test this proposition by using the aggregate measures of news media content *AggPos*$_t$and *AggNeg*$_t$ described in Section 3, which are the average of all company-specific measures of positive and negative news media content, *Pos*$_{i,t}$ and *Neg*$_{i,t}$, on each day *t*. We regress these aggregate measures on FTSE 100 Index daily returns. We also include lags of the aggregate measures of news media content to test whether the return predictability observed at the firm level on day t + 1, is present at the market level. We also consider the effect of aggregate measures of news media content on market-level trading volume; this provides insight into the strength of investor reactions to positive and negative news media content.

[Insert Table 4 around here]

Table 4 displays the results of the OLS regressions for Ln*(FTSE 100 Returns)* and Ln*(FTSE 100 Volume)* regressed on aggregate measures of positive and negative news media content, $AggPos_t$ and $AggNeg_t$, and their lags.We find that the aggregate negative news media content on day *t* has a significant negative relation with FTSE 100 Index returns, and all measures of aggregate news media content have significant relations with the FTSE 100 daily trading volume, although aggregate measures of positive news media content have the strongest. These results also support the findings of Tetlock (2007), that pessimistic media content can forecast patterns of market activity. However, there is no significant relation between FTSE 100 returns and lags of aggregate news media content, suggesting that at the market level, at least, news media content is incorporated quickly. However, as we are using news media content in firm-specific news articles using a financial word-specific dictionary, issues that affect the whole economy—that are likely to be better represented in non-firm–specific news articles and a broader psychosocial dictionary as in Tetlock (2007)—are not accounted for. This may explain the lack of significance in the lagged variables of news media content found at the aggregate level.

We determine the economic significance of the relation between news media content and market-level returns by constructing a trading strategy using aggregate news media content to determine buy and sell signals. Our simple news-based trading strategy takes either a long or a short position in the FTSE 100 Index on each trading day *t*, determined by the greater of the aggregate positive or aggregate negative media content on day *t*. This is feasible because aggregate measures of news media content are constructed before market opening on day *t* when the news articles are published. However, since the characteristics of the data show that, on average, negative news media content is 2.13 times greater than positive news media content, we weight positive news media content by a factor of 2.13 so the two measures are more comparable and more likely to determine the correct signal. This is more effective than using aggregate negative news media content alone. Table 4 displays the risk-adjusted daily returns of this news-based trading strategy broken down over five-year time periods from 1986 to 2010. The period 1981–1985 was excluded from the trading strategy, since there were too many days with no company-specific media articles so trading signals could not be determined. There are no such breaks in the news, however, from 1986 to 2010.

[Insert Table 5 around here]

Table 5 shows the time series regression results displaying alpha and factor loadings with their associated t-statistics. We use the Fama–French (1993) three-factor model to adjust for contemporaneous market, size, and book-to-market factors in Panel A of Table 5 and also adjust for the Carhart (1997) fourth factor of momentum in Panel B. We did not consider transactions costs in this trading strategy. In the most recent period 2006–2010, the news-based trading strategy earns significant abnormal returns of only 17 bps per day, with mixed performance throughout the rest of the sample period. Given that this strategy only trades in the FTSE 100 Index itself, it is no surprise that the market has significant loadings in every period but one. Our results are very similar to those of the hypothetical market-level trading strategy constructed by Tetlock (2007), which has a daily average return of 4.4 bps, compared to the daily average return of 4.6 bps that we find.

For the whole period 1986–2010, size and momentum factors also derive significant relations with the risk-adjusted returns of our news-based trading strategy. This is sharply different from the US evidence of Tetlock *et al.* (2008), which could be due to the difference in the construction of the strategy, where the authors construct portfolios of individual stocks with firm-specific risk; we, however, trade only in the market index, which is evidently related to the other factors. Figure 2 provides a visual representation of the continuously compounded returns of the trading strategy compared to the FTSE 100 Index over the same period.

[Insert Figure 2 around here]

One reason for the strong positive abnormal returns during the most recent period could be that the volume of news greatly increased, producing more accurate signals. However, we would have seen some improvement in the period 1996–2000, when the volume of news also increased. Since the news over the most recent period was generally negative and since the FTSE 100 was experiencing strongly negative returns itself, generating the correct signal was perhaps considerably easier. These results are in contrast to the news-based trading strategy of Tetlock *et al.* (2008), who constructed a strategy that returns significant positive abnormal returns in every time period from 1980 to 2004. However, the authors were using intraday news from the Dow Jones News Service to determine their long and short positions. It would appear that the economic significance does not apply when using news media content from daily news publications such as those in our sample.

6. Conclusion

This study examines the relations between semantic measures of news media content and stock returns for FTSE 100 companies over the period 1981–2010 and tests whether there is any stock return predictability inherent in measures of news media content. Our main results show that the effect of semantic measures of news media content on stock returns varies according to firm size. First, we find that large and medium firms' stock returns have a negative relation with negative words the day after the news articles are published, which is consistent with Tetlock *et al.* (2008). Small and medium firms stock returns have positive relations with positive words the day news articles are published, and small firms stock returns have a significant negative relation with negative words on the day news articles are published. This suggests that for more visible firms, where reaction to news media content is strongest, investors react more slowly to negative news media content and hence display more conservatism or cognitive dishonesty about their investment decisions regarding more visible stocks.

Second, we show that media coverage, which we proxy for recognition or attention, predicts low returns and that this effect is driven by large firms. This is consistent with the informational risk hypothesis of Merton (1987) and the results of Fang and Peress (2009). Importantly, when we consider the joint effect of volume and tone of news media information, we find that stock prices overreact to highly visible news, whether positive or negative in tone, and there is some reversal on the following trading day but the overreaction is not completely corrected. This effect is strongest for large highly visible stocks, consistent with Barber and Odean (2008), where investor overreaction is driven by attention-grabbing stocks. Further research should investigate whether this overreaction to highly visible news causes persistent deviations in price away from fundamental values, as suggested by Shiller (2005).

Lastly, we construct a trading strategy using aggregate levels of news media content to demonstrate the application of these results to financial practice that earns average returns of 4.6 bps per day and strongly positive abnormal returns in the most recent period. These results suggest that the UK market is fairly efficient at incorporating information contained in semantic measures of news media content into stock prices. However, the fact that there is some return predictability due to negative news media content on the day following publication indicates some cognitive dishonesty and conservatism towards bad news by investors, resulting in some underreaction on the day of the news article publication. These results find support from the literature, as in Grossman and Stiglitz (1980), who find the underreaction to negative news provides motivation for market participants to monitor financial news releases. The evidence of this underreaction to negative news is also confirmed in behavioural finance theories (Shefrin and Statman, 1985; Barberis *et al.* 1998; Frazzini 2006). Future research should investigate more thoroughly the application of media data to financial market participants and its wider impact concerning the efficiency of markets.

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Table 1.Summary statistics for raw media data.

This table presents the summary statistics of the media data used in this study.News data were downloaded from LexisNexis UK. Coverage statistics give the proportion of media articles that came from specific publications. The variables $Pos_{i,t}$ and $Neg_{i,t}$ are the average proportions of positive and negative words, respectively, in company-specific news articles published on day t, determined by using textual analysis to identify words that are either positive or negative according to Loughran and McDonald's (2011) financial news word lists. News articles are sourced from the *Financial Times (FT)*, *The Times*, *The Guardian*, and *TheMirror*.

Year	Total Articles	Coverage				Average Article Words	Mean $Pos_{i,t}$	Mean $Neg_{i,t}$
		FT	Times	Guardian	Mirror			
1981–1985	17,399	78%	6%	11%	0%	452	0.0095	0.0163
1986–1990	35,304	44%	35%	19%	0%	442	0.0078	0.0158
1991–1995	44,060	50%	26%	20%	4%	565	0.0079	0.0163
1996–2000	64,377	49%	16%	21%	9%	490	0.0086	0.0151
2001-2005	44,237	43%	24%	19%	13%	453	0.0090	0.0183
2006-2010	98,728	67%	17%	10%	5%	477	0.0090	0.0224
1981–2010	304,105	55%	20%	16%	5%	484	0.0086	0.0183

Table 2. News media content and UK excess returns: 1981–2010.

This table reports the relations between stock returns and the tone and coverage of media content. The dependent variable is excess returns on day *t*. Media articles were downloaded from LexisNexis UK and $Pos_{i,t}$and $Neg_{i,t}$ are, respectively, the average proportions of positive and negative words in company-specific media articles published on day *t*, calculated before market opening on day *t*. Since the media articles are published before market opening on day *t*, their effect on stock returns should be realised on day *t*. They are determined by using textual analysis to identify words that are either positive or negative according to Loughran and McDonald's (2011) financial news word lists. Media coverage (*MC*) is defined as the number of media articles about a particular company on a given day.The sample of FTSE 100 firms is split by market capitalisation. The top third by market capitalisation make up the large firms, the second third make up the medium firms, and the bottom third make up the small firms.In the regressions we control for *Size*, using daily firm-level market equity, *Book-to-Market*, *Turnover*, and lagged excess stock returns.Robust *t*-statistics are reported in parentheses below the parameter coefficients.

	Firm Size by Market Capitalisation			All Firms
Independent Variables	Small	Medium	Large	
$R_{i,t-1}$	0.0326	0.0282	0.0392	0.0334
	(12.53)	(10.47)	(15.21)	(22.05)
$R_{i,t-2}$	-0.0029	-0.0263	-0.0262	-0.0179
	(-1.13)	(-9.76)	(-10.17)	(-11.82)
$Pos_{i,t}$	0.0687	0.0472	-0.1206	-0.0441
	(2.49)	(2.23)	(-8.28)	(-4.00)
$Pos_{i,t-1}$	0.0242	0.0151	0.0211	0.0166
	(0.89)	(0.73)	(1.45)	(1.52)
$Neg_{i,t}$	-0.0350	-0.0131	0.0575	0.0247
	(-2.54)	(-1.13)	(8.28)	(4.46)
$Neg_{i,t-1}$	0.0015	-0.0336	-0.0343	-0.0274
	(0.11)	(-2.91)	(-4.94)	(-4.95)
Ln$(Size_{i,t})$	-0.0001	-0.0001	-0.00003	-0.00006
	(-1.72)	(-2.47)	(-0.74)	(-2.54)
Ln$(Book\text{-}to\text{-}Market_{i,t})$	-0.0002	-0.0004	-0.0002	-0.0003
	(-3.72)	(-6.29)	(-3.71)	(-7.86)
Ln$(Turnover_{i,t})$	0.00007	0.00007	0.00002	0.00005
	(3.19)	(3.30)	(1.07)	(4.31)
$MC_{i,t}$	0.0002	0.00007	-0.0003	-0.0001
	(1.37)	(0.54)	(-4.04)	(-2.51)
$(MC_{i,t})*Pos_{i,t}$	0.0226	0.0215	0.1019	0.0710
	(1.70)	(2.02)	(17.20)	(14.44)
$(MC_{i,t})*Neg_{i,t}$	-0.0190	-0.0179	-0.0366	-0.0291
	(-3.59)	(-4.86)	(-15.63)	(-15.44)
$(MC_{i,t-1})*Pos_{i,t-1}$	-0.0168	-0.0135	-0.0195	-0.0167
	(-1.57)	(-1.72)	(-4.24)	(-4.42)
$(MC_{i,t-1})*Neg_{i,t-1}$	0.0049	0.0114	0.0162	0.0132
	(1.14)	(3.60)	(8.71)	(8.66)
Constant	0.0002	0.0003	0.0002	0.0001
	(0.69)	(1.09)	(0.72)	(0.87)
Observations	147912	137970	150663	436545
Adjusted R-squared	0.0017	0.0024	0.0063	0.0030

Table 3. News media content and UK Fama–French adjusted returns: 1981–2010.
This table reports the relations between the stock returns and the tone and coverage of media content. The dependent variable is abnormal return adjusted by the Fama–French three-factor model (*$FFCAR_{i,t}$*)estimated by a trading period between 252 and 31 days prior to the media article's publication day *t*. Media articles were downloaded from LexisNexis UK and *$Pos_{i,t}$*and *$Neg_{i,t}$* are, respectively, the average proportions of positive and negative words in company-specific media articles published on day *t*, calculated before market opening on day *t*. Since the media articles are published before market opening on day *t*, their effect on stock returns should be realised on day *t*. They are determined by using textual analysis to identify words that are either positive or negative according to Loughran and McDonald's (2011) financial news word lists. Media coverage (*MC*) is defined as the number of media articles about a particular company on a given day. The sample of FTSE 100 firms is split by market capitalisation. The top third by market capitalisation make up the large firms, the second third make up the medium firms, and the bottom third make up the small firms.In the regressions we control for *Size,* using daily firm-level market equity, *Book-to-Market*, *Turnover*, and lagged abnormal returns. Robust t-statistics are reported in parentheses below the parameter coefficients.

	Firm Size by Market Capitalisation			All Firms
Independent Variables	Small	Medium	Large	
$FFCAR_{i,t-1}$	0.0270	0.0327	0.0282	0.0295
	(8.41)	(10.96)	(10.06)	(17.08)
$FFCARR_{i,t-2}$	-0.0195	-0.0205	-0.0170	-0.0188
	(-6.05)	(-6.86)	(-6.06)	(-10.91)
$Pos_{i,t}$	0.0939	0.0160	-0.0907	-0.0398
	(2.04)	(0.49)	(-4.28)	(-2.38)
$Pos_{i,t-1}$	0.0577	0.0063	0.0226	0.0192
	(1.26)	(0.20)	(1.07)	(1.16)
$Neg_{i,t}$	-0.0752	0.0197	0.0502	0.0266
	(-3.23)	(1.14)	(4.92)	(3.19)
$Neg_{i,t-1}$	-0.0067	-0.0252	-0.0263	-0.0211
	(-0.29)	(-1.48)	(-2.57)	(-2.53)
Ln($Size_{i,t}$)	-0.0002	-0.0002	-0.00003	-0.0001
	(-2.03)	(-2.16)	(-0.42)	(-2.43)
Ln($Book\text{-}to\text{-}Market_{i,t}$)	0.00006	0.00002	-0.00008	-0.00001
	(0.54)	(0.20)	(-0.89)	(-0.18)
Ln($Turnover_{i,t}$)	0.0001	0.0001	0.00004	0.00009
	(3.12)	(3.72)	(1.35)	(4.52)
$MC_{i,t}$	0.0003	0.0001	-0.0003	-0.0001
	(1.45)	(1.04)	(-3.33)	(1.60)
$(MC_{i,t})*Pos_{i,t}$	0.0024	0.0057	0.0932	0.0613
	(0.12)	(0.37)	(11.04)	(8.60)
$(MC_{i,t})*Neg_{i,t}$	-0.0014	-0.0153	-0.0285	-0.0218
	(-0.17)	(-2.98)	(-8.59)	(-8.10)
$(MC_{i,t-1})*Pos_{i,t-1}$	-0.0282	-0.0152	-0.0220	-0.0196
	(-1.73)	(-1.34)	(-3.37)	(-3.59)
$(MC_{i,t-1})*Neg_{i,t-1}$	0.0013	0.0072	0.0149	0.0107
	(0.19)	(1.65)	(5.66)	(4.93)
Constant	0.0009	0.0003	-0.00006	0.0001
	(1.25)	(0.61)	(-0.13)	(0.51)
Observations	96885	112286	127099	336270
Adjusted R-squared	0.0014	0.0016	0.0027	0.0017

Table 4. Market-level returns and volume predictability of aggregate news media content.
The dependent variables are the FTSE 100 log of returns and the log of the FTSE 100 volume. The variables *$AggPos_t$* and *$AggNeg_t$* are, respectively, the aggregate measures of the average proportions of positive and negative words in company-specific media articles on days *t*, constructed by taking the average of the *$Pos_{i,t}$* and *$Neg_{i,t}$* measures of all companies that have news articles published about them on day *t*. These measures are determined by using textual analysis to identify words that are either positive or negative according to Loughran and McDonald's (2011) financial news word lists. Media articles were downloaded from LexisNexis UK. The regression also includes lags of the aggregate measures of media content.

Variable	FTSE 100 Returns	Ln(FTSE 100 Volume)
$AggPos_t$	0.1085	92.3371
	(1.6231)	(13.56)
$AggPos_{t-1}$	0.0015	78.0783
	(0.02)	(11.47)
$AggNeg_t$	-0.0747	36.5289
	(-2.15)	(10.30)
$AggNeg_{t-1}$	0.0109	30.0787
	(0.3134)	(8.49)
Constant	0.0003	10.5772
	(0.3716)	(177.69)

Table 5. Risk-adjusted news-based trading strategy results.

This table shows the regression results of the trading strategy with daily risk-adjusted returns from the news-based trading strategy as the dependent variable. The regressions use the Fama–French (1993) three-factor model to adjust the trading strategy returns for the impact of contemporaneous market (*Market*), size (*SMB*), and book-to-market (*HML*) contents in Panel A. We also account for the Carhart (1997) momentum factor (*UMD*) in Panel B. *Alpha* (Jensen's) is abnormal returns. Robust t-statistics are reported in parentheses below the parameter coefficients.This news-based trading strategy uses aggregate news media content calculated as the average news media content of all stocks that have news published about them on a particular day before trading opens, taken on a daily basis to determine whether to take a long or short position in the FTSE 100 Index. To determine the most accurate trading signal, daily aggregate positive news media content is weighted by a content of 2.13. We do this because the characteristics of the data show that the aggregate negative news media content is 2.13 times greater than the aggregate positive news media content. The strategy takes a long or short position on a daily basis, reinvesting all continuously compounded returns to date. It takes a long position in the FTSE 100 Index if the weighted aggregate positive news media content is greater than the aggregate negative media content, and a short position if aggregate negative media content is greater than the weighted aggregate positive media content. It is assumed that the execution of such a strategy can be performed using an exchange traded fund or futures with no transactions costs being accounted for.

	1986–1990	1991–1995	1996–2000	2001–2005	2006–2010	1986–2010
Panel A: Fama–French Three-Factor Model						
Alpha	0.00003	-0.0002	-0.0003	-0.0005	0.0017	0.0002
	(0.09)	(-0.82)	(-1.18)	(-1.39)	(4.46)	(1.34)
Market	0.1133	-0.2437	0.3692	0.0860	-0.1930	0.0411
	(2.28)	(-3.69)	(7.10)	(0.92)	(-3.98)	(1.69)
SMB	0.0853	-0.2353	-0.0279	0.0423	0.1246	0.0849
	(3.98)	(-4.90)	(-0.74)	(0.81)	(4.42)	(6.13)
HML	0.1216	0.1422	-0.0382	0.1783	0.0230	-0.0189
	(3.57)	(3.01)	(-1.53)	(5.33)	(1.16)	(-1.62)
Trading days	1059	1269	1274	1264	1216	6082
Adjusted R-squared	0.0246	0.0243	0.2101	0.0295	0.1524	0.0120
Panel B: Carhart Four-Factor Model						
Alpha	0.00007	-0.0003	-0.0003	-0.0004	0.0017	0.0001
	(0.20)	(-1.27)	(-1.23)	(-1.33)	(4.33)	(0.90)
Market	0.1151	-0.1883	0.3692	0.0863	-0.1766	0.0592
	(2.32)	(-2.68)	(6.20)	(0.92)	(-3.64)	(2.43)
SMB	0.0844	-0.2098	-0.0441	0.0571	0.1110	0.0764
	(3.94)	(-4.26)	(-1.11)	(1.07)	(3.92)	(5.51)
HML	0.1147	0.1441	-0.0368	0.1745	0.0641	0.0077
	(3.33)	(3.06)	(-1.48)	(5.20)	(2.77)	(0.63)
UMD	-0.1004	0.1297	0.0513	-0.0603	0.1201	0.1279
	(-1.29)	(2.28)	(1.29)	(-1.22)	(3.45)	(6.74)
Trading days	1059	1269	1274	1264	1216	6082
Adjusted R-squared	0.0252	0.0275	0.2106	0.0299	0.1599	0.0192

Figure 1. Aggregate measures of the proportions of positive and negative words in media articles: 1981–2010.

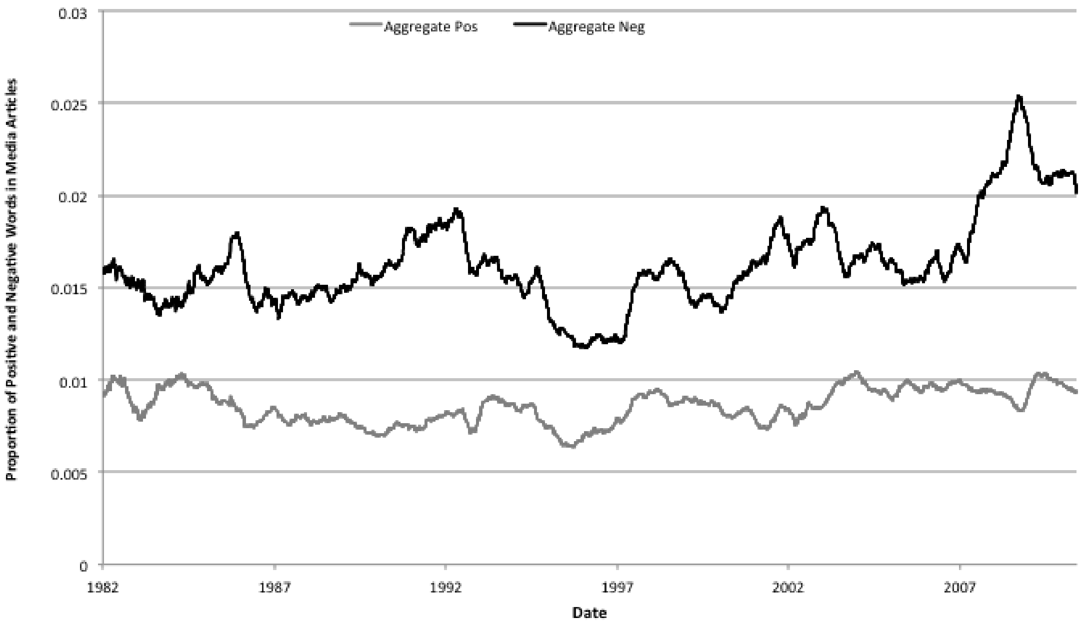
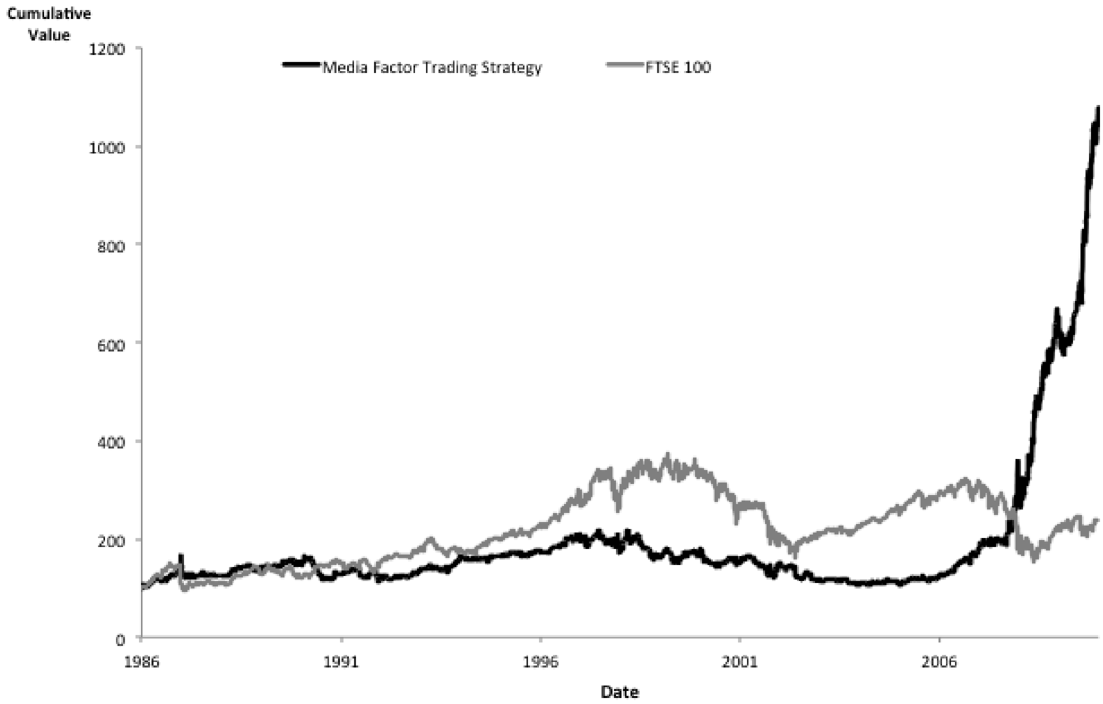


Figure 1 shows the rolling 100-day averages of the aggregate measures of the average proportions of positive and negative words in company-specific media articles, constructed by taking the average of the $Pos_{i,t}$ and $Neg_{i,t}$ measures of all companies on day *t*. Media articles were downloaded from LexisNexis UK and $Pos_{i,t}$ and $Neg_{i,t}$ are, respectively, the average proportions of positive and negative words in company-specific media articles on day *t*, determined by using textual analysis to identify words that were either positive or negative according to Loughran and McDonald's (2011) financial news word lists.

Figure 2. Continuously compounded performance of news-based trading strategy.



This news-based trading strategy uses aggregate measures of the average proportions of positive and negative words in media articles on a particular day before trading opens, taken on a daily basis to determine whether to take a long or short position in the FTSE 100 Index. To determine the most accurate trading signal, the daily aggregate positive news media content is weighted by a content of 2.13. We do this because the characteristics of the data show that the aggregate negative news media content is 2.13 times greater than the aggregate positive news media content. The strategy takes a long or short position on a daily basis, reinvesting all continuously compounded returns to date. It takes a long position in the FTSE 100 Index if the weighted aggregate positive news media content is greater than the aggregate negative news media content, and a short position if the aggregate negative news media content is greater than the weighted aggregate positive news media content.