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News Media and Investor Sentiment during Bull and Bear Markets

Alan J. Hanna, John D. Turner and Clive B. Walker*

Abstract

The news media have been described by Shiller (2000) as fundamental propagators of speculative price movements. We test whether investors react differently to sentiment in bull and bear markets using the tone of reporting in the *Financial Times* as a proxy for sentiment. Our sentiment proxy is a daily measure covering the period from 1899 to 2010. We find that the tone of the *Financial Times* influences trading volume during bull markets. These findings are consistent with noise traders driving trade during speculative booms and Shiller's press-as-propagators hypothesis.

JEL classification: G12, N23, N24

Keywords: News media, investor sentiment, stock market, bull, bear

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I. Introduction

Shiller (2000, 2017) argues that the press plays an important role in propagating stock-market booms and market sentiment through their narratives and hype. The tone of newspaper reporting—the percentage of positive and negative words—provides an empirical measure to test the influence of sentiment. Tetlock (2007) formally tests this role of the press and finds that the negative tone of reporting in a *Wall Street Journal* market column predicts daily stock returns. Similarly, García (2013) finds that the negative and positive tone of reporting in financial columns in the *New York Times* over a century predicts daily stock returns, but that the effect is concentrated in recessions. This paper contributes to this literature by using daily data on the tone of the *Financial Times* (FT) from 1899 to 2010 to test whether the effect of press reporting on daily returns and trading volume on the London Stock Exchange is greater during bull markets. We find that although the effect of tone on returns is not greater in bull markets, tone shifts trading volume during bull markets. These findings are consistent with noise traders driving trade during speculative booms (Baker and Stein, 2004) and Shiller’s press-as-propagators hypothesis.

In this paper, we use the four principal sections from the FT - Editorials and Leaders, Lex, News in Brief, and Market News columns - and count the number of positive and negative words used in each section to generate a daily proxy of investor sentiment. The sections we include are broader than those used in previous studies in that they cover more than stock-market news. They also include explicit commentary and opinion pieces (Editorials and Leaders and Lex).

In order to test the effect of investor sentiment, as proxied by the FT’s reporting, on stock returns, we create a daily blue-chip index for the U.K. market. This is necessary because the

FTSE 100 was only created in 1984. From 1930 onwards, we use pre-existing blue-chip indices. Prior to 1930, we collect the relevant data to construct a daily index of the largest stocks in the United Kingdom to imitate the post-1930 daily blue-chip index. As a result, this paper presents the first daily stock-market index for the United Kingdom dating back to 1900.

Investor sentiment is viewed as being highly correlated with the prevailing state of the stock market (Baker and Wurgler, 2007). Thus, the effect of investor sentiment on the market may vary with the market's prevailing state. If the stock market is in a bullish/bearish mood, positive/negative reporting by the press may exacerbate or dampen the overall mood of the market. While there is no formally agreed definition for 'bull market' and 'bear market' phases, these terms have become commonplace and are widely understood to mean periods of time when market prices are generally rising or falling (Chauvet and Potter, 2000). Google's Ngram viewer reveals these specific terms were a well-established part of the financial lexicon by the end of the nineteenth century. These terms capture and express something akin to prevailing market sentiment.¹ We therefore test whether the overall state of the stock market affects investor sentiment as well as Shiller's (2000) press-as-propagators hypothesis. We also test García's (2013) hypothesis, based on the personality and psychology literature, that newspaper sentiment has a greater effect during periods of hardship. To identify whether the market is in a bull or bear state, we develop algorithms based firstly on the performance of our blue-chip index and secondly on the FT's use of 'bullish'/'bearish' words.

¹ By contrast, business cycles capture aggregate activity across an entire economy. Moreover, the economic data used to define business cycles is released only periodically, lacks immediacy, is backwards looking, is subject to subsequent and frequent revision, and ultimately may not matter to investors - markets can sustain high returns during economic downturns and *vice versa*.

This paper is part of a growing literature which examines the role of the press in financial markets. The importance of the press has long been recognized in the literature, from Bagehot's (1893) observation that the press affects the behavior of central bankers, to Niederhoffer's (1971) study of market reaction to front-page news of the *New York Times*. However, the digitization of newspaper content since the turn of the millennium has increased the opportunities available to researchers in this field and as a result there has been a dramatic increase in the depth of the literature. Building on computational linguistic concepts and techniques, textual analysis has offered researchers opportunities to assess the informational and behavioural role of the press in financial markets (Mira and Mitra, 2011; Kearney and Liu, 2014; Boudoukh et al., 2019). While a comprehensive review is beyond the scope of this paper, interested readers should refer to Raimondo (2019) for an up-to-date review of the literature.

This literature can be categorized into five distinct areas, namely the role of the press as a financial watchdog (Dyck et al., 2008; Taylor, 2012; Liu and McConnell, 2013); the role of the press as information providers to investors (Chan, 2003; Fang and Peress, 2009; Birz and Lott, 2001; Engelberg and Parsons, 2011; Griffin et al., 2011; Groß-Klußmann and Hautsch, 2001; Turner et al., 2017, Engelberg et al., 2018); the role of bias and incentives in the financial press and financial reporting (Dyck and Zingales, 2003; Bignon and Miscio, 2010); the role of the media in financial bubbles or speculation (Shiller, 2000; Huberman and Regev, 2001; Bhattacharya et al., 2009; Campbell et al., 2012); and the use of media content as a way of quantifying animal spirits or sentiment in the stock and housing markets (Tetlock, 2007; Dougal et al., 2012; García, 2013; Jegadeesh and Wu, 2013; Soo, 2013; Hillert et al., 2014; Uhl, 2014; Walker, 2014; Smales, 2015; Ahmad et al., 2016; Goetzmann et al., 2016; Heston et al., 2017;

Kräussl and Mirgorodskaya, 2017; Johnman et al., 2018; Larsen and Thorsrud, 2018; Püttmann, 2018; Calomiris and Mamaysky, 2018).

The part of the literature which this paper is most closely related to is the sentiment work of Tetlock (2007) and García (2013). Similar to both of these papers, we find that newspaper tone has an economically and statistically significant relationship with the returns on that day's stock-market index. A one standard deviation rise in negative tone predicts a 4.3-basis point decrease in our blue-chip index and a 3.3-basis point increase in our blue-chip index for positive tone, which is of a similar order of magnitude to the effect found by both Tetlock (2007) and García (2013). However, unlike these two papers, we identify whether the market is in a bull or bear state to test if the effect of media is greater during boom markets. We find evidence in favor of Shiller's hypothesis that the press propagates the amount of trading through their sentiment during bull markets.

The paper also augments the investor sentiment literature, which suggests that some investors are not fully rational and that their demand for stocks is driven by sentiment which is not justified by fundamental news (De Long et al., 1990; Shleifer and Summers, 1990; Barberis et al., 1998; Brown and Cliff, 2005; Baker and Wurgler, 2006, 2007, Chung et al., 2012; Bathia and Bredin, 2013; DeVault et al., 2019). For example, Kamstra et al. (2003) and Edmans et al. (2007) document how the weather and soccer results affect stock prices. We find that news media tone, our proxy for investor sentiment, predicts stock returns as well as trading volume.

We are the first paper to assess Shiller's (2000) claim that news media are fundamental propagators of speculative price movements using daily sentiment data. Given the long-run predictability in share prices (Shiller, 1984; Summers, 1986), long-run data are necessary to capture variation in market price movements. For example, there have only been two sustained

episodes of decreasing prices over the last 40 years: following the dotcom bubble and global financial crisis. Thus, even the last 40 years of daily data demonstrate insufficient variation in market states to test empirically if the effect of media sentiment during expansionary periods differed from non-expansionary periods. Consequently, we have collected 111-years of daily reporting and stock market data for the UK to test Shiller's claim.

The rest of the paper is structured as follows. The next section describes our media and stock-market data. Section III tests whether FT tone affects the stock market. Section IV compares the effect of media tone across bull and bear markets. Section V serves as a robustness check by asking whether there is information in our sentiment measure. The final section is a brief conclusion.

II. Data

News Media

The FT has been the United Kingdom's premier financial newspaper for well over a century. During its early years, the *Financial News* was its main competitor, but this newspaper's circulation was only one quarter of the FT's in the 1910s and eventually, in October 1945, it merged with the FT. Consequently, given this dominance, the FT was the main newspaper read by investors and participants in financial markets.

The FT was first published in 1888. Facsimiles of the original print editions are available from the *Financial Times Historical Archive* (FTHA).² Our analysis commences in 1899 due to the low quality of the print in the FT prior to this period. The FTHA does not have articles after

² <http://find.galegroup.com/ftha>

2010, and though alternative sources are available after this date, they lack the section classification used in our analysis, and are thus not suitable. Our sample period coincides with the era of ‘New Financial Journalism’, which recognized the responsibility of editors to inform the vastly increased number of investors (Porter, 1998).

Using the FT to quantify investor sentiment over the long run has several advantages. Firstly, the United Kingdom has long standing freedoms for the press which reduces the chance of bias. Secondly, the FT is a daily financial newspaper. As such, its content should more accurately reflect market activity and prevailing investor sentiment. Thirdly, the FT has a large circulation and a readership actively engaged in financial markets.³ The first issue of the paper ran with the banner, “[This paper is] the friend of the honest financier, bona fide investor, respectable broker, genuine director and legitimate speculator”. More recent demographic surveys confirm a professional and wealthy readership.⁴ As a result, the potential for this news medium to influence market activity is high. Fourthly, while the format and content of the paper has evolved over time, the continuity provided by long-standing features, journalists and editors makes the FT a useful vehicle for a long-run analysis of media tone.

The final, and possibly most important, advantage of using the FT is that the FTHA classifies all articles. This allows us to identify articles which are focused primarily on the stock market as well as articles which provide wider macroeconomic and financial news. It also allows us to identify editorials which provide explicit commentary. For this study, we selected articles

³ Kynaston (1988) reports average daily net sales in the early 1900s of about 12,000, rising to over 250,000 by 1986. The FT currently claim an ‘average daily global audience’ of 2.1 million across print and digital platforms. See <http://aboutus.ft.com/corporate-information/history/>

⁴ <http://fttoolkit.co.uk/d/audience/>

from the four areas of the FT which are most pertinent to the stock market and which are most likely to reflect investor sentiment in the London market. It also means that we ignore firm-specific reporting by the FT, which is much more likely to contain new information than the sections of the newspaper included in this study.

The four sections of the FT used in this study are based on FTHA classifications. Editorials and Leaders are typically limited to two or three separate subjects per edition and focus on key political and economic issues. The Lex column is described by the FT as setting “the agenda on everything from company analysis and macroeconomics to financial markets to critical trends of the day”.⁵ Lex was published in the FT from October 1945, following the merger with the *Financial News*. News in Brief articles summarize general macroeconomic and political news. Finally, Market articles come from the ‘Market News’ section, with the additional criteria that articles contained the word ‘market’ in the title. These articles reported on what had been happening in the stock market during previous trading sessions.

To ensure a plausible causal relation, it is important to establish when the FT was in the hands of investors and traders. While it is likely that the publication of some commentary articles lags market events by at least one day, to ensure there is a plausible causal relationship, we adopt a cautious approach to aligning our measures of media tone with market activity. The physical paper was published, printed and distributed prior to the opening of U.K. financial markets (Ferguson et al., 2015). The FT.com was launched in 1995, and some articles published in the print version of the newspaper were available online before the market close of the preceding trading day. However, this is not an issue for this study because the four sections we examine

⁵ <http://www.ft.com/lex> (see ‘About Lex’)

were not available until well after the close of the markets. Thus, following García (2013), we date our media measures to the day written rather than the day published.

Articles from the FTHA were converted from PDF files to text files using ABBYY Optical Character Recognition (OCR) software. Loughran and McDonald (2015) highlight various problems with using generic text analysis software. Thus, subsequent processing and analysis was performed using bespoke Python programs developed by the authors. Following a process of data cleansing, we used tokenization to decompose text into the single words and punctuation characters from which sentences are constructed (see Appendix 1 for details of data cleansing and process of tokenization). Total, positive and negative word counts were compiled at the article level and aggregated by publication date. Positive and negative word categories are taken from Loughran and McDonald (2011). Of the 2,329 (354) words expressing negative (positive) tone in their dictionary, 38 (19) were modified to reflect the FT’s use of British English (e.g., replacing ‘penalize’ with ‘penalise’). The six negation terms used by Loughran and McDonald (2011) were extended to include ‘nor’, ‘cannot’, ‘lack of’, ‘loss of’, ‘end of’ and contractions of words with the word ‘not’ (e.g., couldn’t). The counts of words in both positive and negative word categories that were preceded by any of these negation terms were decremented rather than incremented. Tone measures were expressed as a percentage of the total sum of dictionary recognized words from the corresponding articles. Thus, tone j aggregated for dates T is:

$$s_j(T) = \frac{\sum_{t(i) \in T} as_{ij}}{\sum_{t(i) \in T} wc_i} \quad (1)$$

where as_{ij} is the score for tone j in article i with total dictionary word count wc_i .

Table 1 contains the descriptive statistics for daily tone measures. The mean and median positive tone is just under 1 per cent, whilst the mean and median negative tone is 1.64 and 1.59

per cent respectively. The pessimism tone, which is negative minus positive tone, has a mean and median of 0.69 and 0.66 per cent respectively. These mean tone scores are slightly lower than those found by García (2013) for the *New York Times* financial column - 1.2 for positive tone and 2.1 for negative tone. These differences could reflect cultural differences or the narrow financial media focus of García's study. Table 1 also shows that in bull (bear) markets positive tone is higher (lower) and negative tone lower (higher) than in bear (bull) markets. We find that during bull markets average negative sentiment is 4% lower and positive sentiment is 7% higher than during bear markets. This is greater than the differences reported in García (2013) who found that negative sentiment is 2% lower and positive sentiment is 5% higher in non-recessionary as opposed to recessionary periods.

To assess the validity of our sentiment measures we compare them to the sentiment index of Baker and Wurgler (2006) and the tone of financial reporting in the *New York Times* in García (2013). The Baker and Wurgler data are only available from 1965 and the data of García (2013) is not available after 2005. The Baker and Wurgler data are only available at a monthly level, and so we calculate the monthly mean for the *Financial Times* and *New York Times* data. Figure A2 in the Appendix shows that our sentiment measure appears more closely related to the *New York Times* measure than Baker and Wurgler (2006), although all three series demonstrate similar trends. The largest correlation between the three series is between Baker and Wurgler (2006) and the *Financial Times* with a correlation coefficient of 0.33. The correlation between the *Financial Times* and *New York Times* is 0.14. The correlation coefficient between Baker and Wurgler and *New York Times* data is 0.0006. This is a similar finding to Chan et al. (2017) that the Baker and Wurgler index is not correlated with news sentiment measures. Thus, it appears that our measure of sentiment is broadly in line with measures that exist in the literature.

TABLE 1: Descriptive Statistics

Returns are log close to close from our blue-chip indices. From 1899 to 1930 we use a proprietary index generated from Global Financial Data price and Investor Monthly Manual market capitalization data to identify the 30 largest companies for which we have data. Trade data is taken from Global Financial Data and is available from February 1930 to June 2008, excluding November 6, 1973 to December 28, 1979. Word count, columns, negative, positive and pessimism are calculated from the Financial Times Historic Archive 1899 to 2010. It includes articles published in the News in Brief, Market, Editorial and Leaders and Lex sections. Negative and Positive are based on 2,337 and 353 words from Loughran and McDonald (2011). Our pessimism measure is the daily difference between the percentage of negative and positive words.

		Obs.	Mean	Median	St. Dev.	25%	75%
Panel A: All Periods							
Returns	Basis Points	27,708	1.21	0.10	98.87	-35.76	40.25
Trades	No. ('000s)	20,615	40.76	11.08	98.90	6.30	25.46
Word Count	No.	34,044	5,549	5,155	2,692	3,668	7,042
Columns	No.	34,044	9.31	8.00	7.58	5.00	10.00
Negative	%	34,044	1.64	1.59	0.51	1.27	1.98
Positive	%	34,044	0.95	0.93	0.27	0.77	1.11
Pessimism	%	34,044	0.69	0.66	0.61	0.25	1.11
Panel B: Bull Periods							
Returns	Basis Points	16,531	9.26	7.38	83.07	-25.96	42.87
Trades	No. ('000s)	12,418	36.31	12.98	71.86	7.24	28.80
Word Count	No.	17,682	5,442	4,967	2,751	3,566	6,826
Columns	No.	17,682	8.36	7.00	5.50	5.00	10.00
Negative	%	17,682	1.60	1.55	0.50	1.23	1.94
Positive	%	17,682	0.97	0.95	0.27	0.79	1.13
Pessimism	%	17,682	0.62	0.59	0.61	0.19	1.06
Panel C: Bear Periods							
Returns	Basis Points	11,163	-10.77	-5.65	117.50	-53.07	36.03
Trades	No. ('000s)	8,001	48.14	9.02	130.29	5.29	16.85
Word Count	No.	12,024	5,630	5,330	2,714	3,677	7,274
Columns	No.	12,024	10.64	8.00	9.93	5.00	11.00
Negative	%	12,024	1.66	1.60	0.51	1.30	1.98
Positive	%	12,024	0.91	0.89	0.26	0.74	1.06
Pessimism	%	12,024	0.74	0.70	0.61	0.33	1.14

Stock-market Data

We use a daily blue-chip index to assess the impact of media tone on the stock market. We use the FT30 index from 1 July 1935 to 2010; it is an unweighted price index of 30 leading industrial and commercial shares and is the United Kingdom's oldest continuous daily index. For the period January 1930 to June 1935, we use the forerunner to the FT30 - the *Financial News* 30 or FN30, which was rebased to match the FT30. Replicating the FT30 before 1930 is not possible because the constituents of the index were chosen by journalists at the FT. Instead, we create an equally-weighted daily index of the 30 largest companies listed in the *Investor's Monthly Manual* (IMM) and that had daily data in Global Financial Data (GFD). For each year from 1899, we use the December issue of the IMM to rank matched companies by market capitalization. We then form a portfolio of the 30 largest companies by market capitalization for every day over the next year.

The descriptive statistics for our blue-chip index are in Table 1. The mean daily return is 1.21-basis points and the standard deviation at 98.87-basis points is unsurprisingly high. During bull markets, mean daily returns increase to 9.26-basis points and during bear markets the mean daily return is -10.77-basis points.

Because we want to assess the effect of sentiment on abnormal trading volume, we obtained data from GFD which measures the number of trades that were executed on the constituent companies of the FN30 and FT30. The data begins on the 6 February 1930 and ends on the 30 June 2008 and for the period 7 November 1973 to 28 December 1979, the data is

missing⁶. Volume data is not available for the FT30, but the number of trades may better capture how traders react to extreme sentiment.

As can be seen from Table 1, there are 20,615 days with trading data. On average, 40,757 trades were executed per day. The high standard deviation reflects the fact that the number of trades increased substantially from the 1970s onwards, with the maximum reaching 1,428,031 on 22 January 2008.

III. Does Sentiment Affect the Market?

In this section, we test the effect of FT sentiment on the returns on our blue-chip index. Following García (2013), we date our media measures to the day written rather than the day published and normalize our media measures to have a mean of zero and a unit standard deviation. To analyze the effect of FT sentiment, we use the following model:

$$R_t = \beta \mathcal{L}_s(M_t) + \gamma \mathcal{L}_s(R_t) + \psi \mathcal{L}_s(R_t^2) + \eta X_t + \epsilon_t \quad (2)$$

where the dependent variable R_t is daily returns on our blue-chip index. $\mathcal{L}_s$ is a lag operator set to five. The variable M_t is one of our media measures. As a set of exogenous variables X_t , we include a constant term, day-of-the-week dummies, month-of-the-year dummies, editor dummies, as well as a dummy for whether date t belongs to a bull or bear market.⁷ We exclude public holidays, Sundays and Saturdays after 10 November 1929, and non-trading dates for

⁶ We queried Global Financial Data on why the data was missing and were informed that the data up to 6 November 1973 was available from *The Economist* after which it stopped publishing the data and GFD were unable to obtain any more data until 29 December 1979.

⁷ Editors were obtained from ft.com ("FT at 125: The world in focus", Lionel Barber, accessed 8 August 2017). We control for editors because they each may have had a different policy which affected choice of negative and positive words.

calculating lags.⁸ The sample comprises 30,033 trading days for which we have return data for 27,708 days and volume data for 20,615.

⁸ We treat the following as non-trading dates: Sundays, Saturdays after 9 November 1929 (when no more trades are observed), 25 and 26 December (or the subsequent Monday/Tuesday if observed on Saturday/Sunday), 1 January after 1920 (when no more trades are observed), Easter Monday and Good Friday, Whit Monday until 1964, the last Monday in May after 1964, the first Monday in May from 1978 onwards, the first Monday in August until 1965, thereafter the last Monday of the month. The emergency bank holiday following the Sterling crisis on 15 March 1968.

TABLE 2: Feedback from FT to the Blue-Chip Index, 1899–2010

This table reports β coefficients and t -stats from the model $R_t = \beta \mathcal{L}_s(M_t) + \gamma \mathcal{L}_s(R_t) + \psi \mathcal{L}_s(R_t^2) + \eta X_t + \epsilon_t$. R_t is our daily stock market index log returns. M_t is one of our media measures. X_t is our exogenous variables including day-of-the-week dummies, month-of-the-year dummies, editor dummies and a dummy for whether date t is a bull or bear market. All results are based on 23,017 observations. Panel A and B report results with robust standard errors. Panel B uses returns on our daily stock index discounted by conditional variance as calculated by a GARCH (1,1) model. Panel C controls for outliers through Huber (1973) M -regression.

	Negative		Positive		Pessimism	
	β	t -stat	β	t -stat	β	t -stat
Panel A: OLS Regression Coefficients						
M_{t-1}	-0.043	-4.75	0.034	5.50	-0.059	-6.62
M_{t-2}	0.002	0.17	0.009	1.59	-0.005	-0.54
M_{t-3}	0.010	1.14	0.002	0.31	0.007	0.82
M_{t-4}	0.012	1.33	-0.014	-2.35	0.020	2.25
M_{t-5}	0.029	3.22	-0.002	-0.35	0.026	2.87
Tests						
	β	F -stat.	p -val.	β	F -stat.	p -val.
$\beta_1 = 0$	-0.043	22.51	0.000	0.034	30.25	0.000
$\sum_{j=2}^5 \beta_j = 0$	0.053	4.20	0.002	-0.005	1.94	0.101
Panel B: Volatility-Adjusted Returns Coefficients						
	β	t -stat	β	t -stat	β	t -stat
M_{t-1}	-0.050	-5.47	0.040	5.36	-0.069	-7.30
M_{t-2}	0.002	0.23	0.005	0.67	-0.001	-0.10
M_{t-3}	0.018	1.98	-0.004	-0.60	0.018	1.96
M_{t-4}	0.007	0.73	-0.008	-1.10	0.012	1.25
M_{t-5}	0.015	1.62	0.003	0.38	0.011	1.16
Tests						
	β	F -stat.	p -val.	β	F -stat.	p -val.
$\beta_1 = 0$	-0.050	29.90	0.000	0.040	28.74	0.000
$\sum_{j=2}^5 \beta_j = 0$	0.042	2.31	0.055	-0.004	0.54	0.708
Panel C: Huber Regression Coefficients						
	β	t -stat	β	t -stat	β	t -stat
M_{t-1}	-0.036	-4.85	0.028	4.62	-0.048	-6.48
M_{t-2}	-0.008	-1.06	0.007	1.11	-0.010	-1.36
M_{t-3}	0.015	1.96	-0.002	-0.40	0.014	1.89
M_{t-4}	0.005	0.70	-0.005	-0.81	0.008	1.09
M_{t-5}	0.020	2.65	-0.003	-0.42	0.018	2.50
Tests						
	β	F -stat.	p -val.	β	F -stat.	p -val.
$\beta_1 = 0$	-0.036	23.52	0.000	0.028	21.31	0.000
$\sum_{j=2}^5 \beta_j = 0$	0.032	3.64	0.006	-0.003	0.53	0.713

Table 2 shows the relationship between tone for the FT and returns. The results in Panel A show that both the positive and negative tone of the FT published in the morning have an economically and statistically significant relationship with that day's returns. A one standard deviation rise in negative tone predicts a 4.3-basis point decrease in returns, a one standard deviation rise in positive tone predicts a 3.4-basis point increase in returns, and a one standard

deviation rise in pessimism predicts a 5.9 decrease in returns. This is consistent with previous literature. Tetlock (2007), for example, found that a one standard deviation rise in negative tone of the “Abreast of the Market” column in the *Wall Street Journal* predicted a 4.4-basis point fall in the Dow Jones Industrial Average. Similarly, García (2013) found that a one standard deviation increase in the negative tone of financial columns in the *New York Times* predicted a 4.3-basis point decrease in the Dow Jones Industrial Average, with a 3.9-basis point increase for positive tone and 5.5-basis point decrease for pessimism.

Consistent with the extant literature, the effect of sentiment on returns appears to be temporary. Table 2 shows that only the first lag of our negative tone and the first two lags of pessimism measure are negative, but the subsequent lags are positive. The first three lags of positive tone have positive coefficients. However, the fourth and fifth lags have negative coefficients with the former being the only lag other than the first to have a significant statistical relationship with returns. Collectively, with the exception of positive tone, the lags of tone greater than 1.0-basis point are statistically significant, with their coefficients suggesting that they reverse the initial effect of media tone. This is consistent with the view that negative or pessimism shocks to sentiment create immediate downward pressure on prices because noise traders sell to arbitrageurs. However, after the negative/pessimism sentiment shock, rational traders drive the stock price back to its fundamental value. Hence the reversal of the initial media effect. In the case of positive sentiment shocks, there is no reversal, which may suggest that positive words contain information that is permanently priced into the market.

Table 2 also reports the relationships between the FT’s tone and returns, with corrections for time-varying volatility and outliers. In Panel B, the returns on our daily blue-chip index are discounted by conditional variance as calculated by a GARCH (1,1) model. The previously

identified relationships between tone and returns are robust to this correction and the economic impact of sentiment appears to be greater, with a one standard deviation rise in negative (positive) tone predicting a 5.0-basis point decrease (4.0-basis point increase) in returns. Panel C corrects for the effect of outliers using Huber (1973) M-regressions. This robustness check reveals that there are still statistically significant relationships between both negative and positive tone and subsequent returns. However, the economic effect falls slightly using this approach - a 3.6-basis point decrease in returns for a one standard deviation rise in negative tone and 2.8-basis point increase for a one standard deviation change in positive tone.

Whereas the relationship between news media and returns can help us understand if the media influenced the prices at which traders bought or sold stock, the relationship of tone with trading volume can help us understand if the FT influenced traders to alter the amount of stocks that they bought or sold. In particular, one would expect that extreme positive or negative sentiment shocks would create large disagreement between rational and noise traders, moving the latter to buy or sell stocks. Following Tetlock (2007) and García (2013), we analyze the absolute value of our standardized sentiment measures as well as the daily minimum and maximum sentiment expressed in a single article. Collectively, we refer to these measures as extreme sentiment.

We follow Gallant, Rossi, and Tauchen (1992) in removing the time trend and known causes of variability in trading. Our results are robust to alternative approaches such as that of Campbell, Grossman, and Wang (1993).

To normalize the volume data, we model log trading volume as in Equation (3). Specifically, we model it as a function of its previous five lags, $\mathcal{L}_s$, as well as a set of dummy variables, X_t , to control for day of the week and month of the year effects. The residuals from

Equation (3), ε_t , are then standardized by their annual standard deviation $\hat{\tau}_t = \frac{\varepsilon_t}{\sigma_\varepsilon}$. This results in a detrended and white noise variable of abnormal trading, $\hat{\tau}_t$, as plotted in Appendix Figure A2.

$$\tilde{\tau}_t = \beta \mathcal{L}_s(V_t) + \eta X_t + \varepsilon_t \quad (3)$$

T

To assess the impact of media on abnormal trading, we model the relationship as per Equation (4). Where $\hat{\tau}_t$ is our measure of abnormal trading, R_t is our daily stock market index returns, R_t^2 is the squared return of our daily stock market index and X_t is a dummy for whether date t is a bull or bear market. M_t is one of our media measures. To proxy extreme sentiment we use the absolute value of our standardized media measures ($|M_{t-1}|$) which is used as per Tetlock (2007) and the maximum (M_t^+) or minimum (M_t^-) percentage of words for any article published in the FT on date t as per García (2013).

$$\hat{\tau}_t = \beta \mathcal{L}_s(M_t) + \gamma \mathcal{L}_s(\hat{\tau}_t) + \zeta \mathcal{L}_s(R_t) + \psi \mathcal{L}_s(R_t^2) + \eta X_t + \epsilon_t \quad (4)$$

TABLE 3: Feedback from Extreme News Content to Abnormal Trading

This table reports β coefficients and t -stats from the model $\hat{\tau}_t = \beta \mathcal{L}_s(M_t) + \gamma \mathcal{L}_s(\hat{\tau}_t) + \zeta \mathcal{L}_s(R_t) + \psi \mathcal{L}_s(R_t^2) + \eta X_t + \varepsilon_t$. R_t is our daily stock market index returns. M_t is either the absolute value of one of our standardized media measures ($|M_t|$), the maximum (M_t^+) or minimum (M_t^-) percentage of words for any article published in the Financial Times on date t . X_t is our exogenous variables, including editor dummies and a dummy for whether date t is a bull or bear market. $\hat{\tau}_t$ is abnormal trading which is calculated from the equation $\tilde{\tau}_t = \beta \mathcal{L}_s(\tau_t) + \eta X_t + \varepsilon_t$. Where τ_t is log number of trades (000's). The residuals are standardized by the annual standard deviation in the residuals. Thus $\hat{\tau}_t = \frac{\varepsilon_t}{\sigma_\varepsilon}$ which results in a detrended and white noise variable of abnormal trading. Data begins on February 6, 1930 and ends June 30, 2008. Trading data is sourced from Global Financial Data and is not available from November 6, 1973 to December 28, 1979. A dummy is included to control for the break in the data. Results based on 16,973 obs.

	Negative			Positive			Pessimism		
	β	t -stat		β	t -stat		β	t -stat	
Panel A: Absolute Sentiment									
$ M_{t-1} $	0.032	3.76		0.007	0.93		0.006	0.77	
$ M_{t-2} $	0.006	0.75		0.028	3.62		0.036	4.41	
$ M_{t-3} $	-0.016	-1.92		0.009	1.13		-0.009	-1.11	
$ M_{t-4} $	-0.009	-1.06		-0.016	-2.01		-0.010	-1.30	
$ M_{t-5} $	0.015	1.89		-0.005	-0.59		0.005	0.63	
	β	F -stat.	p -val.	β	F -stat.	p -val.	β	F -stat.	p -val.
$\Sigma_{j=1}^5 \beta_j = 0$	0.028	4.54	0.000	0.023	3.87	0.002	0.028	4.61	0.000
Panel B: Maximum Sentiment									
	β	t -stat		β	t -stat		β	t -stat	
M_{t-1}^+	0.006	0.64		-0.023	-2.64		0.003	0.32	
M_{t-2}^+	-0.024	-2.43		0.032	3.85		-0.021	-2.34	
M_{t-3}^+	0.008	0.87		0.009	1.21		-0.013	-1.46	
M_{t-4}^+	-0.003	-0.21		0.003	0.43		0.024	2.80	
M_{t-5}^+	-0.001	-0.05		-0.019	-2.60		-0.008	-0.98	
	β	F -stat.	p -val.	β	F -stat.	p -val.	β	F -stat.	p -val.
$\Sigma_{j=1}^5 \beta_j = 0$	-0.014	1.39	0.226	0.002	5.37	0.000	-0.015	3.61	0.003
Panel C: Minimum Sentiment									
	β	t -stat		β	t -stat		β	t -stat	
M_{t-1}^-	-0.048	-5.74		-0.037	-4.65		-0.005	-0.53	
M_{t-2}^-	0.008	1.02		0.019	2.42		-0.033	-3.63	
M_{t-3}^-	-0.008	-1.03		-0.010	-1.26		-0.013	-1.61	
M_{t-4}^-	0.016	2.09		0.004	0.47		0.001	0.13	
M_{t-5}^-	0.019	2.51		0.031	3.99		0.014	1.86	
	β	F -stat.	p -val.	β	F -stat.	p -val.	β	F -stat.	p -val.
$\Sigma_{j=1}^5 \beta_j = 0$	-0.013	8.59	0.000	0.007	8.65	0.000	-0.036	4.21	0.001

Table 3 shows that extreme levels of sentiment are positively correlated with trading. A one standard deviation shock to the absolute value of our standardized measure of negative (pessimism) tone in today's FT causes tomorrow's abnormal trading volume to increase by 3.6 (2.8) standard deviations and a one standard deviation shock to negative tone in today's FT causes today's abnormal trading volume to increase by 3.2 standard deviations. Table 3 also

shows that the absence of sentiment—the daily minimum percentage of positive and negative words in our articles—is negatively correlated with abnormal trading volume. These results are consistent with the theory that extreme sentiment shocks result in a one-off change in trading by noise traders. The final finding of interest from Table 3 is that the daily maximum percentage of positive words is negatively correlated with abnormal trading volume. This goes against our previous results and those of García (2013). However, it perhaps suggests that market-makers treat very positive articles as trading floor noise (Coval and Shumway, 2001). This noise approximates trader anxiety thereby increasing trading costs and lowering volume. In summary, the results in Table 3 suggest that media tone affects the abnormal trading volume of noise traders.

IV. Sentiment in Bull and Bear Markets

Whereas García (2013) identifies recessionary and non-recessionary periods, we identify bear and bull markets. This distinction is not trivial. Recessions are less frequent than bear markets and are associated with greater economic hardship. However, the most important distinction is between non-recessionary periods and bull markets. Non-recessionary periods can be thought of as normal market conditions. The economy may be stagnant, it may be growing or there may even be a single quarter of negative growth. Bull markets are defined by increasing stock prices. Thus, non-recessionary periods are not equivalent to bull markets. This distinction allows us to investigate the role of the media in propagating market movements in both bull and bear markets; a claim put forward by Shiller (2000).

The reaction of traders to sentiment may differ depending on the prevailing state of the stock market. On the one hand, if the prevailing state of the market is bearish, then investors may

pay more attention to and be influenced by the news and its tone. As a result, sentiment will more easily move returns and trading volume during bear markets. For example, García (2013) finds that the effect of news tone on the stock market is much greater during recessions than during expansions. Notably, there is evidence from the experimental psychology literature that during times of anxiety people are more open to advice (Gino et al., 2012). If traders are more prone to sentiment during times when the prevailing state of the stock market is negative, then we would expect to see tone have a greater effect during bear markets.

On the other hand, investors may be more susceptible to sentiment during times of excitement in the stock market. Indeed, the media may even create narratives to explain stock market movements, thus helping to shape and perpetuate prevailing market states (Shiller, 2017). If media tone perpetuates bull runs as per Shiller (2000), then we would expect to see media tone to effect abnormal trading volume during bull but not bear runs. As the media discourse on the bull-run becomes more emotional we would expect to see an increase in the use of positive and negative words and for both positive and negative tone to increase the levels of abnormal trading volume. During a prolonged bull market, which may be marked by more noise traders entering the market, a sentiment shock may cause there to be substantially more disagreement between noise and rational traders and hence much more trading than there would be caused by sentiment shocks in bear markets.

FIGURE 1: Bull and Bear Markets in the London Stock Exchange, 1899–2010.

Notes: We identify bull and bear phases in the stock market using the algorithm of Pagan and Sossounov (2003). From 1899 to 1930 we use a proprietary index generated from Global Financial Data price and Investor Monthly Manual market capitalization data to identify the 30 largest companies for which we have data. From 1930 to 1935 we use the Financial News 30 index. From 1935 to 2010 we use the FT30 index.

We identify bull and bear phases in the stock market using the algorithm of Pagan and Sossounov (2003). Their ex-post methodology assumes that the market is either in a bull or bear state and observes that bull and bear market phases are naturally bounded by turning points (peaks and troughs) achieved by the underlying time series of prices. While the interested reader is referred to the original paper for full details, we provide an outline of their algorithm which applies successive filters to identify appropriate turning points. Initial filters identify local maxima and minima (within a 16-month window) in the time series. At all stages in the algorithm, filtering is applied to ensure that peak and trough turning points alternate. Further filtering imposes minimum duration constraints including a minimum 16-month cycle length between successive peaks. Individual bull and bear phases are required to be at least 4-months in length with exceptions for shorter periods where the absolute price change exceeds 20 per cent.

Figure 1 shows the performance of our blue-chip index and the classification of market states. We have 30 bull and 30 bear phases during our period. Bull markets tend to last longer with the average length of bull phases being 23.89 months and the average length of bear phases being 16.21 months. In total, out of 30,033 trading days, 12,136 were during bear markets, and the remainder were in bull markets. Figure 1 also shows that price changes tend to be greater in bears with daily returns falling an average 10.8-basis points in bear markets compared to increasing 9.2-basis points during bull markets.

TABLE 4: Feedback from FT to the Blue-Chip Index by Bull/Bear Market

This table reports β coefficients and t -stats from the model $R_t = \beta \mathcal{L}_s(M_t) + \gamma \mathcal{L}_s(R_t) + \psi \mathcal{L}_s(R_t^2) + \eta X_t + \epsilon_t$. R_t is our daily stock market index returns. M_t is one of our media measures. X_t is our exogenous variables including day-of-the-week dummies, month-of-the-year dummies, editor dummies and a dummy for when the market state switches between a bull and bear state. Differences are tested by running the above model.

	Negative		Positive		Pessimism	
	β	t -stat	β	t -stat	β	t -stat
Panel A: Bull Market (13,695 obs.)						
M_{t-1}	-0.045	-3.73	0.022	2.74	-0.052	-4.49
M_{t-2}	0.008	0.68	0.010	1.31	-0.000	-0.03
M_{t-3}	0.005	0.44	0.009	1.15	-0.002	-0.19
M_{t-4}	0.022	1.89	-0.013	-1.70	0.028	2.45
M_{t-5}	0.031	2.62	-0.002	-0.20	0.026	2.30
Tests						
	β	F -stat.	p -val.	β	F -stat.	p -val.
$\beta_{1Bull} = 0$	-0.045	13.93	0.000	0.022	7.51	0.006
$\sum_{j=2}^5 \beta_{jBull} = 0$	0.066	3.56	0.007	0.004	1.40	0.232
Panel B: Bear Market (9,322 obs.)						
	β	t -stat	β	t -stat	β	t -stat
M_{t-1}	-0.049	-3.34	0.057	5.82	-0.079	-5.60
M_{t-2}	-0.012	-0.81	0.014	1.51	-0.019	-1.33
M_{t-3}	0.012	0.84	-0.002	-0.16	0.012	0.83
M_{t-4}	-0.005	-0.36	-0.009	-0.90	0.002	0.12
M_{t-5}	0.023	1.57	0.001	0.07	0.019	1.32
Tests						
	β	F -stat.	p -val.	β	F -stat.	p -val.
$\beta_{1Bear} = 0$	-0.049	11.18	0.001	0.057	33.82	0.000
$\sum_{j=2}^5 \beta_{jBear} = 0$	0.018	0.92	0.449	0.004	0.70	0.591
Panel C: Testing Effect Differences						
	χ^2	p -value	χ^2	p -value	χ^2	p -value
$\beta_{1Bull} = \beta_{1Bear}$	0.67	0.413	13.85	0.000	5.86	0.016

Table 4 shows that FT tone has a significant effect on returns in both bull and bear markets. All measures of tone appear to influence subsequent returns in both market states. In terms of positive tone and pessimism, the effect during bear markets is much larger than that experienced during bull markets. A one-standard deviation change in positive (pessimism) tone in bull markets is associated with a 2.2-basis point increase (5.2-basis point increase) in the return of our blue-chip index compared to a 5.7-basis point increase (7.9-basis point decrease) in bear markets. The difference between the effects across market states is statistically significant. The effect of FT negative tone is also greater in bear markets, although the difference is not statistically or economically significant.

A final interesting finding from Table 4 is that the initial effect of media tone only reverses during bull markets. The sum of coefficients on lags two through to five exactly equal the coefficient of the first lag for media pessimism in bull markets. In bear markets the sum of coefficients on lags two through to five is less than the coefficient of the first lag, implying that the effect of the first lag is not reversed. Further, the coefficients on lags two through to five are not statistically significantly different from zero in bear markets. Thus, there is some evidence to support the view that media tone plays a greater role during bear markets, which is consistent with the findings of García (2013) for U.S. recessions. The results may also indicate that negative words contain information in bear but not bull markets.

As an alternative way of classifying bull and bear markets, we use the occurrence of the words ‘bull’ and ‘bullish’ in the FT to define whether a particular month is in a bull or bear phase. We calculate the daily occurrence of bullish and bearish words as a percentage of total words and aggregate to a monthly level using the mean. When the occurrence of bullish (bearish) words has increased for two successive months, both months are classified as bull (bear) months.

If a month is not classified as a bull (bear), but the preceding and succeeding are, that month is reclassified as a bull (bear) month. If a month is classified as both bull and bear, no classification is used. Bull (bear) runs that last only one month are declassified. This results in 321 months being classified as bull months and 650 as bear months. Table A1 in the Appendix shows that using this alternative classification produces results which are consistent with our previous findings in Table 4. All measures of tone appear to influence subsequent returns in both market states. However, there is no statistically significant difference between bull and bear months for the effect of tone on our blue-chip index.

As a further robustness exercise, we use GDP data to classify expansions and contractions in the economy. We then use these classifications to see whether the effect of media tone differs across them. The Office for National Statistics has quarterly GDP data for the United Kingdom from 1955 onwards. We use the standard definition of a recession (i.e., two consecutive quarters of negative GDP growth) in our analysis. Because this analysis is limited to the post-1955 period, we also use annual GDP data back to 1899, which was obtained from the Bank of England. We classify each year as an expansion or contraction, depending on whether its GDP growth was positive or negative. We then compare the effect of FT tone across these various states of the economy. The untabulated results broadly concur with those that we found for bull and bear markets. The state of the overall economy appears not to have a significant bearing on the effect of sentiment on stock-market returns.

TABLE 5: Effect of FT Absolute Sentiment on Abnormal Trading by Bull/Bear

This table reports β coefficients and t -stats from the model $\hat{\tau}_t = \beta \mathcal{L}_s(|M_t|) + \gamma \mathcal{L}_s(\hat{\tau}_t) + \zeta \mathcal{L}_s(R_t) + \psi \mathcal{L}_s(R_t^2) + \eta X_t + \epsilon_t$. R_t is our daily stock market index returns. $|M_t|$ is one the absolute value of our standardized media measures. X_t is our exogenous variables including editor dummies and a dummy for when the market state switches between a bull and bear state. $\hat{\tau}_t$ is abnormal trading which is calculated from the equation $\hat{\tau}_t = \beta \mathcal{L}_s(\tau_t) + \eta X_t + \epsilon_t$. Where τ_t is log number of trades (000's). The residuals are standardized by the annual standard deviation in the residuals. Thus $\hat{\tau}_t = \frac{\epsilon_t}{\sigma_\epsilon}$ which results in a detrended and white noise variable of abnormal trading. $\hat{\tau}_t$ is standardized to have a mean of zero and unit variance. Data begins on February 6, 1930 and ends June 30, 2008. Trading data is sourced from Global Financial Data and is not available from November 6, 1973 to December 28, 1979. A dummy is included to control for the break in the data. Results based on 16,725 obs.

	Negative		Positive		Pessimism	
	β	t -stat	β	t -stat	β	t -stat
Panel A: Bull (10,750 obs.)						
$ M_{t-1} $	0.033	3.19	0.002	0.26	0.007	0.74
$ M_{t-2} $	0.008	0.79	0.032	3.32	0.038	3.77
$ M_{t-3} $	-0.015	-1.48	0.008	0.76	-0.009	-0.86
$ M_{t-4} $	-0.006	-0.61	-0.016	-1.54	-0.013	-1.32
$ M_{t-5} $	0.023	2.45	-0.006	-0.64	0.012	1.25
Tests						
	β	F -stat.	p -val.	β	F -stat.	p -val.
$\sum_{j=1}^5 \beta_{jBull} = 0$	0.034	3.89	0.002	0.002	2.80	0.016
Panel B: Bear (6,223 obs.)						
$ M_{t-1} $	0.028	1.80	0.014	1.04	0.001	0.05
$ M_{t-2} $	0.002	0.12	0.018	1.42	0.029	2.04
$ M_{t-3} $	-0.021	-1.33	0.008	0.67	-0.012	-0.83
$ M_{t-4} $	-0.018	-1.29	-0.017	-1.33	-0.009	-0.63
$ M_{t-5} $	-0.006	-0.41	-0.003	-0.26	-0.012	-0.83
Tests						
	β	F -stat.	p -val.	β	F -stat.	p -val.
$\sum_{j=1}^5 \beta_{jBear} = 0$	-0.015	1.28	0.268	0.020	1.07	0.374
Panel C: Testing Effect Differences						
	χ^2	p -value	χ^2	p -value	χ^2	p -value
$\beta_{1Bull} = \beta_{1Bear}$	2.76	0.096	0.00	0.958	1.23	0.267

Table 5 shows how the relationship between extreme FT tone and abnormal trading volume varies with the prevailing state of the market. The first thing to note is that there appears to be no effect of extreme tone on trading volume during bear markets. The cumulative effect of five days of all sentiment measures are insignificant and individually there is no evidence of daily sentiment influencing subsequent abnormal trading volume. Table 5 shows that tone is associated with an effect on abnormal trading volume in bull markets only. This finding works against the view that investors are more sensitive to sentiment during bear markets. Although

the difference is only statistically significant for negative tone, the effect appears to be economically and statistically more significant in bull markets all measures of sentiment. A one standard deviation increase in negative tone causes 0.033 (0.028) standard deviations increase in trading volume during bull (bear) markets. The combined effect of the first two lags of extreme positive tone is associated with an increase of 0.032 standard deviations during bear markets, whereas a one standard deviation increase in positive tone in today's and yesterday's newspaper during a bull market increases today's trading volume by 0.035 standard deviations. This finding is consistent with the view that noise traders drive trading volume during speculative booms and that the news media plays a role in propagating such booms. It is also consistent with Baker and Stein (2004) who suggest that irrational investors are more likely to trade when they are optimistic and speculate on stocks rising than when they are pessimistic.

Table A2 in the Appendix presents the relationship between extreme FT sentiment and abnormal trading volume using the previously defined bull and bear definitions based on the occurrence of bullish and bearish words in the FT. The results confirm our previous finding that the effect of FT tone on abnormal trading volume is concentrated in bull states. This alternative definition of bull and bear states appears to capture better more pronounced periods of rising and falling market sentiment. Fewer days are classified as bull or bear states, with the overlap from the returns-based definition being 23.4% (45.2%) of days for bull (bear) states. Table A2 shows the economic effect of negative tone is twice as large during bull markets as compared to bear markets and the difference is statistically different from zero.

Together, Tables 4 and 5 show that the tone of the *Financial Times* influences returns during bull and bear markets, but it only influences abnormal trading during bull markets. Our economic explanation is that noise traders drive trade during speculative booms as per Shiller's

press-as-propagators hypothesis. The tone of news media reporting influences the prices at which noise traders trade independently of whether the market is in a bull or bear state. However, Table 1 shows that media coverage during bull markets is more positive. Consistent with Shiller, this entices noise traders to trade, resulting in a correlation between abnormal trading volume and media tone. Media coverage during bear markets is more negative and cognitive dissonance (as per Festinger, 1962) prevents noise traders from selling stocks on such a scale as to be identified in abnormal trading volume (Goetzmann and Peles, 1997).

VI. Information in sentiment?

Consecutive and Non-consecutive Trading Days

Although we have carefully selected the columns used in the analysis to avoid those which focus on individual company performance, it is still possible that our sentiment measures contain some information and that this effect is different in bull and bear markets. Our results above have shown that FT tone has a short-term effect on returns. If this effect is due to a behavioral bias, then we would expect it to be similar on consecutive and non-consecutive trading days (i.e., Mondays and days after public holidays). However, if there is informational content in tone to which traders are responding to, we would expect information to aggregate over non-consecutive trading days and thus the effect to differ from when the market was open for consecutive days. Since the FT has never been published on a Sunday, Monday editions have two days of information to report. Alternatively, if information production is focused on weekdays, then we might expect the papers published on Tuesday through Friday to contain more information. Non-consecutive trading days are identified as trading dates having no return data on the previous day while consecutive trading days are those with return data on the previous day. Non-consecutive

trading days are Mondays and days after market holiday closures, whereas consecutive trading days are Tuesdays to Fridays in the absence of any holidays. Saturday trading ceases in our sample on 9 November 1929. Prior to this, Saturday is treated as a trading date. After 1929, Saturdays are treated as non-trading dates. We do not incorporate the sentiment of Saturday editions into our measures of tone on Monday since the effect on traders may have already dissipated before trading resumes.

TABLE 6: Feedback from FT Negative Sentiment to the Blue-Chip Index on Consecutive and Non-Consecutive Trading Days

This table reports β coefficients and t -stats from the model $R_t = \beta \mathcal{L}_s(M_t) + \gamma \mathcal{L}_s(R_t) + \psi \mathcal{L}_s(R_t^2) + \eta X_t + \epsilon_t$. R_t is our daily stock market index log returns. M_t is one of our media measures. X_t is our exogenous variables including day-of-the-week dummies, month-of-the-year dummies, editor dummies and a dummy for whether date t is a bull or bear market. All results are reported with robust standard errors. Non-consecutive trading days are identified as having no return data on the previous day. Consecutive trading days are those with return data on the previous day.

	Bull and Bear Markets			Bull Market			Bear Market		
	β	t -stat		β	t -stat		β	t -stat	
Panel A: Consecutive Trading Days									
Neg_{t-1}	-0.046	-4.50		-0.053	-3.92		-0.046	-2.84	
Neg_{t-2}	-0.003	-0.32		0.003	0.21		-0.016	-1.04	
Neg_{t-3}	0.021	2.07		0.021	1.61		0.016	1.03	
Neg_{t-4}	0.011	1.03		0.013	0.99		0.003	0.15	
Neg_{t-5}	0.030	2.94		0.030	2.24		0.027	1.67	
Tests									
	β	F -stat.	p -val.	β	F -stat.	p -val.	β	F -stat.	p -val.
$\beta_{1Con.} = 0$	-0.046	20.28	0.000	-0.053	15.39	0.000	-0.046	8.06	0.005
$\sum_{j=2}^5 \beta_{jCon.} = 0$	0.059	4.41	0.002	0.067	2.69	0.029	0.030	1.25	0.289
Obs.	18,461			10,973			7,488		
Panel B: Non-Consecutive Trading Days									
Neg_{t-1}	-0.056	-2.78		-0.036	-1.46		-0.077	-2.36	
Neg_{t-2}	0.024	1.07		0.030	1.16		0.008	0.20	
Neg_{t-3}	-0.019	-0.90		-0.023	-0.85		-0.005	-0.13	
Neg_{t-4}	0.013	0.67		0.053	2.12		-0.034	-1.06	
Neg_{t-5}	0.027	1.29		0.040	1.54		0.017	0.50	
Tests									
	β	F -stat.	p -val.	β	F -stat.	p -val.	β	F -stat.	p -val.
$\beta_{1Non-Con.} = 0$	-0.056	7.74	0.005	-0.036	2.12	0.145	-0.077	5.58	0.018
$\sum_{j=2}^5 \beta_{jNon-Con.} = 0$	0.045	1.31	0.264	0.100	2.54	0.038	-0.014	0.34	0.849
Obs.	4,556			2,722			1,834		
Panel C: Differences Between Consecutive and Non-Consecutive Trading Days									
	χ^2	p -value		χ^2	p -value		χ^2	p -value	
$\beta_{1Con.} = \beta_{1Non-Con.}$	0.37	0.540		0.26	0.612		1.05	0.305	

Table 6 shows that the immediate effect of FT tone on returns does not depend on

whether the market was closed on the preceding day. The findings reported in Table 6 are robust to the use of volatility-adjusted returns and for brevity only negative tone is reported. From Table 6, we see that a one-unit standard deviation rise in negative tone is associated with a 4.6-basis point decrease in returns on consecutive trading days and a 5.6-basis point decrease on non-consecutive trading days. While the immediate effect of FT tone on returns does not depend on whether the market was closed on the preceding day, the effect over subsequent days does. On consecutive trading days, the effect of lagged tone is the same as the results reported above; collectively they are statistically significant with the size and direction of coefficients suggesting that the immediate impact of FT tone is reversed. This is consistent with sentiment creating a behavioral bias in traders. However, on non-consecutive trading days, lags 2 to 5 of our negative tone measures are statistically insignificant, suggesting that the initial effect is not reversed. Although only suggestive, it may be that there is more informational content in the tone of newspaper reporting than has been previously thought in that there is greater informational content in the day after a market closure. Table 6 also shows that the distinction between consecutive and non-consecutive trading days does not affect the initial impact of tone on returns during bear markets. However, the correlation between tone and returns is weak during non-consecutive trading days in bull markets. This may suggest that as markets boom, information is not sought out by the press during weekends, or traders may pay less attention to media on weekends.

Financial Times Sections

Our FT content analysis uses four principal sections from the newspaper. The Market News section of the paper contains reporting and commentary upon what was happening in the

financial markets, whereas the Lex column provides pure commentary on macroeconomic and financial markets. The News in Brief section simply contains a summary of the major news items of the day, which includes, but is not limited to financial and economic news. Finally, the Editorials and Leaders section are opinion pieces commenting on a range of financial and non-financial issues.

To test further whether the informational content of articles is driving results, we analyze the tone of each of the four sections and its effect on the market. We do so for two reasons. First, commentary, rather than reporting, is unlikely to contain new information on companies or the economy - they simply reflect the views of the FT's journalists and editors on the issues of the day. As a consequence, the tone of the two commentary sections of the newspaper provide a relatively uncontaminated measure to assess how the stock market responds to sentiment. Second, one might expect commentary sections of the FT to be more sentiment laden, containing the sort of speculative language that might reflect the excitement and dismay of investors.

Table 7 displays the key characteristics of the four sections. We use the *Harvard Psychosocial Dictionary* to quantify the use of economic and political words and Loughran and McDonald (2011) word lists to measure words that express uncertainty in the four sections of the FT. Average word count and average uncertainty demonstrate that the Editorials and Leaders section and Lex columns are more commentary in nature; they are both longer than News in Brief and Market articles and express much more uncertainty, which is typical of commentary articles which are scanning the future or speculating about the present. Thus, it appears that the commentary articles are more subjective in their assessment of events than the articles from the Market and News in Brief sections. The average political content of the four sections demonstrate that the scope of our non-financial columns (Editorials and Leaders and News in

Brief) is broader than the two narrowly-focused financial sections. Table 7 also shows the differences between the use of positive and negative words across sections. Editorials and Leaders contain the highest percentage of both negative and positive words, while News in Brief contains the lowest percentage of both measures.

TABLE 7: FT Articles by Section, 1899–2010

Uncertainty is based on 297 words from the Loughran and McDonald (2011) word lists. Negative and Positive are based on 2,337 and 353 words from Loughran and McDonald (2011). Our pessimism measure is the daily difference between the percentage of negative and positive words. Economic and political words are taken from the Harvard Psychosocial Dictionary ECON and POLIT categories. “ECON@ comprises 510 words of an economic, commercial, industrial, or business orientation, including roles, collectivities, acts, abstract ideas, and symbols, including references to money. Includes names of common commodities in business.” “POLIT@ 263 words having a clear political character, including political roles, collectivities, acts, ideas, ideologies, and symbols.” <http://www.wjh.harvard.edu/~inquirer/homecat.htm>

	All Sections	News in Brief	Market	Editorials	Lex
Total Columns	316,787	115,537	118,014	58,304	24,932
Total Words	188,900,000	44,870,000	71,430,000	48,960,000	22,770,000
Words per Column	596	388	605	840	913
Uncertainty, %	0.76	0.55	0.56	1.01	1.2
Economic, %	4.30	4.53	4.37	4.01	5.25
Political, %	1.36	1.79	1.01	1.88	0.95
Negative, %	1.64	1.59	1.46	2.06	1.69
Positive, %	0.95	0.68	0.99	1.05	0.97
Pessimism, %	0.68	0.91	0.48	1.02	0.73

Table 8 shows the effect of the tone of each of the four sections on returns during bull markets. The first thing of note is that the effect of the overall newspaper (i.e., the aggregation of the four sections) is greater than any of the individual sections. Thus, it is not just the narrow Market News section which is affecting investor sentiment. This finding extends the extant literature which has been focused on financial-market columns.

The next thing to note is that the effect of pessimism, which aggregates positive and negative content, is greatest for the Market News section. Interestingly, the results in Table 8 suggest that the initial returns are all reversed over following days. However, the economic effect of the Market News section is more than one half that of the overall FT.

The negative tone of the Lex column has the next greatest economic effect on returns. Similar to previous results, this effect appears to reverse over subsequent days. The positive tone of the Lex column does not affect the stock market. We put this down to the fact that the Lex column by its nature is critical in its stance and is not necessarily given to positive commentary. The fact that the Lex column affects returns suggests that our sentiment measure is not a proxy for new information being communicated to the market.

The tone of the FT's Editorials and Leaders does not have a meaningful economic effect on returns. The final thing to note is that the positive tone and pessimism of the News in Brief section affects returns. Notably, however, the initial returns over subsequent days are not reversed. This implies that News in Brief is the section of the FT which is most likely to convey new information that permanently affects prices.

TABLE 8: Feedback from FT Sections to the Blue-Chip Index

This table reports β coefficients and t -stats from the model $R_t = \beta \mathcal{L}_s(M_t) + \gamma \mathcal{L}_s(R_t) + \psi \mathcal{L}_s(R_t^2) + \eta X_t + \epsilon_t$. R_t is our daily stock market index returns. M_t is one of our media measures. X_t is our exogenous variables including day-of-the-week dummies, month-of-the-year dummies, editor dummies and a dummy for whether date t is a bull or bear market.

	Negative		Positive		Pessimism	
	β	t -stat	β	t -stat	β	t -stat
PANEL A: News in Brief (13,626 Obs.)						
M_{t-1}	-0.007	-0.72	0.021	2.73	-0.017	-1.71
M_{t-2}	-0.014	-1.43	0.002	0.28	-0.012	-1.36
M_{t-3}	-0.001	-0.08	-0.002	-0.20	0.001	0.05
M_{t-4}	0.002	0.22	-0.001	-0.09	0.002	0.25
M_{t-5}	0.015	1.53	0.011	1.47	0.008	0.78
Tests						
	β	F -stat.	p -value	β	F -stat.	p -value
$\beta_1 = 0$	-0.007	0.52	0.470	0.021	7.45	0.006
$\sum_{j=2}^5 \beta_j = 0$	0.002	0.99	0.413	0.010	0.60	0.666
PANEL B: Market (16,557 Obs.)						
M_{t-1}	-0.015	-1.60	0.017	2.056	-0.023	-2.44
M_{t-2}	0.017	1.80	0.017	1.98	0.004	0.40
M_{t-3}	0.006	0.64	-0.002	-0.27	0.006	0.68
M_{t-4}	0.024	2.63	-0.003	-0.40	0.022	2.39
M_{t-5}	0.007	0.71	-0.018	-2.16	0.016	1.77
Tests						
	β	F -stat.	p -value	β	F -stat.	p -value
$\beta_1 = 0$	-0.015	2.56	0.110	0.017	4.23	0.040
$\sum_{j=2}^5 \beta_j = 0$	0.054	3.06	0.016	-0.006	2.03	0.087
PANEL C: Editorials and Leaders (17,312 Obs.)						
M_{t-1}	-0.009	-0.93	0.009	1.32	-0.012	-1.35
M_{t-2}	0.001	0.16	-0.009	-1.22	0.006	0.70
M_{t-3}	0.008	0.83	0.006	0.77	0.003	0.40
M_{t-4}	0.006	0.62	-0.006	-0.78	0.008	0.86
M_{t-5}	0.015	1.65	0.014	1.91	0.005	0.55
Tests						
	β	F -stat.	p -value	β	F -stat.	p -value
$\beta_1 = 0$	-0.009	0.86	0.354	0.009	1.74	0.187
$\sum_{j=2}^5 \beta_j = 0$	0.030	1.06	0.373	0.005	1.41	0.228
PANEL D: Lex (11,686 Obs.)						
M_{t-1}	-0.023	-2.11	0.002	0.20	-0.018	-1.84
M_{t-2}	0.024	2.23	-0.006	-0.62	0.020	2.12
M_{t-3}	0.006	0.51	0.020	2.14	-0.007	-0.75
M_{t-4}	-0.004	-0.39	-0.018	-1.94	0.007	0.71
M_{t-5}	0.015	1.41	-0.025	-2.73	0.025	2.58
Tests						
	β	F -stat.	p -value	β	F -stat.	p -value
$\beta_1 = 0$	-0.023	4.45	0.035	0.002	0.04	0.841
$\sum_{j=2}^5 \beta_j = 0$	0.041	2.25	0.061	-0.029	3.89	0.004

Overall, the findings from the sections suggest that the more narrowly focused the section is on financial markets, the more likely it is that tone has an effect on the stock market. In addition, the fact that the tone in commentary sections of the FT affects returns suggests that our sentiment measure does not appear to contain information. However, the sentiment-laden parts of the FT do not affect investors more than the other sections of the newspaper which focus on reporting news. This implies that the words used to report events and the commentary integrated into such reporting is just as sentiment laden as pure commentary sections of the FT.

VII. Conclusions

The main finding of this paper is that from 1899 to 2010, the tone of the *Financial Times* shifts trading volume in bull markets, but not in bear markets. We interpret this as evidence consistent with Shiller's press-as-propagators hypothesis; that noise traders are affected by sentiment and drive trade during speculative booms. We also find that tone affects returns. The effect of tone is found in all periods, in bull runs and in bear runs. There is mixed evidence as to whether or not the effect is different between market states.

Our dataset opens up other research questions. While our paper reveals that the effect of sentiment does not always reverse, it would be insightful to understand how limits to arbitrage vary over the long run and across bull and bear markets and the extent to which limits to arbitrage explain the non-reversal. In addition, it would be helpful to understand how the narratives created and shaped by the *Financial Times* affected the stock market.

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Internet Appendix for “News Media and Investor Sentiment over the Long Run”

Appendix 1 – Data Cleansing and Tokenization

In this appendix, we describe the procedure used to extract sentiment measures from the *Financial Times* (FT) articles.

Before sentiment analysis was conducted a process of data cleansing was performed to address as many of the digitization issues as possible. Given the original format of the articles OCR errors were inevitable. While there is dramatic improvement over time, image quality is significantly lower for articles around the turn of the 20th century. The quality of an article is ultimately measured in terms of its readability: ideally all the text in the article would be comprised of recognisable words. This is broadly the goal of the data cleansing process. Errors remaining after the data cleansing process should be random and therefore have no impact on results.

Before we can determine if a word is recognisable or valid in some sense, we need to define what we mean by a word and how it will be validated. Words are normally delimited using a combination of punctuation (commas, periods, etc) and white space (spaces, line returns, etc). The article text must therefore be decomposed into individual tokens. While the comma and period character are typically used for punctuation, in financial publications they are frequently also used for abbreviation (e.g., U.S.A.), as a decimal point (e.g., 5.2%) and as a thousand separator (e.g., £10,000). To prevent excessive tokenization, allowances were made for such occurrences. A ‘token’ could therefore refer to any contiguous set of alphanumeric or symbolic characters that form a natural group but is most often synonymous with a word.

We must also define which tokens we consider valid. Naturally this will include a regular vocabulary of words as defined by a standard dictionary. Our base dictionary comprises version 6 of the ‘2of12inf’ and ‘3ofall’ dictionaries sourced from <http://wordlist.aspell.net/12dicts/>. The former is used by Loughran and McDonald (2011) and contains words that appear in at least 2 out of 12 different English language dictionaries. The latter is used specifically to incorporate British spellings, but also includes common contractions (e.g. wouldn’t, we’re, etc). Note that the choice of dictionary should have no material impact on the results since it merely determines the

total word count and denominator of sentiment measures. However, commonly used dictionaries are likely to be incomplete and omit words from the standard financial lexicon. We must consider treatment of proper nouns, hyphenation, and other words containing non-alphabetic characters. We augmented our base dictionary through manual inspection to identify additional valid tokens.

1. Data cleansing

To improve the quality of articles three major areas were considered.

1.1-Substitutions

A list of substitutions was compiled to address common OCR errors and improve document quality. Substitutions are performed on a ‘find and replace’ basis. Firstly, these were used to correct generic issues such as removing the line breaks immediately following hyphens or correcting repeated non-alphanumeric characters. Custom substitutions were also constructed based on a review of initial token classification to target high frequency issues. For example, substituting instances of the misspelt token ‘diflicult’ with the word ‘difficult’. Such substitutions naturally arose from commonly occurring OCR errors such as:

- Confusion between the letters ‘e’ ‘c’ and ‘a’
- Confusion between the letters ‘f’ ‘l’ and ‘t’
- Confusion between the letters ‘h’ and ‘b’
- Confusion between the letters ‘y’ and ‘v’
- Confusion of the letter ‘e’ with the copyright symbol ©
- Confusion between the letter ‘O’ and the number ‘0’

A cautious approach must be adopted when defining these substitutions due to the potential to cause erroneous substitutions. Particular care must be taken with stem words. As an example, consider how one might deal with the word ‘compet’. If one replaces ‘compet’ with ‘compete’ in the entire article text (rather than on a word by word basis) one risks changing ‘compete’ to ‘competee’. Moreover, the source text may actually have used the word ‘competition’.

1.2-Hyphenation

Hyphenated words, particularly those used to accommodate newspaper justified formatting rules, are a common source of errors. The hyphen character was often omitted in the OCR translation or included along with spurious white space or random characters that did not appear in the original article. For example, the word ‘demand’ could easily be captured as ‘de-mand’, ‘de

mand' or even 'de-;mand'. Such errors lead to two separate words which may or may not be valid dictionary words. A list of commonly split tokens was compiled. These were recombined when their two halves were separated by selected characters associated with hyphenation errors. Hyphens were also removed when doing so created a valid dictionary word.

1.3-Filtering

The OCR process produced text files separated into 'lines' that would naturally be delimited by carriage returns. Thus, a single line of text could represent an entire article paragraph. Filtering was used to exclude entire lines of text that did not directly relate to the article, or meaningfully contribute to its sentiment. Firstly, boiler plate content that appears on a regular basis was removed. For example, the FT's 'without fear and without favour' motto. Secondly, text that was evidently not part of the article itself was removed. For example, text appearing before the article's title was excluded. This issue relates to the image capture process used to archive the FT. Thirdly, lines containing low quality or significant amounts of spurious text were removed. This seeks to address issues arising from the digitization of non-text content such as tables, graphs and photographs embedded in the article.

Criteria to exclude such lines were:

- Contain less than 5 tokens
- Valid words make up less than 50% of the total word count
- Valid words contribute less than 50% of the total character count of the line
- Have more than 50% of letters in upper case
- Contain more than one tab character

2. Tokenization

Tokenization attempts to decompose text into the single words and punctuation characters from which sentences are constructed. The NLTK package was used for this purpose. Tokens consisting of single punctuation characters, or those representing numeric quantities, clearly contain no sentiment and can therefore be ignored. While the possibility of incorrect OCR conversion cannot be entirely discounted, tokens matching entries in a chosen dictionary were considered valid tokens. Remaining tokens consisted of valid words that did not appear in the chosen dictionary, proper nouns, and tokens containing non-alphabetic character. These remaining tokens were first sorted into descending order of frequency. Unclassified tokens

occurring more than 30 times, in any one of the four sections, were manually inspected. Where appropriate these tokens were added to an extended custom dictionary or, in the case of obvious OCR errors, appropriate substitutions were created. Two researchers reviewed the list to confirm their validity and spot checks were performed against the original source documents. Note that tokens appearing less frequently than this threshold would be expected to appear on average at most every 3 years. Unclassified tokens reflect Zipf's (1949) law; the threshold accounts for approximately 40% of the total number of unrecognised tokens. A total of 564 words were added to the custom dictionary.

Examples of words added to the custom dictionary include terms specific to finance, those with distinct British spellings, and also some archaic terms (e.g. 'interbank', 'annualised', 'copecks'). Particular care was taken to include only words that would typically be used in the articles, and those could not easily have been incorrectly derived. For example, in the case of words such as 'belter', 'colonics' and 'groat', one could argue that these are valid words that may have been used by journalists, but adding them to the dictionary is likely to lead to lower quality articles: it is far more likely that these are incorrect digitizations of 'better', 'colonies' and 'great'.

An indication of the quality of the converted text files is given by two measures (see Figure A1: Document quality). The first 'non-word' compares the ratio of recognised dictionary words to total token count. The second 'non-text' additionally includes proper nouns, abbreviations and numeric tokens in the numerator. The closer the ratios get to one, the less unrecognised tokens (i.e., non-dictionary words and non-alphabetic strings) appear in the converted text documents. The increasing quality of the generated text files reflects the increasing quality of the source images.

Figure A1: Document quality

References

Loughran, T. and McDonald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, 66(1), pp.35-65.

Appendix 2 – Sample Articles

Example of 'News in Brief' article published 14th April 1902.

PEACE NEGOTIATIONS.

BOER LEADERS AT PRETORIA

RUMOCRED RECEIPT OP IMPORTANT XE WS IN LONDON.

Pretoria, Sat., 12th April Mr. Schalk Burger, General Ixmish Botha, Commandant Locaa Meyer, General Delarey, Mr. Steyn and General De Wet arrived her« this morning by special train from Klerka-dorp.—[Reuter.]

Utrecht, Rat., 12th April.

Dr. Leyds had a Conference vesterday erening with the memebra of the Bo er deputation here. The Boer delegates had , another oonfrcnce with Dr. Leyds this I afternoon. At the closc of the oonferenc« 1 Dr. Leyda, on being asked whether the mect-ing which he came to attend had been sum-moned with re fe re nee to the peace negotia-tiona, said tliat the oonference had been merely an ordinary one such as he was in the habit of holding with th« membre of the Boer deputation.—(Reuter.)

Example of 'News in Brief' article published on 15th June 1903.

NEW YORK BANK STATEMENT.

The return of the New York Associated Banks gives further evidence of a welcome improvement in the financial conditions in Wall Street, and, though its effect had been so discounted that the market weakened after the publication of the statement, this was due merely to profit-taking sales and did not reflect any disappointment with the position disclosed. There is a further sharp reduction in the loan account, which is matched by an almost identical decrease in net deposits, while the cash reserves are actually increased by \$1,760,000. The gain in surplus reserves amounts to \$4,700,000, and the balance above the legal minimum is now back again practically at the figure at which it stood a fortnight ago.

OCR output after cleansing processes applied:

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Iranian call for Opec output cut gives oil market brief fillip

By Deborah Hargreaves

OIL PRICES edged upwards yesterday in light trading in the run-up to Christmas, only to slip back again later in the day to close unchanged on the day. North Sea Brent crude for February delivery was at \$18.55 a barrel.

Prices got a brief fillip early in the day from reports in the Middle East Economic Survey, which quoted Mr Gholamreza Aqazadeh, Iran's oil minister, calling for a 2 per cent cut in output by the Organisation of Petroleum Exporting Countries.

A 2 per cent cut in production would take Opec's ceiling

to 24.09m barrels a day from its present level of 24.58m b/d. But many market traders are sceptical that members have even implemented the slight cutbacks required under their latest agreement.

Traders at one international oil company said there was little physical evidence of Opec cutbacks.

"Iran is talking up the oil price," said Mr Fareed Mohammadi at the Petroleum Finance Company in Washington, "I can't see them getting anyone to agree to a meeting before February".

Oil prices have found some support in the past week after being extremely weak since

October, but traders believe that, if Opec members fail to cut their production in the New Year, prices will continue to slide.

● Russia and Kazakhstan are looking at plans to join together energy producing states from the former Soviet Union in a "mini Opec", the Reuter news agency reported yesterday. The agreement was reached at the weekend in talks between Mr Viktor Chernomyrdin, Russian prime minister and Mr Nursultan Nazarbayev, Kazakhstan's president.

Russia and Kazakhstan were reported last month to be interested in joining Opec.

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Appendix 3—Additional Tables and Figures

Figure A2: Normalised Blue-Chip Index Volume Data, 1930–2008.

Notes: Based on data from Global Financial Data which measures the number of trades that were executed on the constituent companies of the FN30 and FT30. The data begins on the 6 February 1930 and ends on the 30 June 2008. For the period 7 November 1973 to 28 December 1979, the data is missing. The data up to 6 November 1973 was available from The Economist after which The Economist stopped publishing the data and Global Financial Data were unable to obtain any more data until 29 December 1979. We follow Gallant, Rossi, and Tauchen (1992) in removing the time trend and known causes of variability in trading. Specifically, we use the residuals from a five-lag auto-regressive linear model with day-of-week and month-of-year dummies and divide by the annual standard deviation of the residuals.

Figure A3: Comparison of Sentiment Measures, July 1965 to December 2005.

Notes: Data is sourced from Baker and Wurgler (2006), *New York Times* data is sourced from García (2013) and the *Financial Times* data is as detailed in the paper. The Baker and Wurgler data are only available from 1965 and García's data is not available after 2005. The Baker and Wurgler data are only available at a monthly level, and so we aggregate the *Financial Times* and *New York Times* data to that level.

TABLE A1: Feedback from FT to the Blue-Chip Index by Alternative Bull/Bear Definitions, 1899–2010

This table reports β coefficients and t -stats from the model $R_t = \beta \mathcal{L}_s(M_t) + \gamma \mathcal{L}_s(R_t) + \psi \mathcal{L}_s(R_t^2) + \eta X_t + \epsilon_t$. R_t is our daily stock market index returns. M_t is one of our media measures. X_t is our exogenous variables including day-of-the-week dummies, month-of-the-year dummies and editor dummies. Differences are tested by running the above model. We identify bull (bear) states as any month for which the FT increased its use of bullish (bearish) words for two-successive months. Months that are preceded and proceeded by bull (bear) months are classified as bull (bear) months. Bull runs cannot last less than one month. Months classified as bull and bear months are declassified.

	Negative		Positive		Pessimism	
	β	t -stat	β	t -stat	β	t -stat
Panel A: FT Bull Periods (5,150 obs.)						
M_{t-1}	-0.054	-2.76	0.042	3.38	-0.075	-4.03
M_{t-2}	0.013	0.66	0.009	0.72	0.004	0.20
M_{t-3}	-0.013	-0.63	0.021	1.68	-0.025	-1.22
M_{t-4}	0.022	1.07	-0.017	-1.42	0.031	1.52
M_{t-5}	0.015	0.79	-0.007	-0.56	0.018	0.95
Tests						
	β	F -stat.	p -val.	β	F -stat.	p -val.
$\beta_{1Bull} = 0$	-0.054	7.63	0.006	0.042	11.41	0.001
$\sum_{j=2}^5 \beta_{jBull} = 0$	0.037	0.66	0.619	0.006	1.34	0.253
Panel B: FT Bear Periods (9,362 obs.)						
M_{t-1}	-0.041	-2.77	0.037	3.99	-0.058	-4.09
M_{t-2}	-0.023	-1.69	0.010	1.04	-0.025	-1.87
M_{t-3}	0.016	1.17	-0.002	-0.22	0.015	1.12
M_{t-4}	0.012	0.84	-0.014	-1.36	0.019	1.44
M_{t-5}	0.029	2.14	0.009	0.94	0.018	1.38
Tests						
	β	F -stat.	p -val.	β	F -stat.	p -val.
$\beta_{1Bear} = 0$	-0.041	7.67	0.006	0.037	15.90	0.000
$\sum_{j=2}^5 \beta_{jBear} = 0$	0.034	2.37	0.051	0.003	0.87	0.480
Panel C: Testing Effect Differences						
	χ^2	p -value	χ^2	p -value	χ^2	p -value
$\beta_{1Bull} = \beta_{1Bear}$	0.17	0.682	0.01	0.904	0.26	0.609

TABLE A2: Effect of FT Absolute Sentiment on Abnormal Trading by Alternative Bull/Bear Definitions

This table reports β coefficients and t -stats from the model $\hat{\tau}_t = \beta \mathcal{L}_s(|M_t|) + \gamma \mathcal{L}_s(\hat{\tau}_t) + \zeta \mathcal{L}_s(R_t) + \psi \mathcal{L}_s(R_t^2) + \eta X_t + \epsilon_t$. R_t is our daily stock market index returns. $|M_t|$ is one the absolute value of our standardized media measures. X_t is our exogenous variables including editor dummies and a dummy for when the market state switches between a bull and bear state. We identify bull (bear) states as any month for which the FT increased its use of bullish (bearish) words for two-successive months. Months that are preceded and proceeded by bull (bear) months are classified as bull (bear) months. Bull runs cannot last shorter than one month. Months classified as bull and bear months are declassified. $\hat{\tau}_t$ is abnormal trading which is calculated from the equation $\hat{\tau}_t = \beta \mathcal{L}_s(\tau_t) + \eta X_t + \epsilon_t$. Where τ_t is log number of trades (000's). The residuals are standardized by the annual standard deviation in the residuals. Thus $\hat{\tau}_t = \frac{\epsilon_t}{\sigma_\epsilon}$ which results in a detrended and white noise variable of abnormal trading. $\hat{\tau}_t$ is standardized to have a mean of zero and unit variance. Data begins on February 6, 1930 and ends June 30, 2008. Trading data is sourced from Global Financial Data and is not available from November 6, 1973 to December 28, 1979. Results based on 16,725 obs.

	Negative		Positive		Pessimism	
	β	t -stat	β	t -stat	β	t -stat
Panel A: Bull (3,826 obs.)						
$ M_{t-1} $	0.058	3.32	0.009	0.53	0.023	1.33
$ M_{t-2} $	0.016	0.92	-0.011	-0.67	0.036	2.10
$ M_{t-3} $	-0.026	-1.48	0.014	0.79	-0.018	-1.03
$ M_{t-4} $	-0.005	-0.30	-0.007	-0.39	0.002	0.14
$ M_{t-5} $	0.002	0.12	0.006	0.39	0.001	0.09
Tests						
	β	F -stat.	p -val.	β	F -stat.	p -val.
$\sum_{j=1}^5 \beta_{jBull} = 0$	0.045	2.85	0.014	0.013	0.30	0.912
Panel B: Bear (6,815 obs.)						
$ M_{t-1} $	0.022	1.62	0.002	0.12	-0.003	-0.23
$ M_{t-2} $	0.012	0.86	0.038	3.35	0.045	3.47
$ M_{t-3} $	-0.024	-1.67	0.003	0.23	-0.011	-0.84
$ M_{t-4} $	0.000	0.03	-0.020	-1.67	0.004	0.31
$ M_{t-5} $	0.014	1.10	-0.007	-0.54	-0.007	-0.53
Tests						
	β	F -stat.	p -val.	β	F -stat.	p -val.
$\sum_{j=1}^5 \beta_{jBear} = 0$	0.024	1.36	0.234	0.030	2.82	0.015
Panel C: Testing Effect Differences						
	χ^2	p -value	χ^2	p -value	χ^2	p -value
$\beta_{1Bull} = \beta_{1Bear}$	0.24	0.623	0.03	0.867	0.17	0.679

TABLE A3: Effect of FT Absolute Sentiment on Abnormal Trading by GDP Growth

This table reports β coefficients and t -stats from the model $\hat{\tau}_t = \beta \mathcal{L}_s(|M_t|) + \gamma \mathcal{L}_s(\hat{\tau}_t) + \zeta \mathcal{L}_s(R_t) + \psi \mathcal{L}_s(R_t^2) + \eta X_t + \epsilon_t$. R_t is our daily stock market index returns. $|M_t|$ is one the absolute value of our standardized media measures. X_t is our exogenous variables. $\hat{\tau}_t$ is abnormal trading which is calculated from the equation $\tilde{\tau}_t = \beta \mathcal{L}_s(\tau_t) + \eta X_t + \epsilon_t$. Where τ_t is log number of trades (000's). The residuals are standardized by the annual standard deviation in the residuals. Thus $\hat{\tau}_t = \frac{\tilde{\tau}_t}{\sigma_{\epsilon}}$ which results in a detrended and white noise variable of abnormal trading. $\hat{\tau}_t$ is standardized to have a mean of zero and unit variance. Data begins on February 6, 1930 and ends June 30, 2008. GDP Expansions are any days for which there was positive GDP growth over the course of that year. GDP Contractions are any days for which there was negative GDP growth over that year. GDP data is sourced from the Bank of England. Trading data is sourced from Global Financial Data and is not available from November 6, 1973 to December 28, 1979. A dummy is included to control for the break in the data

	Negative		Positive		Pessimism	
	β	t -stat	β	t -stat	β	t -stat
Panel A: GDP Expansion (14,809 obs.)						
$ M_{t-1} $	0.032	3.50	0.012	1.37	0.005	0.58
$ M_{t-2} $	0.008	0.89	0.027	3.30	0.038	4.32
$ M_{t-3} $	-0.018	-1.96	0.009	1.11	-0.011	-1.27
$ M_{t-4} $	-0.009	-1.04	-0.012	-1.50	-0.006	-0.71
$ M_{t-5} $	0.016	1.87	-0.009	-1.11	0.003	0.37
Panel B: Bear Periods that are also GDP Expansions (5,481 obs.)						
$ M_{t-1} $	0.030	1.89	0.019	1.28	-0.002	-0.14
$ M_{t-2} $	0.006	0.39	0.009	0.70	0.029	1.91
$ M_{t-3} $	-0.020	-1.22	0.010	0.72	-0.010	-0.67
$ M_{t-4} $	-0.014	-0.98	-0.018	-1.27	-0.002	-0.11
$ M_{t-5} $	-0.006	-0.36	-0.004	-0.30	-0.014	-0.94
Panel C: Bull Periods that are also GDP Expansions (9,320 obs.)						
$ M_{t-1} $	0.032	2.86	0.006	0.58	0.008	0.74
$ M_{t-2} $	0.009	0.83	0.036	3.39	0.041	3.82
$ M_{t-3} $	-0.017	-1.56	0.008	0.76	-0.012	-1.11
$ M_{t-4} $	-0.008	-0.80	-0.008	-0.83	-0.010	-0.92
$ M_{t-5} $	0.025	2.51	-0.013	-1.30	0.010	1.02
Panel D: GDP Contraction (2,172 obs.)						
$ M_{t-1} $	0.028	1.11	-0.018	-0.84	0.009	0.38
$ M_{t-2} $	-0.013	-0.52	0.033	1.57	0.021	0.91
$ M_{t-3} $	-0.014	-0.56	0.004	0.19	-0.004	-0.18
$ M_{t-4} $	-0.006	-0.26	-0.044	-1.60	-0.040	-1.70
$ M_{t-5} $	0.003	0.13	0.019	0.83	0.009	0.38
Panel E: Bear Periods and GDP Contraction (742 obs.)						
$ M_{t-1} $	-0.014	-0.26	-0.015	-0.41	0.021	0.44
$ M_{t-2} $	-0.044	-0.91	0.090	2.48	0.043	1.02
$ M_{t-3} $	-0.036	-0.76	0.021	0.60	-0.025	-0.56
$ M_{t-4} $	-0.066	-1.47	-0.003	-0.08	-0.070	-1.65
$ M_{t-5} $	-0.017	-0.37	0.004	0.09	0.001	0.01
Panel F: Bull Periods and GDP Contraction (1,430 obs.)						
$ M_{t-1} $	0.040	1.46	-0.017	-0.65	0.006	0.25
$ M_{t-2} $	-0.004	-0.14	0.010	0.38	0.014	0.50
$ M_{t-3} $	-0.006	-0.21	-0.004	-0.14	0.007	0.28
$ M_{t-4} $	0.010	0.36	-0.061	-1.67	-0.031	-1.08
$ M_{t-5} $	0.010	0.37	0.024	0.85	0.013	0.51