Time Variation in the News-Returns Relationship*

Paul Glasserman† Fulin Li‡ Harry Mamaysky§

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Abstract

We find that the well-documented underreaction of stock prices to news exhibits substantial time variation, and we use this time variation to investigate the nature of the underreaction. The risk-bearing capacity of financial intermediaries and the degree of passive ownership of stocks are important conditioning variables for how contemporaneous and future prices respond to news. Once we control for likely institutional trading motives, we find the surprising result that stock prices *overreact* to news. Changing informativeness of news explains a portion but not all of the time variation in the news-returns relationship. The particular association of entropy, a text-based measure of news informativeness, with the news-returns relationship supports our interpretation that strategic institutional trading induces persistent price moves in response to news.

Keywords: Information choice; asset pricing; price efficiency; attention

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†Columbia Business School, pg20@columbia.edu.

‡University of Chicago Booth School of Business, fli3@chicagobooth.edu.

§Columbia Business School, hm2646@columbia.edu.

1 Introduction

Tetlock, Saar-Tsechansky, and Macskassy (2008) (hereafter TSM) show that stock prices of S&P 500 firms briefly underreact to the information content of daily news flow. The economic magnitude of this underreaction turns out to be quite large.[1] While the literature has not reached a definitive conclusion on the mechanism underlying this phenomenon, the price underreaction to news flow is often attributed to an informational capacity constraint: market participants are unable to respond to all relevant daily news flow about a given firm, and a portion of the news is therefore impounded into stock prices with a lag.[2] In this paper, we provide evidence consistent with an alternative interpretation.

We begin by confirming that TSM's results on stock price underreaction to news hold in our data. TSM find that a one standard deviation news sentiment shock on day t forecasts a 2.5 basis point abnormal return in the same direction as the news on day $t+1$. This will be our definition of *underreaction* — a day $t+1$ (or longer) abnormal return in the same direction as the sentiment of day t news. Table 1 replicates TSM's findings for S&P 500 firms using data from 1996–2018.[3] In our sample, a one standard deviation news sentiment shock on day t forecasts a 1.9 basis point cumulative abnormal return on day $t+1$. However, this full-sample result masks a substantial amount of time variation in this relationship. In the earliest part of the sample, 1996–2000, the degree of underreaction is roughly twice as high as it is in the most recent subperiod, 2015–2018.[4] One possible interpretation of this result is that, as natural language processing techniques coupled with faster computers and larger data sets have become more widely used by practitioners, investors have become better able to trade on information about the hard-to-quantify aspects of firms' fundamentals described in TSM, diminishing the price underreaction to news and suggesting increased informational efficiency of the market.[5]

If greater information processing capacity has decreased the amount of return underreaction to news, then we would expect that the reaction of contemporaneous returns to news must have increased. If the total reaction to a quantum of news is constant, and less of the reaction happens in the days after the news comes out, then more of the reaction should happen on the day of the news event itself. However, while the degree

[1]TSM show that, in the absence of trading frictions, long-short strategies that exploit this effect earn annual alphas of over 20%. Heston and Sinha (2017) and Ke, Kelly, and Xiu (2018) reach similar conclusions.

[2]See the survey chapter by Tetlock (2015) and the references there.

[3]Our news data is from Thomson-Reuters and TSM's is from Dow Jones.

[4]However, the full-sample and most recent magnitudes of underreaction are similar.

[5]This is consistent with recent work showing that S&P 500 equity prices are better predictors of earnings than in the past (Bai, Philippon and Savov 2016 and Farboodi, Matray, and Veldkamp 2017).

of underreaction is now roughly half of what it was in the 1996–2000 subperiod, the contemporaneous price response to news is also a little smaller. Markets are currently *less* sensitive to both contemporaneous and lagged news than in the past, a finding that would be difficult to explain solely through an increase in the analysis of news.

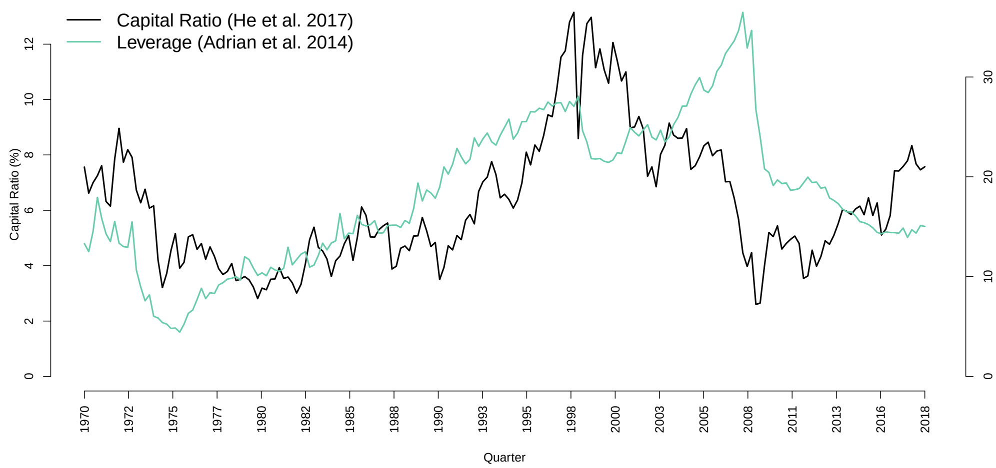

Fig. 1. This chart shows the quarterly intermediary capital ratio and leverage. These series are defined in Section 3.4.

An important part of the explanation for this finding has to do with time variation in intermediary risk-bearing capacity, as indicated by the *capital ratio* measure of He, Kelly, and Manela (2017). There has been growing awareness in the literature of the importance of financial intermediaries for price formation in financial markets (see Adrian, Etula and Muir 2014 and He, Kelly, and Manela 2017), and we find strong evidence of this in our analysis. As Figure 1 shows, the 1996–2006 part of our sample was characterized by high intermediary capital ratios, which fell dramatically during the financial crisis, but have subsequently rebounded to their pre-crisis levels. We find strong evidence that higher intermediary capital ratios are associated with higher contemporaneous stock price reactions to news. We find equally strong evidence that higher intermediary capital ratios are associated with *greater* underreaction over the subsequent one to ten days following news. We interpret the intermediary capital ratio as a measure of the degree of market participation of either the financial intermediaries themselves, or of levered investors (such as hedge funds) who obtain financing for their positions from the financial intermediation sector. These are the types of investors that would be best positioned to apply novel computational tools to extract information from news flow, so the increased contemporaneous reaction is expected, but the increased underreaction requires a different explanation. We will argue that the underreaction results from strategic trading by institutions.

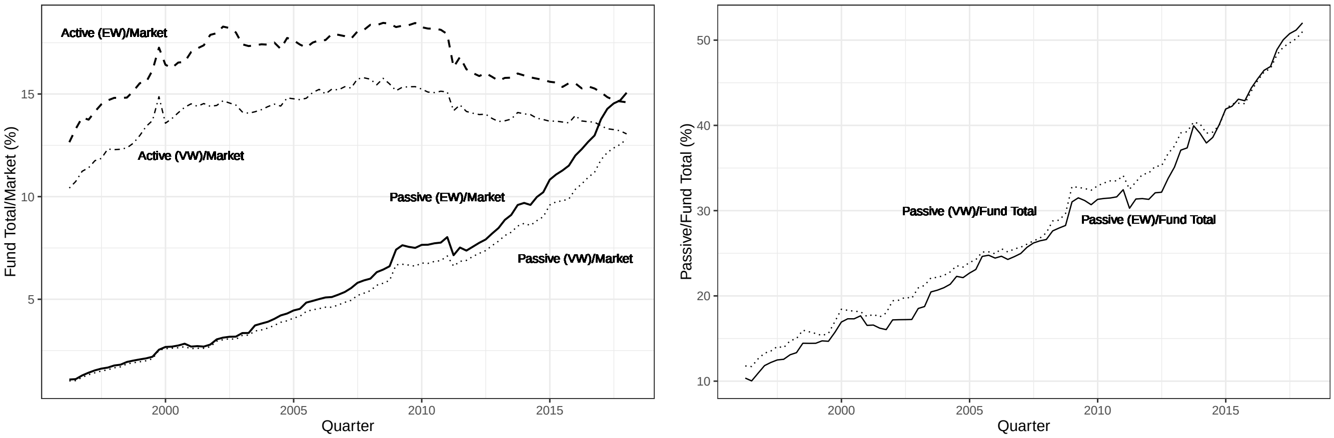

Fig. 2. The left chart shows the fraction of S&P 500 firms' market capitalization that is owned by either active or passive mutual funds. The right chart shows the ratio of passive mutual fund assets invested in S&P 500 firms to total mutual fund assets invested in those firms.

Along with changes in the risk-bearing capacity of the intermediation sector, the last two decades have witnessed a move of investors towards passive, and away from actively managed, mutual funds. Figure 2 shows that the fraction of all S&P 500 stocks that are owned by funds with passive strategies has steadily grown over the past several decades.[6] We find that stocks with a higher degree of passive ownership have a smaller contemporaneous reaction to news than do stocks with a lower degree of passive ownership. Furthemore, stocks with greater passive ownership experience *less* one-day and ten-day underreaction to news than do stocks with a lower degree of passive ownership. These results suggest that more passive investors impeded contemporaneous price discovery, but also dampened the reaction of prices to lagged news. Both effects would be explained if passive funds squeezed out active investors and the trading activity of the active funds *caused* a price reaction to lagged news.

Our financial intermediary and passive ownership results are both consistent with a strategic trading explanation for the stock price underreaction to news. Large investors react to news very quickly, but then, aware of the price impact of their trading on the market, trade strategically in response to such news, therefore causing a delayed stock price reaction to news. Perhaps they all read Kyle (1985) while in business school. Smaller

[6] We use the fund classification scheme in Appel, Gormley, and Keim (2016). See also Figure 2.8 in either the 2018 or 2019 Investment Company Institute Fact Book, showing the relative sizes of active funds and index funds in the U.S. equity market.

amounts of strategic trading, proxied for by either lower intermediary risk-bearing capacity or more passive mutual funds, result in lower contemporaneous stock price reaction to news, but also result in less pronounced subsequent abnormal returns in the direction of lagged news (i.e., less underreaction). If short-term underreaction was being caused by informational capacity constraints, then when those constraints become more binding, i.e., when there are fewer institutional traders active in the market, we would expect to see more underreaction, not less.

Since institutional trading appears to be an important determinant of the news-returns relationship, we control for situtations where the institutional trading motive will be the most pronounced. In our forecasting regression, we interact sentiment with indicator variables for two double sorts. In the first we double sort stocks based on their short interest and news sentiment, and in the second we double sort stocks based on their institutional ownership and news sentiment. We find that heavily shorted stocks that experience positive (negative) news on day t exhibit strong positive (negative) abnormal returns over the ensuing one or ten days.[7] Furthermore, heavily institutionally owned stocks that experience negative sentiment news on day t tend to have very negative abnormal returns over the subsequent one or ten days. These observations appear to be pronounced *underreactions* to news, but there is a more natural interpretation: what appears to be underreaction to news is actually a delayed price response due to strategic trading by large institutional investors (exactly as suggested by Kyle 1985). The underreaction is thus a market microstructure effect, as opposed to an information processing effect. This finding is consistent with our intermediary and passive investor interactions. It is not consistent with an explanation based on investor inattention, as we would expect heavily shorted and heavily institutionally owned stocks to be particularly closely monitored by savvy investors.

Once the above institutional trading motives are removed from sentiment, the coefficient loading of future ten-day abnormal returns on day t news sentiment turns out to be strongly negative! Thus we are left with an *overreaction* to news. We can therefore interpret stock price underreaction to news as an unconditional average of two effects. The first effect, which appears as underreaction in the regressions, is strategic trading by large institutions in response to news. The second effect is an overreaction to news by the non-institutional investors. We do not see the latter until we control for the former. Evidence of investor overreaction has a long history, including De Bondt and Thaler (1985)

[7]Only the one-day reaction of heavily-shorted stocks to positive news is not significant at the 10% level.

and Chopra, Lakonishok, and Ritter (1992), to which we return in Sections 1.1 and 5.2

To understand the time variation in the news-returns relationship, we study whether the information content of news has itself changed over time. One way to measure the information content of news is to check the extent to which news can forecast company fundamentals. To test for this relationship, we regress future standardized unexpected earnings (SUE) and standardized analyst forecast errors (SAFE) on current sentiment, as well as a large set of controls. As in TSM, we find that news sentiment robustly forecasts both SUE and SAFE. However, as before, we find that the news-earnings relationship displays substantial time series variation. While sentiment remains a significant forecaster of SAFE, its forecasting power for SUE is lower in the most recent subperiod (2015–2018) than it was earlier in the sample.[8]

We then find that the sentiment coefficients in annual versions of the earnings regressions are highly correlated with the average entropy measure of news articles in that year. Glasserman and Mamaysky (2019b) show that article entropy — calculated as the average log probability of four-word phrases — is an effective indicator of the informativeness of a news story. Therefore, we may expect that average entropy would proxy for the information content of news, and that more informative news would be better at forecasting future earnings. Indeed, this is what we find.

Interestingly, we find that the sentiment coefficients from annual versions of our abnormal return forecasting regressions are also highly correlated with annual entropy. This result is consistent with both the institutional trading and the information processing stories. If news is more informative, and market participants are informationally capacity constrained, then there is more content in the news to be impounded into future prices. Likewise, when news is more informative, institutional investors may trade in response to news more actively, thus leading to more return persistence due to the strategic trading. However, when we control for institutional trading motives, via our short interest-sentiment and institional ownership-sentiment double sorts, the annual sentiment coefficient (which has now changed sign relative to the uninteracted regression) is uncorrelated with entropy. Therefore, after taking out the microstructure effects, the news-returns relationship is no longer related to the information content of news. This is consistent with our interpretation of price underreaction to news being driven by institutional trading, rather than by the difficulty of processing news content.

The rest of the paper proceeds as follows. Section 2 describes the data and the methodology used to construct our sentiment measures. Section 3 discusses the informational

[8] We discuss some reasons for this in Section 4.1.

versus institutional trading drivers of the news-returns relationship. Section 4 discusses time variation in the informativeness of news. Section 5 discusses interpretations for some of the results in the paper, such as why we may expect to see news overreaction in abnormal returns, and also details some robustness checks on our results. Section 6 concludes. An Internet Appendix contains further technical details and supporting results.[9]

1.1 Relation to the literature

Our paper contributes to a growing literature on the use of news sentiment analysis and natural language processing techniques in finance. We revisit Tetlock, Saar-Tsechansky, and Macskassy (2008), which built on Tetlock (2007) in predicting returns from news sentiment. Engelberg, Reed, and Ringgenberg (2012), Garcia (2013), Heston and Sinha (2017), Sinha (2016), Larsen and Thorsrud (2017), Froot et al. (2018), Calomiris and Mamaysky (2019), Ke, Kelly, and Xiu (2018), and others also find return predictability using various measures of sentiment and news events. Our work exploits time variation in the news-returns relationship to investigate sources of predictability. Garcia (2013) finds that return predictability is greatest in recessions, and we take this finding into account in forming sub-periods for our analysis. Like several other studies, we base our sentiment calculations on the dictionary of Loughran and McDonald (2011). In measuring the information content of news, we use an entropy measure that proved valuable in Calomiris and Mamaysky (2019) and Glasserman and Mamaysky (2019b). Antweiler and Frank (2005) and Das and Chen (2007) propose measures of information and sentiment in text from internet message boards.

We focus on the role of institutional investors in the market's reaction (or underreaction) to news. Hendershott, Livdan, and Schürhoff (2015) find that institutions trade ahead of news, whereas Huang, Tan, and Wermers (2019) find that they mainly trade on the tone of early news reports. Sinha (2016) suggests that stocks with greater institutional ownership may not be immune from behavioral biases, while noting a possible role for strategic trading as a factor in return predictability. We argue for the importance of strategic trading in explaining apparent underreaction by interacting sentiment with institutional ownership and short interest, and by controlling for intermediary capital, passive investing, and the informativeness of news.

A large literature offers models of investor underreaction and overreaction grounded in patterns of investor psychology. In Daniel, Hirshleifer, and Subramanyam (1998), over-

[9] Available at `https://sites.google.com/view/hmamaysky/`.

confidence about private information leads investors to overreact to private signals and underreact to public news. Underreaction and overreaction also result from overconfidence in Odean (1998) and Baker and Stein (2004). In Barberis, Shleifer, and Vishny (1998), investor conservatism leads to underreaction and a representative heuristic leads to overreaction. The empirical evidence is mixed. For example, De Bondt and Thaler (1985) and Chopra, Lakonishok, and Ritter (1992) find evidence of investor overreaction. Jegadeesh and Titman (2001) find support for a behavioral explanation of momentum, and Hong, Lim, and Stein (2000) explain momentum through the slow diffusion of information; but Llewellen (2002) concludes that underreaction cannot explain momentum in portfolio returns. Our investigation does not rule out a role for investor psychology in the underreaction to news but it documents evidence for the importance of institutional trading in explaining this phenomenon.

We draw on work showing that institutional investors routinely split large orders to buy or sell shares. Starting with Kyle (1985), an extensive literature on models of trading with asymmetric information predicts that informed traders will trade slowly to avoid revealing information. News articles are public but need not reflect all the information available to investors; in the models of Foster and Viswanathan (1996) and Kyle, Obizhaeva, and Wang (2018), multiple informed traders continue to trade strategically if their signals are not perfectly correlated. Although existing theory does not exactly cover our setting, there is ample evidence of strategic trading by institutional investors. The practitioner-oriented work of Almgren and Chriss (2000) and many others develops strategies for optimal trade execution. Sias and Starks (1997) find that "stealth trading" by institutions contributes to serial correlation in returns. Keim and Madhavan (1995) find that more than 40% of institutional trades take more than one day, and Chan and Lakonishok (1995) find that over half of institutional trades are split over more than four days. Using high-frequency trading data from 2000–2010, Huang, Tan, and Wermers (2019) find that institutions trade over several days in the same direction as the tone of news, resulting in return predictability over two weeks; these findings are consistent with our interpretation of the effect of institutional trading on the apparent underreaction to news.

Our paper contributes to the literature on the consequences for price discovery and security valuation of changes in intermediary capital, as in Adrian, Etula and Muir (2014) and He, Kelly, and Manela (2017), and passive investing, as in Appel, Gormley, and Keim (2016) and the many papers discussed in Wermers (2019). Like us, Frank and Sanati (2018) consider intermediary capital in studying the stock market response to news, but their interpretation differs from ours: they seek to control for the ability of arbitrageurs to exploit a tendency of retail investors to overreact to positive news, whereas we focus on strategic trading. An increase in arbitrage capital should produce a stronger contemporaneous response and a weaker lagged response, whereas strategic trading can explain a stronger lagged response.

2 Data

The sample consists of S&P 500 firms, for which we obtain company identifiers and names from CRSP. Our news data start in 1996, and the time period of our analysis runs from 1996 to 2018. Over this period, 1,123 firms were members of the S&P 500 index. Each firm appears in our analysis only in the period in which it was part of the S&P 500 index. We construct two panel datasets for these firms: one at the firm-day level to be used in our returns regressions, and the other at the firm-quarter level for our earnings regressions.

2.1 Text data

We obtain text data from the Thomson Reuters News Feed Direct archive (hereafter TR). Reuters is one the the three major business news providers (the others being Dow Jones and Bloomberg) and offers extensive global markets and asset class coverage. Articles in the TR data set are labeled with a UTC (Coordinated Universal Time) timestamp, which we convert to the New York time zone, a difference of 5 hours during Eastern Standard Time and 4 hours during Daylight Savings Time.

Thomson Reuters tracks articles by assigning each to a unique article chain. Depending on the month, between two thirds and three quarters of all article chains contain only a single article. Chains with multiple articles represent either (1) refinements of the coverage of a specific event (e.g., an initial, short article gets written when some corporate event occurs, and this article gets expanded and refined over time), or (2) regularly occuring news events (e.g., an hourly snapshot of market movers). TR identifies article chains with a Primary News Access Code (PNAC). PNACs can be reused, though within any given month, the vast majority of PNACs are used only once. We divide each day into six-hour windows, and then select the first article with a TR "urgency code" ≥ 2 in each of the PNACs that appear in that window.[10] This rule tries to avoid duplication of articles from type (1) chains and while retaining relevant articles from type (2) chains.

[10]Often the initial article in a PNAC chain is only a headline and has no body. The urgency ≥ 2 rule discards all such articles.

Next, we select Thomson Reuters articles that mention S&P 500 firms. TR tags each article with a Reuters Instrument Code (RIC) for each company mentioned in the article; RICs are usually based on company tickers. We construct a mapping from CRSP company identifiers (PERMNOs) to TR articles through an iterative process of searching for company names in the text of articles and matching RICs with similar stock tickers. The full details of our mapping process are given in Section A1 in the Internet Appendix.

Our news selection procedure yields 1.77 million articles about S&P 500 firms from 1996 to 2018. Around the time of the financial crisis, many short articles containing the terms "NYSE" and "imbalance" in their headlines and only one line of text entered the sample. Dropping these articles leaves 1.48 million news stories. We also drop any article with fewer than 25 words or that mentions more than seven RICs (companies).[11] This leaves us with 1.36 million articles. We then convert articles to lower case, remove stopwords, stem and tokenize the text, and perform sentiment negation using the Das and Chen (2007) method. This process is described in more detail in Section A2 of the Internet Appendix.

The sentiment of article j is calculated as

$$Sent^j = \frac{n_j^{pos} - n_j^{neg}}{n_j}$$

where $n_j^{pos}, n_j^{neg}, n_j$ are the number of positive words, negative words and total words (after dropping stopwords) in article j, respectively. We use the Loughran and McDonald (2011) sentiment dictionary to classify words into positive and negative bins, while ignoring negated sentiment words. We then aggregate article sentiment to firm-day level and firm-month level. At the firm-day level, the 4pm-4pm sentiment for firm j on business day t is the equally-weighted average sentiment of articles for firm j that appear between 4pm on day $t-1$ and 4pm on day t. For some of our specifications we also compute the 4pm-9:30am sentiment. Here we drop articles on day t that occur strictly after 9:30am New York time. For Monday sentiment, in addition to including the 4pm-midnight articles from Sunday, we include articles from 4pm-midnight on the prior Friday.[12]

[11] We identify a RIC by the occurrence of the string "R:" in the article's `subjects` field. As can be seen from Figure 4 there were almost no articles with more than seven RICs in the middle eight years of the sample. Furthermore, as the histogram in Figure A3 of the Internet Appendix shows, there appears to be a sharp drop-off in article frequency when we go from seven to eight RICs. Finally, articles with fewer than 25 words tend to contain headlines like "NYSE ORDER IMBALANCE ⟨WPX.N⟩ 149800.0 SHARES ON BUY SIDE" and "Block Trade - First Data Corp ⟨FDC.N⟩ 100,000," and thus do not convey useful sentiment information.

[12] Our 4pm day $t-1$ to 4pm day t window should be interpreted as (4pm day $t-1$, 4pm day t], i.e. articles strictly after the cutoff on day $t-1$ but including the cutoff on day t. Reuters articles are

For our earnings regressions in Section 4.1, we calculate news sentiment in the month prior to the earnings release. More specifically, our news sentiment measure is the average of the sentiment scores of individual articles mentioning company j within a $[-30, -3]$ trading day window prior to the earnings announcement date t, weighted by the number of words in each article.[13] We lag the sentiment window by three days because of potential uncertainty as to the accuracy of the earnings announcement date.[14] While an earnings event on trading day t will enter our sample only if company j was a member of the S&P500 index on day t, we will use articles about j in the $[t-30, t-3]$ trading day window even if the company was not a member of the S&P500 on those days, as long as the articles satisfy the ≤ 7 RICs and ≥ 25 word requirements.[15] Our return controls in the earnings regressions are from trading day $t-2$ and the $[t-30, t-3]$ trading day window prior to the earnings announcement date t. Our other control variables are from the month prior to the earnings announcement month.

When analyzing time variation in the news–returns and the news–earnings relationships, we calculate entropy as a proxy for an article's information content. This calculation is described in Section 4.2.

2.2 Financial data

We run all of our specifications with either raw excess returns or with cumulative abnormal returns (CARs) relative to our six factor model, which uses the Fama and French (2015) model augmented with momentum. We estimate the six factor model using daily data in the twelve month period preceding day t, but excluding the month immediately prior to t. We obtain daily stock returns from CRSP and factor returns from Ken French's website.

To study time series variation in the news-returns relationship, we use data on intermediary risk-bearing capacity and passive ownership. We obtain the intermediary capital ratios and leverage measures of He, Kelly, and Manela (2017) and Adrian, Etula, and Muir (2014) from Asaf Manela's and Tyler Muir's websites, respectively. We calculate passive and active mutual fund ownership for a given stock following Appel, Gormley, and Keim (2016). Passive ownership is the percent of shares held by passive mutual funds. We

timestamped to the millisecond, so a day t article with a timestamp of 4:00:00.097 would be classified in day $t+1$. A similar rule is applied to the 9:30am and midnight cutoffs.

[13]We also ran the analysis in Section 4.1 using an equally-weighted $[-30, -3]$ trading day news sentiment measure. The results were qualitatively similar. We use the word-weighting to be consistent with TSM.

[14]TSM point out that "Compustat earnings announcement dates may not be exact." Though we use announcement dates from I/B/E/S we follow the TSM convention to be conservative.

[15]Restricting the analysis to articles only on days when company j was a member of the S&P500 index does not change the results.

obtain mutual fund classifications from CRSP and fund holdings from Thomson Reuters Mutual Fund Holdings. We classify a fund into passive or active by searching for certain strings that identify index funds in the fund's name and supplement this information with the index fund indicator from CRSP.[16]

We also construct an extensive set of control variables. Share turnover is defined as trading volume divided by the number of shares outstanding. Share turnover on day t is the average share turnover in the $[t-84, t-21]$ trading day window. We compute day t illiquidity according to Amihud (2002) as the absolute value of the daily return divided by that day's dollar trading volume, and then on day t use the average daily illiquidity over the $[t-84, t-21]$ trading day window. We measure market capitalization and the book-to-market ratio at the end of the preceding calendar year, following Fama and French (1992). We obtain mid-month short interest (SI) from Compustat, and use the most recently available short interest for the day t observation. We retrieve quarterly data on institutional ownership from Thomson Reuters Institutional (13F) Holdings and define institutional ownership (IO) of a stock as the number of shares held by 13F institutions relative to the number of shares outstanding.[17] In our regressions, we time stamp IO with the data date from the 13F filing, even though this information is not yet available to market participants.[18]

For the firm-quarter earnings regressions, we first obtain earnings announcement dates from I/B/E/S for each firm-quarter, then compute standardized unexpected earnings (SUE), following Bernard and Thomas (1989) and TSM, as

$$\begin{aligned} SUE_q &= \frac{UE_q - \mu_q}{\sigma_q} \\ UE_q &= E_q - E_{q-4} \end{aligned}$$

where E_q is the firm's earnings in quarter q, and μ_q and σ_q are the mean and standard deviation of the firm's previous 20 quarters of unexpected earnings UE_q, respectively. We compute standardized analysts' forecast errors (SAFE) as the difference between actual earnings per share and the median of analyst forecasts made within the $[-30, -3]$ trading day window prior to the earnings announcement, divided by the standard deviation of unexpected earnings. We use a $[-30, -3]$ trading day window to avoid stale analyst

[16] More details are given in Section A3 in the Internet Appendix.

[17] 13F filers are institutions with over \$100 million in assets, and include mutual funds, hedge funds, insurance companies, banks, trusts, pension funds and other entities. Short positions are not included in 13F filings.

[18] In our regressions, we are interested in whether IO is an important determinant of the news-returns relationship. We are not claiming that such information would have been known to investors in real time.

forecasts and a potentially inaccurate earnings announcement date. We also include analyst forecast revisions and forecast dispersion as controls. Forecast revision is the sum of changes in the median analyst's forecast of earnings-per-share (EPS) scaled by the stock price at the end of the prior month, with the sum taken from the prior earnings announcement to the current one. Forecast dispersion is the standard deviation of EPS forecasts (either confirmed or revised) from the prior earnings announcement date to the current one, scaled by the same σ_q used to calculate SUE.[19]

2.3 Summary Statistics

Table 2 and Table 3 present summary statistics of the firm-day returns regressions variables, and of the firm-quarter earnings regressions variables, respectively. All return variables are in percentage points. We perform the IHS transformation (Burbridge et al. 1988),

$$\mathrm{IHS}_\theta(x) = \frac{\log\left(\theta x + \sqrt{\theta^2 x^2 + 1}\right)}{\theta},$$

on book-to-market with $\theta = 1$ in order to retain observation where the book-to-market variable is negative (for positive values of x IHS behaves similarly to log). In our analysis, we winsorize SUE and SAFE at the 5% level, and IO, forecast dispersion and forecast revision at 1% level.[20]

3 News-returns relationship

3.1 Measuring news

The left panel of Figure 3 shows the distribution of articles throughout the day. The majority of articles about S&P 500 firms are released from 7am to 5pm. The right panel of Figure 3 shows the average number of daily articles by month of the year. News volume is very seasonal with peaks in February, April, July and October, which partly reflect the earnings release cycle.

Figure 4 shows the time-series behavior of some summary statistics about the text archive. The average number of daily articles, on top of having seasonal patterns, also exhibits lower frequency fluctuations which may be related to the business cycle. The

[19] Not using a three trading day lag with regard to forecast revisions and dispersion is convervative because it means our sentiment measure is lagged relative to the controls.

[20] Winsorization at the X% level means setting all observations above (below) the $100 - X/2$ ($X/2$) percentile to that percentile value.

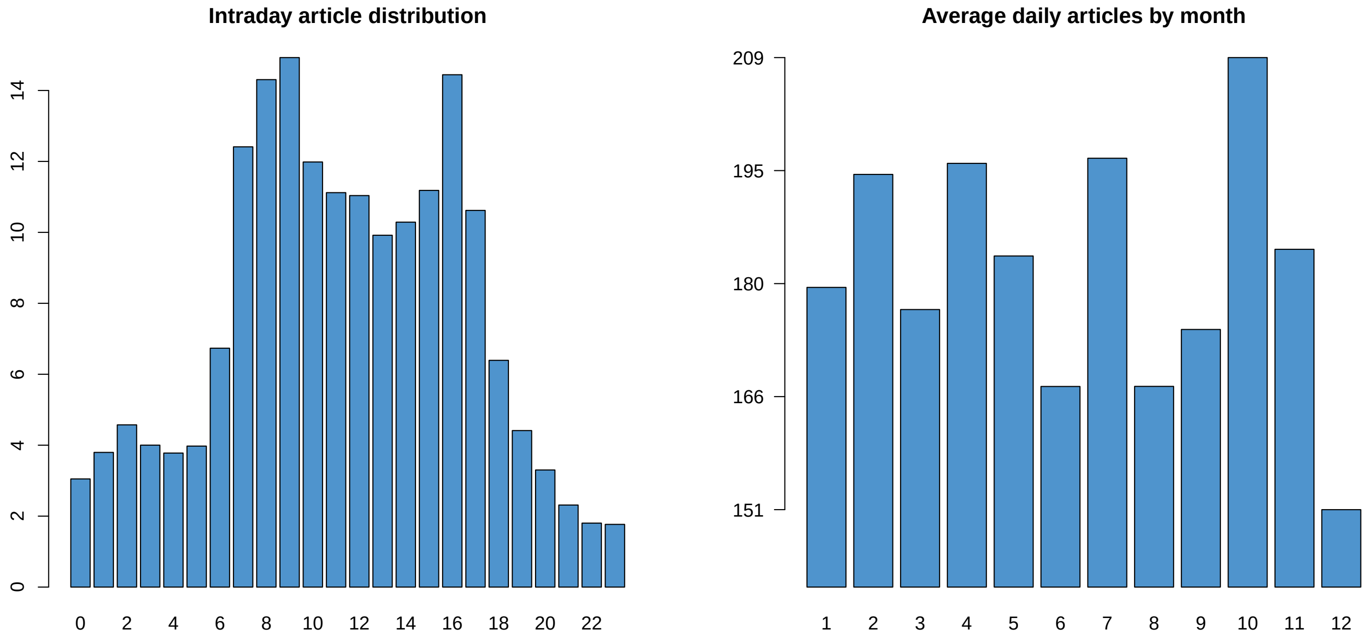

Fig. 3. The left panel shows the average number of articles in each hour of the day. The right panel shows the average number of daily articles within each month.

average number of RICs per article and the number of articles with more than seven RICs are highly correlated, with peaks around 2002 and 2013. The average number of words per articles (after stopwords have been excluded) grew in the early part of the sample, and has been relatively stable since then, with occasional high-frequency spikes, at just over 200 words per article. The average daily sentiment is highly procyclical, experiencing its lowest points around market downturns and recessions. The red, dashed line is the negative of the VIX, an index of short-term implied volatility of S&P 500 options, scaled to have the same range as the sentiment series. Aggregate sentiment and the VIX are seen to be strongly negatively correlated. The standard deviation of daily sentiment (across all articles on a given day) is strongly countercyclical, exhibiting peaks during times of market stress.

3.2 The news-returns relationship: A baseline

Stock i enters our analysis on day t if (1) that stock was a member of the S&P 500 index on day t, and (2) a news article about that stock appeared in our news sample from 4pm on business day $t-1$ to 4pm on day t.[21] We refer to such days as event days. Following TSM, our main empirical specification

$$Y^i_{t,u,v} = s \times Sent^i_t + \boldsymbol{\beta}' \boldsymbol{X}^i_t + \epsilon^i_{t,u,v} \tag{1}$$

involves regressing the response variable $Y^i_{t,u,v}$ on lagged sentiment $Sent^i_t$ and lagged control variables $\boldsymbol{X}^i_t$ (which in all our pooled specifications include a constant). As in TSM we run a pooled regression, with no firm fixed effects. $Y^i_{t,u,v}$ measures either excess returns or CARs (relative to the six factor model described in Section 2) for stock i from trading day $t+u$ to $t+v$. Our main specifications involve returns either on the day following the news event ($u = v = 1$) or over the ten trading-day period following the news event ($u = 1$ and $v = 10$).[22]

Our $\boldsymbol{X}^i_t$ vector includes the following control variables: lagged CARs, firm i's 6-factor alpha estimated over trading days $[t-251, t-21]$, the most recent quarterly earnings surprise SUE, as well as the firm's log market capitalization, IHS of book to market, and log illiquidity.[23] These controls are analogous to those used by TSM.[24] In addition to these variables, we also control for short interest and institutional ownership because these will be important interaction terms in our analysis in Section 3.6. Finally, to ensure that the sentiment underreaction effect is not due to the correlation of sentiment and volatility, we include two volatility controls: $CAR^2_{0,0}$ and the level of the VIX on the event day.[25] We partition the data into three five-year subperiods starting in 1996, one four-year subperiod at the end of our sample, as well as two subperiods which were classified as NBER recessions, in light of Garcia's (2013) finding of a changing news-returns relationship over the business cycle. Table 1 shows the results of the regression in (1) over the full sample, as well as over these different subsamples of the data.[26]

[21] TSM use a 3:30pm cutoff. Our results are qualitatively similar when using a 3:30 cutoff. Even in the early parts of our sample, stock prices react to news almost instantaneously, and a half-hour cutoff is unnecessary.

[22] We always report both the raw return and the CAR results. We believe the CAR results are a more accurate reflection of the news-returns relationship and so focus our discussion on these, though the raw excess return results are usually qualitatively similar.

[23] We include four CARs as controls: $CAR_{0,0}$, $CAR_{-1,-1}$, $CAR_{-2,-2}$ and $CAR_{-30,-3}$. For $i \in \{1, 0, -1, -2\}$, $CAR_{i,i}$ is calculated using coefficient estimates from the 6-factor model over the trading days $[t-251+i, t-21+i]$. $CAR_{-30,-3}$ and $CAR_{1,10}$ use the $i = 0$ trading day window coefficient estimates. In all cases the alpha is set to zero when calculating CARs.

[24] TSM use stock turnover rather than the Amihud (2002) illiquidity measure.

[25] We discuss the volatility controls further in Section 5.4 but note that the inclusion of these has little effect on the forecasting ability of $Sent$ in our regressions.

[26] Table A6 of the Internet Appendix shows the results of the specification in (1) run with the original TSM control variables augmented with our two volatility controls. The inclusion of IO, SI and log

Over the full sample, the *Sent* coefficient for one-day ahead CAR is 0.884. From Table 2, the daily standard deviation of the sentiment measure over the full sample (pooled across all companies) is 0.021. Since returns are measured in percent this represents a positive 1.9 basis point (0.884×0.021) return for a one standard deviation positive sentiment shock. In their Table 2, TSM show that a one standard deviation increase in their negative news measure decreases one-day ahead CAR by 2.5 basis points, so our results show remarkable agreement. Turning to the subsample results, we see that the news-returns relationship was stronger in the earlier parts of the sample, with sentiment coefficients of 1.595 (1996–2000), 1.255 (2001), and 0.861 (2002–2006).[27] The predictability of returns by sentiment rises slightly during the financial crisis period of 2007–2009 to 0.963 (significant at the 10% level), then drops sharply to 0.244 in the post-crisis years 2010–2014, and returns to 0.733 (significant at the 1% level) in the most recent time period of 2015–2018.[28] The magnitude of the underreaction in the most recent time period is similar to the full-sample coefficient of 0.884.

We should briefly comment on whether our full-sample 1.9 basis points of return predictability by sentiment represents an economically important effect. TSM document that trading strategies which go long stocks with low negativity and go short stocks with high negativity earn returns above 20% per year when transaction costs are ignored. The main reasons for this large annualized return are that forecasted returns are largely idiosyncratic, and extreme sentiment news stories are relatively frequent. Heston and Sinha (2017) report annualized, zero-transaction-cost returns of over 40% (0.17% times 252 from their Table 3), and Ke, Kelly, and Xiu (2018) report frictionless long/short returns of close to 20% (their Figure 5). The economic significance of this predictability has been shown by the literature to be very large, which renders a deeper understanding of the channels of this predictability an economically important question.

Since we use the Thomson-Reuters news archive versus the Dow Jones news archive in TSM, and since only one third of our 1996–2018 time period overlaps with the 1980–2004 time frame of the analysis in TSM, our analysis represents a largely out-of-sample verification of the underreaction result originally documented in TSM. We are left, though, with several questions. First, why hasn't this effect, which has been known in the literature

illiquidity as control variables in Table 1 slightly diminishes the role of *Sent* in most subperiods.

[27] Of these, only 1.255 is not significant because it represents only the 2001 recession year, and is therefore associated with a high standard error.

[28] Our finding that single-name predictability did not sharply increase in the financial crisis contrasts with the finding in Garcia (2013) that news predictability for index returns is most pronounced during recessions. Interestingly, as shown in Table A9 in the Internet Appendix, *index*-level predicatbility is also highest in our sample during the financial crisis, consistent with Garcia's (2013) results.

since the mid-2000's disappeared? Second, what factors might be responsible for the time variation in the news-returns relationship that we have documented? We now turn to the analysis of these questions.

3.3 Time variation in the news-returns relationship

Time variation in the news-returns relationship may stem from at least three (not mutually exclusive) sources. First, it is possible that the underreaction of stock prices to news is due to investor inattention or difficulty in interpreting the information in news articles, and that such constraints vary over time. We will refer to this explanation as time-varying information processing capacity. This explanation would be consistent with the interpretation of the underreaction phenomenon favored by much of the existing literature.[29] Second, it is possible that differences over time in the stock price underreaction to news are due to time variation in the amount of institutional capital that engages in strategic trading. If institutions engage in large trades in response to and in the same direction as contemporaneous news, and if those large trades move prices, then it is optimal to execute such trades in small increments over a protracted time period. As Kyle (1985) suggested such strategic trading by informed investors will, in turn, lead to a slow incorporation of news into prices.[30] The delayed response induced by such strategic trading will show up in specification (1) as price "underreaction" to news. Finally, it is possible that the information content of news itself varies over time. We address this possibility in detail in Section 4.

The information processing explanation of underreaction posits that investors are slow to become informed. The institutional trading explanation posits that institutional investors are quickly informed but slow to trade. Time variation in the news-returns relationship allows us to differentiate between the two explanations.[31] Under the information processing explanation, periods of greater contemporaneous price responses to news should also be periods of diminished lagged responses because both effects result from investors becoming informed more quickly. The institutional trading explanation makes the opposite prediction: with greater institutional capital in the market, we should see

[29]For example, Tetlock et al. (2008), Heston and Sinha (2017) and Ke, Kelly, and Xiu (2018) all attribute (at least a portion of) the stock underreaction to news to an inability of markets to immediately react to all relevant information in the news flow.

[30]As discussed in Section 1.1, Chan and Lakonishok (1995), Keim and Madhavan (1996), and others document order splitting by institutional investors over multiple days. This practice is also consistent with the prevalence of VWAP (volume-weighted average price) execution strategies employed by large institutions.

[31]This assumes the information content of news remains constant, a point we return to in Section 4.

both a stronger contemporaneous response (as sophisticated investors trade on news) and a stronger lagged response (as large investors trade strategically). Therefore to differentiate between these two explanations, we need to compare the contemporaneous and lagged responses of prices to news. Contemporaneous and lagged responses that go in opposite directions support the information processing channel; but responses that go in the same direction support the strategic institutional trading channel.

To make this comparison, we run a contemporaneous version of the regression in (1)

$$Y_t^i = s \times Sent_t^i + \boldsymbol{\beta}' \boldsymbol{X}_t^i + \epsilon_t^i. \tag{2}$$

All variables in $\boldsymbol{X}_t$ are measured prior to day t so there is no issue with that part of the specification.[32] However, there is a potential endogeneity problem between the day t returns measure and day t news, since the former may have led to the latter (i.e. a large stock price move causes Reuters to write about the stock). To control for this possibility, we additionally run all versions of our contemporaneous regressions using sentiment measured only during non-trading hours, that is from 4pm of day $t-1$ to 9:30am on the event day t. Barclay and Hendershott (2004) show that the number of trades in after hours trading (from 4-6:30pm and then from 8-9:30am) is "less than 1/20 as many trades per unit time" as take place during trading hours. This vastly diminishes the probability that news stories are written in response to trading actvity.[33]

Table 4 shows the sentiment coefficients from our regressions in (1) and (2). The $CAR_{1,1}$ and $CAR_{1,10}$ rows summarize, respectively, the one-day ahead sentiment coefficients from Table 1 and the ten-day ahead sentiment coefficients from Table A7 of the Internet Appendix. The early sample CAR predictability was quite high, then dipped during the period immediately following the financial crisis of 2008–2009, and is currently close to its full-sample average.

The $CAR_{0,0}$ rows of Table 4 (one corresponding to 4pm–4pm day t sentiment, and the other to 4pm–9:30am day t sentiment) show the results of the contemporaneous specification in (2). First, we note that contemporaneous reactions of prices to news are much higher than the reaction of prices to lagged news, as has been documented in the prior

[32] In (2) we drop $\text{CAR}_{0,0}$ as an explanatory variable. This is the same timing as the $FFCAR_{+0,+0}$ specification in Table VI of TSM.

[33] It is, of course, possible that a news event occurred after market close, for example an earnings release, which caused both the stock price to move after hours, as well as a news story to be written. In this case the sentiment of the news story proxies for the information content of the news event, and the relationship we are testing — namely the responsiveness of stock prices to relevant events — is well identified.

literature (TSM, Heston and Sinha 2017 and Ke, Kelly, and Xiu 2018). Furthermore, the qualitiative pattern in the 4pm–9:30am sentiment regressions is similar to that in the 4pm–4pm sentiment regressions, and we focus our discussion on the former to avoid endogeneity issues. Finally, the contemporaneous news-returns relationship also exhibits substantial time variation.

The results in Table 4 do not allow us to definitively conclude in favor of either the information processing or the stategic institutional trading hypothesis to the exclusion of the other.[34] The move from 1996–2000 to the 2001 time period is associated with a higher contemporaneous price–news sensitivity, but a lower reaction to lagged news. This is consistent with an information processing effect. The transition from 2001 to 2002–2006 sees an unchanged contemporaneous but lower lagged effect, consistent with a combination of the informational and institutional explanations. The coefficients move in opposite directions as we go from 2002–2006 to 2007–2009, consistent with an information processing explanation. Moving to 2010–2014 is associated with a lower contemporaneous and a lower lagged news effect, consistent with variation in institutional trading intensity. And finally the move from 2010–2014 to 2015–2018 is associated with an increase in both the contemporaneous and the lagged effects, consistent with an increase in institutional trading. These results do not rule out the possibility that both mechanisms play a role in the time varying response, but they do indicate that greater information processing of news articles cannot by itself explain the observed changes in the news-returns relationship.

3.4 Intermediary capital

In recent years, the asset pricing literature has started to explore the role of financial intermediaries in the price setting process in financial market. Financial intermediaries, in their role as broker/dealers, are active market participants and commentators. Furthermore, the financial intermediation sector provides financing that allows other investors, such as hedge funds and family offices, to engage in risk taking in financial markets. Since financial intermediaries are themselves informed traders, and also since they facilitate market participation by other informed traders, we may expect that the risk-bearing capacity of the financial intermediation sector is a good proxy for the presence of large, informed investors in financial markets. We expect that interacting sentiment with measures of the risk-bearing capacity of the financial intermediation sector will therefore yield important insights into the information processing versus institutional-trading channels

[34]We ignore statistical significance for the time being, but will return to it in Sections 3.4 and 3.5.

of news effects on contemporaneous and future returns.

Two measures of this risk-bearing capacity have been proposed in the literature. Adrian, Etula, and Muir (2014) look at the book leverage of all broker-dealers

$$Leverage_t^{BD} = \frac{Total\ Financial\ Assets_t^{BD}}{Total\ Financial\ Assets_t^{BD} - TotalLiabilities_t^{BD}},$$

which is broker-dealer assets divided by the book equity of the sector. When it is high, $Leverage_t^{BD}$ suggests that broker-dealers are able to take large risk positions relative to their book equity, and thus have high risk-bearing capacity. While it is typically procyclical, this series behaved in an extremely countercyclical way during the financial crisis, when book equity of the broker-dealer sector fell precipitously due to asset write-downs. As Figure 1 shows, $Leverage_t^{BD}$ spiked during the financial crisis, not because of an increase in the asset side of the balance sheet, but because of a large drop in book equity. This was, indeed, a time of very low risk-bearing capacity for the financial intermediation sector.

He, Kelly and Manela (2017) propose an alternative measure of the risk-bearing capacity of the broker-dealer sector, which is less susceptible to the balance-sheet equity issues of the the Adrian et al. (2014) measure. Their capital ratio measure is defined as

$$CR_t = \frac{\sum_i MarketEquity_{i,t}}{\sum_i (MarketEquity_{i,t} + BookDebt_{i,t})},$$

where the sum is taken over all New York Fed primary dealers as of time t, and $MarketEquity_{i,t}$ is the market capitalization of the i^{th} primary dealer. Since market capitalization is the risk-adjusted present value of a broker-dealer's future income, this ratio is high relative to book debt at times that the market thinks either the broker-dealer has a low cost of capital, or high future earnings, or both. Since a broker-dealer cost of capital and earnings capacity are both directly tied to its risk-bearing capacity, CR_t is a real time measure of this quantity for the financial intermediation sector. Furthermore, because market capitalizations fall in times of crises, the CR_t variable has the procyclical behavior that one would expect, as can be seen from Figure 1. For these reasons, our preferred measure is CR_t, though we report the results using $Leverage_t^{BD}$ for completeness.

To understand the role of intermediary capacity, we run the following specification:

$$Y_{t,u,v}^i = s_0 \times Sent_t^i + s_1 \times Capacity_t + s_2 \times Sent_t^i \times Capacity_t + \boldsymbol{\beta'} \boldsymbol{X}_t^i + \epsilon_{t,u,v}^i, \qquad (3)$$

where $Capacity_t$ is the most recently available level of either $Leverage_t^{BD}$ or CR_t as of event day t.[35] While Adrian et al. (2014) and He et al. (2017) use percent changes in their variables, we use these in levels because the level, and not the change in, intermediary capacity determines risk-bearing capacity of the intermediary sector, as well as that of its institutional clients.[36] Table 5 shows the results of this specification. The first three columns use CR_t measured at either the daily, monthly or quarterly frequency (though our preferred specification is the within month or quarter average because the effects of capital ratio levels do not manifest themselves as quickly as changes in the market equity of dealers) and the last column uses $Leverage_t^{BD}$ measured quarterly.[37]

Looking at the middle two columns of the bottom panel of the table, we see that higher CR_t levels are associated with much larger reactions of prices to contemporaneous news (we focus here on the 4pm–9:30am news measure). A 10% increase in CR_t (roughly the range of the series) is associated with a 50% increase in the contemporaneous price–news reaction (0.305×10 for the monthly specification against $s_0 = 5.981$).

Crucially, this 10% increase is also associated with a large increase in the $CAR_{1,1}$ and $CAR_{1,10}$ sensitivities to lagged news. For example, moving from a 3% monthly CR_t level (the sample minimum) to 13% (the sample maximum), the $CAR_{1,10}$ sensitivity to time t sentiment increases by $10 \times 0.898 = 8.98\%$! This is the same order of magnitude as the contemporaneous stock price reaction to news. The low-to-high difference in the $CAR_{1,1}$–sentiment coefficient is $0.206 \times 10 = 2.06\%$. Indeed this amount of variation is enough to capture the entire sample range of both the $CAR_{1,1}$ and $CAR_{1,10}$ sentiment coefficients in Table 4.[38]

The results of the intermediary capacity interaction regression in (3) support the institutional trading hypothesis over the information processing hypothesis because the $Sent \times Capacity$ interaction for lagged sentiment is strongly positive. More informed investors, as proxied for by our intermediary capacity measure, are associated with *higher* underreaction! As explained in Section 3.3, if the information content of news is held constant, higher price responses to contemporaneous *and* lagged news can be explained

[35] We demean the pooled $Capacity_t$ variable to preserve the magnitude of the s_0 coefficient.

[36] Frank and Sanati (2018) use the quarterly growth rate of the capital ratio.

[37] $Leverage_t^{BD}$, because it uses accounting data, is only available at a quarterly frequency.

[38] If it were known with certainty that news would be fully reflected in prices within a fixed time window, then greater underreaction over the first few days would be offset by lesser underreaction later on. But the stock market does not operate on a deadline in impounding information; a decrease in intermediary capital could prolong the time it takes for prices to reflect news and produce a smaller underreaction over any given n-day period at all reasonable horizons. Moreover, news may become stale before being fully absorbed, with new information superseding prior news. The flow of information makes it impractical to measure the response to a single day of news over longer horizons to meaningfully determine how long underreaction persists. For these reasons, we focus on contemporaneous, 1-, and 10-day responses.

by informed intermediaries who quickly respond to the information content of news, and then (in some cases) trade strategically in response to that news in order to minimize their price impact. If the lagged underreaction was driven by constraints on investors' information processing of news, and if greater intermediary capacity relaxed those constraints, we would expect a negative $Sent \times Capacity$ interaction for lagged sentiment. To explain a positive interaction, the information processing hypothesis would need to explain why greater intermediary capacity is associated with investors having greater difficulty interpreting news.

3.5 Mutual fund ownership

We can gain further insights into the information processing versus institutional-trading hypotheses by directly analyzing the effects of informed investors in the market. Many authors argue that active mutual funds represent one class of informed investors, whose presence improves the market's informational efficiency. Wermers (2019) provides a recent overview of the voluminous literature in this area. From our point of view, mutual fund ownership provides rich time-series (as shown in Figure 2) and cross-sectional variation in the investor pool of each S&P 500 stock in our sample, as the mix of active and passive ownership varies across stocks and across time. Active funds trade on information whereas passive funds do not.

For each stock, we employ three quarterly measures of the ownership mix:[39]

- $Passive/Market$ – the fraction of shares outstanding of a given stock that are held by passively managed mutual funds;
- $Active/Market$ – the fraction of outstanding shares held by actively managed funds;
- and $Passive/FundTotal$ – the fraction of mutual fund ownership for a given stock that is passively managed.

Table 6 shows results of estimating the following modification of equation (1),

$$Y^i_{t,u,v} = s_0 \times Sent^i_t + s_1 \times Ownership^i_t + s_2 \times Sent^i_t \times Ownership^i_t + \boldsymbol{\beta}' \boldsymbol{X}^i_t + \epsilon^i_{t,u,v}, \quad (4)$$

where $Ownership^i_t$ is one of the three quarterly measures of the degree of passive and active ownership for stock i just described.[40] The top panel of the table shows results for the raw returns, and the bottom panel shows the results for CARs.

[39] These mutual fund classification are discussed in further detail in Section 2.

[40] We demean the pooled $Ownership^i_t$ variable to preserve the magnitude of the s_0 coefficient.

The middle column of the table shows the results for the $Active/Market$ variable. Stocks whose shares outstanding are more heavily owned by active mutual funds tend to experience higher contemporaneous reactions to news, as indicated by the 0.174 (significant at the 1% level) interaction coefficient for 4pm–9:30am sentiment. However, higher active owership of a stock marginally increases the degree of the underreaction to news one day ahead,[41] and meaningfully increases the degree of underreaction to news ten days ahead with a coefficient of 0.175 (significant at the 1% level).

The third column in the table shows that a higher $Passive/FundTotal$ ratio decreases the contemporaneous stock price response to news with a $Sent \times Ownership$ coefficient of -0.033 (5% level). At the same time, a higher passive share of mutual fund ownership also decreases the price response to lagged news with a -0.017 (10% level) coefficient for one-day responses and a coefficient of -0.106 (1% level) for ten-day responses. The size of the effect is large. When a stock's passive share goes from 40% to 60%, its $CAR_{0,0}$ response to contemporaneous news falls to zero while its $CAR_{1,1}$ response to lagged news is cut by 40% (the 0.88 coefficient is decreased by 0.017×20).[42]

These results are inconsistent with the idea that the effect of lagged news on returns operates through an information processing channel, as we now explain. Increasing $Active/Market$ for a given stock indicates a greater presence of large and potentially informed investors who actively trade that stock. Similarly, a higher $Passive/FundTotal$ ratio means that a larger fraction of the mutual funds that own a given stock follow passive strategies and do not actively trade in response to stock-specific news. Under the information processing hypothesis, a higher $Active/Market$ share would predict a stronger contemporaneous response to news as more active funds quickly react to the information content of a news event. Furthermore, under this hypothesis, the quick and appropriate response of active funds to news suggests that there should be less price response to lagged news, i.e. *less* underreaction. However, we do not see this in the data. Similarly, under the information processing hypothesis, a larger $Passive/FundTotal$ should be associated with a lower contemporaneous price response (which is the case), but with *more* underreaction via a higher response to lagged news in the future (which is not the case).[43]

[41] The sentiment-ownership interaction for one-day ahead CARs and $Active/Market$ is 0.031, as can be seen from the bottom panel of Table 6. The p-value of this coefficient is 0.14.

[42] The coefficients on $Pasive/Market$ are less strong though they are closer to the effects of $Passive/FundTotal$. This is because $Passive/Market$ is positively correlated with both $Active/Market$ and with $Passive/FundTotal$ (see Figure A1 in the Internet Appendix) and these two effects offset. The 2011 spike in the correlation series is discussed in Section A5 of the Internet Appendix.

[43] Although it is possible that an increase in $Passive/FundTotal$ would attract more informed trading by non-fund investors, the lower contemporaneous response we observe does not support this scenario.

On the other hand, under the institutional-trading hypothesis, we would expect higher $Active/Market$ to be associated with a stronger contemporaneous stock price reaction, but also with a more pronounced stock price reaction to lagged news as strategic trading by institutions in response to past news events causes the ultimate price impact from those news events to enter prices only slowly. Similarly, under the institutional-trading hypothesis, a higher $Passive/FundTotal$ should be associated with lower price responses to contemporaneous news (which is the case) as well as a smaller response to lagged news (also true in the data) as there is less strategic trading following news.[44]

We should note that the view that mutual funds improve market efficiency is not universally held, and some authors, for example Akbas et al. (2015) and Edelen, Ince, and Kadlec (2016), argue that mutual funds actually exacerbate anomaly mispricing. To the extent that mutual funds are not informed investors, our results on the institutional-trading transmission channel for news still hold since we do not require strategic trading by mutual funds to be informationally motivated. We only need for it to go in the same direction as contemporaneous news sentiment.

3.6 Controlling for institutional trading motives

If institutional trading is indeed a key determinant of the stock price underreaction to news, then we should be able to decompose the s coefficient in specification (1) into a component due to institutional trading and whatever is left over. This left-over component of s would then presumably measure the pure informational effect of news on future returns. To do this decomposition we need to identify stocks for which institutional trading motives in response to news are particularly strong. The literature has documented that retail investors are less likely to engage in short-selling relative to institutional investors.[45] Thus heavily shorted stocks may indicate situations with many large institutions who actively monitor the stocks, and may want to adjust their positions in response to news. Furthermore, heavily institutionally-owned stocks are also clearly characterized by the presence of large investors, who in turn may be motivated to trade in response to news.

To study the impact of short interest, for stock i on event day t, we interact sentiment

[44] Keim and Madhavan (1995) find that when index funds trade, they execute a substantially higher fraction of their trades within one day than other institutional investors (see their Table 4) thus engaging in less strategic trading. Therefore, even if the direction of index fund trades sometimes coincides with news-based trades, we expect to see less of an apparent underreaction when passive funds make up a larger share of the market.

[45] Barber and Odean (2008) document that only 0.29% of all trading positions for their group of retail traders represent short sales.

with indicator variables for (1) whether that stock is heavily or lightly shorted, and (2) whether that stock's day t sentiment is positive or negative. The SI-sentiment indicator variables take the following values:

Variable	=1	=0
$\mathbf{1}_{SI=H}^{Sent=H}$	$Sent > \bar{S}$ and short-interest in top third	otherwise
$\mathbf{1}_{SI=L}^{Sent=H}$	$Sent > \bar{S}$ and short-interest in bottom third	otherwise
$\mathbf{1}_{SI=H}^{Sent=L}$	$Sent \leq \bar{S}$ and short-interest in top third	otherwise
$\mathbf{1}_{SI=L}^{Sent=L}$	$Sent \leq \bar{S}$ and short-interest in bottom third	otherwise

where $\bar{S}$ is the daily median sentiment. The indicator variables for institutional ownership are similarly defined, except in the second step we sort by institutional ownership instead of short interest. We calculate the terciles of the SI and IO variables for each trading day using the set of stocks experiencing a news event on that day. Therefore, these percentiles change over time. Restricting this calculation to the set of stocks experiencing news events controls for any correlation between SI or IO and the likelihood of having a news event.

We then run the following modified version of the specification in (1):

$$\begin{aligned} Y_{t,u,v}^{i} = s_0 \times Sent_t^i &+ \\ &+ s_{SI=H}^{Sent=H} \times \mathbf{1}_{SI=H}^{Sent=H} \times Sent_t^i \\ &\vdots \\ &+ s_{IO=L}^{Sent=L} \times \mathbf{1}_{SI=L}^{Sent=L} \times Sent_t^i \\ &+ \boldsymbol{\beta}' \boldsymbol{X}_t^i + \epsilon_{t,u,v}^i, \end{aligned} \tag{5}$$

where each of the eight (four SI and four IO) interaction terms is included in the specification.[46] This specification allows us to decompose the unconditional sentiment coefficients in Table 4 into a base component s_0 which applies to all news-day observations, and into incremental components having to do with the interaction of institutional positioning and sentiment tone.

Table 7 shows the full-sample results of the regression in (5) for 1- and 10-day ahead abnormal returns.[47] We focus our discussion on the 10-day ahead horizon because ultimately our interpretation will be that much of the underreaction of returns to lagged

[46]We interpret the specification in (5) as a decomposition of the $Sent_t^i$ variable into a part conditional on institutional positioning and an unconditional part. For this reason we do not include the indicator variables are standalone regressors.

[47]As Tables A10 and A11 of the Internet Appendix show, there is substantical time variation in some of the coefficient estimates in (5).

news sentiment is due to strategic trading by institutions, and this trading frequently takes place over multiple days, rather than over a single day following the news release, as discussed in Section 1.1.[48] When they are significant, the interaction effects in Table 7 are positive, suggesting that in certain sentiment bins increased institutional focus – measured either through SI or IO – leads to more underreaction.[49]

The largest interaction effect by magnitude in Table 7 is 4.326 (p-value of 0.056) for the high-SI, positive news sentiment coefficient, $s_{SI=H}^{Sent=H}$. This means that stocks that are in the top third by short-interest on the event day, and that experience positive news, exhibit the *largest* degree of underreaction over the ensuing ten trading days. Such stocks experience a 5.5 basis point positive abnormal return for a one standard deviation positive sentiment shock (i.e., $[4.326\% - 1.684\%] \times 0.021$) in the ensuing ten days. This is almost three times larger than the 1.9 basis point unconditional one-day CAR underreaction to news sentiment that we documented earlier. As we argued in Section 3.2 this represents a large economic effect when aggregated into long/short portfolios.

Why might this happen? It is unlikely that this ten-day underreaction of heavily shorted stocks to good news is due to an inability of market participants to notice all relevant news flow.[50] It is much more likely that large institutional short-sellers, when confronted with positive news about the stock that they shorted, engage in short covering.[51] But they do not cover their entire short position in a single day of trading. Rather they may space out their trading over the ensuing ten days to minimize the price impact of their trades. This then results in a pronounced "underreaction" of such heavily shorted stocks in respone to good news.[52]

The flip side of short-covering is adding to a short position that is "working." The Wall Street adage of "ride your winners" is related to the momentum effect first document by Jegadeesh and Titman (1993) and also forms the basis for trend following strategies employed by many practitioners. Therefore if a heavily shorted stock experiences bad news, we may expect informed investors to strategically add to their shorts – thus resulting

[48] The three significant interactions in the $CAR_{1,10}$ specification are all positive, and all remain so for the $CAR_{1,1}$ specification. Two of the three remain significant.

[49] Using a novel measure of institutional investor attention, Ben-Rephael et al. (2017) find that an increase in attention (measured as a within firm shock) reduces the underreaction to news. They measure stock-specific changes in attention rather than differences in the levels of ownership, so their results are not directly comparable to ours

[50] Indeed, Engelberg, Reed, and Ringgenberg (2012) find evidence that short sellers trade on public news and are skilled processors of the information in public news.

[51] This might happen when short-sellers use stop-loss rules. See, for example, Kaminski and Lo (2014).

[52] This positive drift is consistent with recent evidence in Boehmer, Duong and Huszár (2018) on the long-term price effects of short-covering in Japanese markets.

in continuing downward pressure on heavily shorted stocks experiencing bad news. This is exactly what we see in Table 7. The interaction effect for $Sent \times 1_{SI=H}^{Sent=L}$ is large at 3.017 and statistically significant at the 1% level.[53]

Thus heavily shorted stocks are associated with pronounced "underreaction" to both good and bad news even though these stocks are closely followed by well-informed institutional short-sellers who are unlikely to be affected by informational capacity constraints.

Lakonishok et al. (1991) famously showed that pension fund managers in the US engage in window dressing by selling past extreme-losers more aggressively than other groups (except past extreme-winners). Window dressing may explain the interaction effect we observe for stocks that are heavily institutionally owned and that have experienced bad news. The incremental sentiment effect for such stocks, $s_{IO=H}^{Sent=L}$, is 3.760 (1% level) higher than the unconditional sentiment loading of ten-day ahead returns. Stocks that are heavily owned by institutions and experience a bad news day have excessively negative abnormal returns.

Again, it is hard to believe that the "underreaction" of heavily institutionally owned stocks to bad news is caused by investors' bounded information capacity, since institutions are likely to closely follow stocks that they own and react quickly to news flow about these stocks. A likelier explanation is that large institutional owners, because of window dressing motives, don't like to own stocks that experience negative news. When heavily institutionally owned stocks experience a negative news event, these institutions slowly trade out of the stocks over the ensuing several days in order to minimize the price impact of their trading. This behavior manifests itself in the data as a pronounced ten-day stock price underreaction to news. Interestingly, Huang, Tan, and Wermers (2019) use high-frequency institutional trading data from 2000-2010 to show that exactly this type of behavior takes place. Large institutional investors sell bad-news stocks relative to good-news stocks on the news event day *and* over the subsequent seven days. Such institutional behavior may result in exactly the interaction effect that we document in Table 7.

Aside from heavily shorted stocks' responses to (good or bad) news and heavily institutionally owned stocks' responses to bad news, the five other interaction effects in Table

[53] A competing explanation for this finding would be a disposition-effect-like tendency to cover short positions that are working (see Frazzini 2006 for a discussion of this phenomenon in a long-only context). In this case, we need to assume that news are fully seen and properly interpreted by all market participants, and then short-sellers irrationally cover their winning positions resulting in temporary price pressure, and not allowing stocks to reach their new low equilibrium prices instantaneously. However this logic implies that heavily shorted stocks with good news should experience no underreaction as news is absorbed into prices immediately while short-sellers hang on to their losing positions hoping they will one day recover. But this is not what we see, and therefore the disposition effect is unlikely to apply here.

7 are all insignificant. Except $s_{SI=L}^{Sent=H}$,[54] their magnitudes are all less than $|s_0|$ implying that after the three important positioning-sentiment interactions have been removed, the net responses of ten-day stock returns in all other cases – conditional (s_0 plus an inteaction term) or unconditional (just s_0) – are negative.[55] Thus, the "typical" stock *overreacts* to news as measured by its abnormal returns over the subsequent ten trading days.

The s_0 coefficient in (5) of -1.684 is significant at the 5% level. This implies that for every standard deviation of event-day sentiment, ten-day abnormal returns move 3.5 basis points ($-1.684\% \times 0.021$) in the *opposite* direction of the news event. The 0.722 (insignificant) unconditional $CAR_{1,10}$ sentiment coefficient in Table 4 thus masks two effects. Stocks strongly underreact to news over the ensuing ten-days when that news triggers institutional trading flows in the same direction as the news event itself. In the absence of such institutional trading effects, stocks strongly overreact to news. This fundamentally changes our understanding of the mechanism underlying the news-returns relationship, a point we discuss in greater detail in Section 5.2.

4 The informativeness of news

To understand time variation in the stock market's response to news, we need to investigate potential changes in the informativeness of news articles over time. In particular, if news articles have simply become less informative over time, we would expect to see a diminished market response to news sentiment. We find evidence that the informativeness of news does vary over time, but this variation cannot by itself explain the changes we observe in the relationship between sentiment and returns. We will show that time variation in the informativeness of news provides further support for the importance of the microstructure effects discussed in Section 3. We quantify informativeness through the ability of news to forecast earnings and through an entropy measure from the natural language processing literature.

[54]The positive, though insignificant, interaction effect for non-heavily-shorted stocks that experience good news may be explained by the findings in Beneish, Lee, and Nichols (2015) that low SI stocks are often "special" and hard to borrow, and Nagel's (2005) finding that short selling is difficult for stock with low institutional ownership.

[55]The s_0 coefficients for one-day returns in Table 7 are positive, though not statistically significant and very close to zero. The one-day post-news time horizon is not long enough for the strategic trading effects to manifest themselves.

4.1 Earnings predictability

As in TSM, in measuring earnings predictability we use two measures of earnings as dependent variables: standardized unexpected earnings (SUE) and standardized analysts' forecast errors (SAFE); see Section 2.2 for precise definitions of these variables.

Figure 5 plots the quarterly cross-sectional standard deviations of SUE and SAFE over time. The figure shows considerable time variation in these measures, indicating time variation in the baseline predictability of earnings. The standard deviation of earnings surprises peaks around the time of the financial crisis.[56]

Our earnings regressions take the form

$$SUE^i_{t+1} \text{ or } SAFE^i_{t+1} = s_0 \times Sent^i_t + \boldsymbol{\beta}'\boldsymbol{X}^i_t + \epsilon^i_t, \tag{6}$$

using quarterly data. The sentiment measure $Sent^i_t$ is stock i's average sentiment in the month preceding the announcement date of the quarter $t+1$ earnings, as described in Section 2.1. We use the same controls $\boldsymbol{X}^i_t$ in both regressions, except that we include lagged SUE (but not lagged SAFE) in the SUE regression, and we include lagged SAFE (but not lagged SUE) in the SAFE regression. The controls are the most recently available observations in the month prior to the announcement date of the quarter $t+1$ earnings. The other controls and their summary statistics are shown in Table 3. We winsorize SUE and SAFE at 5%.

Table 8 summarize the results of this analysis.[57] The table reports the $Sent^i_t$ coefficient s_0 for the SUE and SAFE regressions for the same time periods we used in our return regressions. First, the results confirm that for the full time period and in most subperiods, sentiment is a significant predictor of earnings, and the fact that SAFE is forecastable by lagged sentiment indicates that analysts do not fully incorporate the information in news sentiment in forecasting earnings.[58] The informativeness of news, as measured by the

[56]The spike in both series in 1Q2018 is due to the very low number of observations we have for that quarter. The spike in the cross-sectional standard deviation of SUE in 4Q2017 is due to the recognition of large, one-time gains (losses) on deferred tax liabilities (assets) as a result of the Tax Cut and Jobs Act of 2017. For example, in their 2017 Annual Report, the CME Group said that "2017 net income included a $2.6 billion net income tax benefit due to recognition of a reduction in deferred tax liabilities as a result of the Tax Cut and Jobs Act of 2017." This gain was recognized in their 4Q2017 earnings. In 4Q2017, the standard deviation of $SAFE$ shows no commensurate increase as analyst expectations already incorporated these effects. Excluding 4Q2017 and 1Q2018 from our sample does not meaningfully affect our results in Table 8 (discussed below), as Table A12 in the Internet Appendix shows. Also, the results in Figures 6, 7, and 8 (discussed in Sections 4.2 and 4.3) are not impacted by the exclusion of these quarters.

[57]Table A13 of the Internet Appendix shows the full regression results.

[58]Prior work has found evidence for both underreaction and overreaction to news by analysts; see

magnitudes and significance of the coefficients in Table 8, has varied over time, but the results do not suggest a systematic decline in informativeness. The coefficient for SUE in 2010–2014 is close to the coefficient for the full period 1996–2018, and the coefficient for SAFE in 2015–2018 is identical to the coefficient in 1996–2000.

4.2 Entropy

To shed light on the time variation in the Sent-SUE and Sent-SAFE relationships in Table 8, we investigate how the sentiment coefficients covary with properties of the news flow. To trace these relationships consistently over time, we estimate annual coefficients s_0 in (6) and compare them with various annual measures calculated from news articles.

In each plot of Figure 6, the dashed line shows the annual sentiment coefficient for SUE, and the dotted line shows the annual sentiment coefficient for SAFE. The solid line in each plot shows a feature of the news articles; each plot also reports the correlation between the news feature and the sentiment coefficients for SUE and SAFE.

The first six plots in Figure 6 show the number of articles per day, the number of RICs (companies) per article, the percentage of articles that mention more than seven RICs, the article length (in number of words), the daily average sentiment, and the daily standard deviation of article sentiment. None of these features exhibits meaningful association with the SUE and SAFE sentiment coefficients.

The last plot shows our entropy-based measure, which quantifies the "unusualness" of an article relative to an earlier training corpus of text. As in Calomiris and Mamaysky (2019) and Glasserman and Mamaysky (2019b), we evaluate the unusualness of an article relative to an earlier training corpus through the frequencies of 4-grams, which are simply consecutive strings of four words (or, more generally, tokens). We measure the cross-entropy (or entropy, for short) of an article as

$$-\sum_{i \in \text{4-grams}} \hat{p}_i \log \hat{q}_i,$$

where $\hat{p}_i$ is the empirical frequency of a 4-gram in the article, and $\hat{q}_i$ is the estimated conditional probability of the 4-gram in the training corpus.[59] This entropy measure is

Abarbanell and Bernard (1992) and Easterwood and Nutt (1999).

[59]More precisely, $\hat{q}_i$ is the estimated conditional probability of the fourth word in the 4-gram given the first three words defined as $(\hat{c}(w_1w_2w_3w_4)+1)/(\hat{c}(w_1w_2w_3)+10)$ where $\hat{c}$ counts the occurence of a given phrase, e.g. $w_1w_2w_3w_4$, in the training corpus. The 1 and the 10 adjust for the possibility of encountering a previously unseen 4-gram. We use 4-grams to strike a balance between shorter strings (which carry less information) and longer strings (which are observed less frequently). See Jurafsky and Martin (2008)

large when 4-grams appearing in the new text are rare in the training corpus — that is, when the new text is unusual relative to the training corpus. Table A14 in the Internet Appendix shows the headlines of sample articles from our corpus, sorted by entropy.[60]

Glasserman and Mamaysky (2019b) have found that interacting news sentiment with entropy increases the ability of sentiment to forecast returns and volatility.[61] News is more informative when it is more unusual, relative to previously seen articles. But these earlier references did not investigate the relationship between entropy and earnings. The last plot of Figure 6 shows the average article entropy within each year of the sample.[62] These plots show an interesting relationship that is consistent with our previous interpretation of the informativeness of sentiment: the sentiment coefficients in the SUE and SAFE regressions covary with average entropy. In other words, the sentiment signal in news is more predictive of earnings (as measured by the regression coefficients) when the news is more informative (as measured by entropy).

4.3 Entropy and the news-returns relationship

We now build on the link between earnings predictability and entropy documented in the last plot of Figure 6 to revisit the relationship between returns (specifically, $CAR_{1,1}$ and $CAR_{1,10}$) and sentiment. This analysis provides further evidence for the microstructure effects introduced in Section 3.

Figure 7 plots sentiment coefficients (solid lines) for various rolling regressions, together with the scaled annual entropy series (dash-dot lines). In the leftmost plots, the independent variables are SUE and SAFE. In the center plots, the independent variables are $CAR_{1,1}$ and $CAR_{1,10}$, and the solid lines show the annual $Sent$ coefficients from the regressions in (1), as in Table 4. In the rightmost plots, the independent variables are again

for background on n-grams and cross-entropy. For the training corpus, we use a rolling window of 24 months, lagged by three months from the month in which an article appears. The justification for this and further details are in Glasserman and Mamaysky (2019b).

[60]For example, in June of 2005, the lowest entropy article that satisfied our filter criteria had an entropy of 0.08 and the headline "AMEX Nabors Industries Ltd (us;NBR) MOC Buy Imbalance: 193,000 shrs. ⟨NBR.A⟩." In that month the highest entropy article had an entropy of 3.20 and the headline "FACTBOX-European aluminium smelters face energy threat."

[61]Calomiris and Mamaysky (2019) find that uninteracted entropy forecasts country-level returns and drawdowns.

[62]Average entropy is calculated within a year for articles with ≤ 7 RICs and ≥ 25 words. Furthermore we drop all articles containing the string "RESEARCH ALERT-" in their headline (using case insensitive match). Such articles are brief summaries of Wall Street produced research pieces, and typically have very low entropies. The number of such articles carried by Reuters spiked in the 2010–2015 period, as shown in Figure A2 in the Internet Appendix, which causes a sharp drop in our aggregate entropy series in this time period if these articles are not excluded.

$CAR_{1,1}$ and $CAR_{1,10}$, but the solid lines now show the annual Sent coefficients from the regressions in (5), which include the interactions with institutional ownership and short interest (as in Table 7). Figure 8 shows the same information but with the sentiment coefficients and entropy levels graphed in scatter plots rather than as time series.[63]

The two center plots in each figure show a positive association between entropy and the strength of the relationship between sentiment and returns; in particular, we see a positive association in the $CAR_{1,10}$ plots in the bottom center of Figures 7 and 8. One might explain this pattern as underreaction, arguing that when news is more informative the impact of the information overlooked by investors is greater. Indeed, TSM find that news that is more relevant to fundamentals (in the sense that it mentions earnings) results in a greater market response after the day the news appears.

Our analysis suggests a different explanation: when news is more informative, institutions engage in greater portfolio rebalancing through strategic trading, and this shows up as the appearance of a large stock price "underreaction." Both explanations are consistent with the observation that the sentiment coefficient in the $CAR_{1,10}$ regression (1) tends to be larger (and positive) when the entropy measure is greater. But when we control for the microstructure effects in the $CAR_{1,10}$ regression (5) the effect disappears: in the bottom right plots of Figures 7 and 8, we see that the sentiment coefficient now becomes negative, on average, indicating an overreaction to news, and the correlation between the sentiment coefficient and the entropy measure largely disappears. Once we control for the interaction effects with institutional ownership and short interest, we do not find evidence of an underreaction to news. Nor do we find evidence that the overreaction to news has any correlation with news informativeness. This finding supports our explanation of the apparent underreaction to news and is difficult to reconcile with an explanation based solely on investor information processing capacity.

4.4 Interaction of investor interest and news infomativeness

We have seen from the SUE and SAFE regressions in Table 8 and the entropy measures in Figure 6 that the informativeness of news varies over time. A complete investigation of the factors leading to time varying informativeness is beyond the scope of this article, but it is interesting to consider how intermediary capital and informativeness interact with each other, given the importance we have attached to institutional trading.

The monthly capital ratio measure of He et al. (2017), discussed in Section 3.4, and

[63]Figure 8 also shows slopes and R^2s from regressing the annual sentiment coefficients on entropy.

the monthly entropy measure of Section 4.2 have a correlation of 0.37. The correlation between overlapping annualized versions of these measures is 0.50. This association between news informativeness and intermediary capital is intriguing: does more news attract more investment or the other way around? The direction of causality (if there is causality) is unclear. The Grossman and Stiglitz (1980) paradigm suggests higher signal precision (proxied by more informative news articles) leads to an increase in informed investors (proxied by greater institutional capital). At the same time, studies have found evidence that the news media caters to clienteles (as in Gentzkow and Shapiro 2010 and Golez and Karapandza 2018). If news providers devote more resources to reporting financial news (making their articles more informative) during periods of greater demand for news by institutional investors, that could also produce the positive correlation we observe.

News informativeness and institutional capital may both be influenced by time variation in the mix of common risk factors and idiosyncratic risk in market returns. Glasserman and Mamaysky (2019b) find that stock-specific news is impounded in prices more quickly than aggregate market news, and it is possibile that journalists add more value in reporting stock-specific news than aggregate news. As the mix of systematic and idiosyncratic risk varies over the business cycle, we might therefore expect to see changes in news informativeness together with changes in intermediary capital over the cycle. An investigation of these possibilities would require a separate analysis; but a role for the business cycle in driving news informativeness is suggested by Garcia (2013) and our discussion in Sections 3.2 and 5.2.

5 Interpretation of results

In this section we discuss: (i) whether the news-returns relationship is symmetric with regard to good versus bad news; (ii) how to interpret our finding that stocks overreact to news sentiment after controlling for IO- and SI-news interactions; (iii) whether our results are driven by news around earnings announcements dates; and (iv) the role that volatility plays in our forecasting regressions.

5.1 Is stock underreaction symmetric?

We decompose sentiment into its cross-sectional mean on each event day t, as well as positive and negative deviations of stock i's sentiment from the cross-sectional mean, as follows,

$$Sent_t^i = \overline{Sent}_t + (Sent_t^i - \overline{Sent}_t)^+ + (Sent_t^i - \overline{Sent}_t)^-, \tag{7}$$

where $(x)^+ \equiv \mathbf{1}[x > 0] \times x$ and $(x)^- \equiv \mathbf{1}[x < 0] \times x$. We then drop $Sent_t^i$ from the specifications in (1) and (2), and replace it with the three terms in the above decomposition. This specification nests the ones in (1) and (2) by allowing for the different components of sentiment to have different impacts on returns. Table 9 shows the results from this modified regression. We see that contemporaneous abnormal returns $CAR_{0,0}$ load positively on all three components of $Sent_t^i$ in (7); all loadings are economically and statistically large. The largest loading though is on news sentiment that deviates positively from the cross-sectional mean. The results are similar for the 4pm-4pm and the 4pm-9:30am sentiment measures.[64]

Interestingly, the one-day ahead abnormal return $CAR_{1,1}$ loading on sentiment remains higher for positive idiosyncratic sentiment than for negative idiosyncratic sentiment. Thus stocks react more to positive news on the event day, but also *underreact* more to positive news, at least over the short-term. This finding is similar to TSM's Figure 3, an event study, which shows a larger abnormal return response to contemporaneous and lagged good news relative to bad news. Keim and Madhavan (1995) find that buy orders tend to be spread over more days than sell orders for institutional traders. Our strategic trading explanation for the underreaction to news is thus consistent with the asymmetry we observe in the lagged response to positive and negative news, although it does not explain the asymmetric contemporaneous response.[65]

5.2 Do stocks overreact to news?

As Table 7 shows, the ten-day ahead abnormal return loads negatively on today's uninteracted sentiment, suggesting that, as measured by abnormal returns, stocks overreact to news. To investigate potential channels for this effect, we note in Table 9 that the loading of ten-day raw excess returns on lagged cross-sectional sentiment is strongly positive (top panel), suggesting that stocks react to the systematic component of news flow with a pronounced lag. Over a ten-day period, however, abnormal returns overreact to aggre-

[64] The fact that the positive deviation from cross-sectional sentiment has a larger coefficient than either the negative deviation or the cross-sectional mean further mitigates endogeneity concerns in our contemporaneous $CAR_{0,0}$ regressions because journalists are much more responsive to bad news (Garcia 2018) than to good news. This makes it less likely that positive abnormal returns are causing journalists to write positive news stories.

[65] In contrast to our results, Frank and Sanati (2018) find that stocks overreact to positive news; they attribute this pattern to a tendency of retail investors to trade more on positive news and argue that retail investors are also more prone to overreact to news. They define good or bad news by whether the event day abnormal return is positive or negative, and not by the tone of news. Due to the different sorting criteria (their abnormal returns vs. our news sentiment), our results aren't directly comparable.

gate sentiment, i.e., the ten-day abnormal return $CAR_{1,10}$ loading on $\overline{Sent}_t$ is strongly negative, significant and large (bottom panel). This would occur if individual stocks respond more quickly to stock-specific news than stock indexes (or priced factors) respond to the aggregate component of stock news flow. For example, say individual stock prices respond positively to their own good news while the stock market index reacts more slowly to aggregate positive news flow.[66] In this case, future abnormal returns would be negative as individual stock prices (of the subset of stocks that received positive day t news) stop moving while the index level slowly increases as positive news flow trickles into the market. Indeed, Table A9 of the Internet Appendix provides direct evidence that ten-day ahead aggregate stock market excess returns, as well as the ten-day ahead returns on the Fama and French (2015) factor RMW, all underreact to day t sentiment. Thus abnormal returns may be caused by an immediate stock price reaction to firm-specific news, followed by a delayed stock index price reaction to aggregate news flow.

As discussed in Section 1.1, there are also behavioral theories of overreaction which may explain the negative loading on uninteracted sentiment in Table 7. Some work (such as De Bondt and Thaler 1985) invokes a psychological propensity to overweight new information in updating expectations. Much of the relevant behavioral literature associates overreaction with overconfidence, particularly overconfidence in private signals. Our news events are public information. But if news about companies reflects hard-to-quantify information about fundamentals, as suggested by TSM, perhaps individual investors who follow the news are overly confident in their private interpretation of the news. We do not pursue tests of these possibilities in the present paper.

5.3 The role of earnings announcements

TSM show that the sentiment of articles containining any word beginning with "earn" is more strongly associated with contemporaneous returns and is a stronger predictor of future returns than sentiment of articles that do not contain earnings-related words (though the latter remains statistically and economically important). To ensure that our results are not driven by articles about earnings, we run a version of the specifications in (1) and (2) that drop all event days that take place either on earnings announcement days,

[66]As would occur in models of capacity constrained, sector-specialized investors, who would have a harder time responding to the aggregate compoment of stock-specific news than they would responding to the idiosyncratic component of stock-specific news. See Glasserman and Mamaysky (2019a) for a theoretical treatment of this phenomenon, and Glasserman and Mamaysky (2019b) for related empirical results in the context of forecasting volatility.

or on the trading day following the earnings announcement.[67] Dropping these two-day announcement periods reduces the number of observations in our full-sample regression from 611 thousand to 559 thousand.

Table A15 in the Internet Appendix is the analogue of Table 4, but after the two-day announcement windows are dropped. The magnitudes of the contemporaneous coefficients drop in the absence of earnings-related news, but remain economically and statistically important. The lagged sentiment coefficients for one-day ahead returns react less, and are only slightly lower in most subperiods (and higher in one subperiod). The lagged sentiment coefficients for ten-day ahead returns are almost completely unchanged (and higher for the full sample). Overall the qualitative conclusions about the ability of sentiment to forecast returns hardly change when earnings announcement days are excluded from our sample. We conclude that earnings-related news, while important (both contemporaneously and as forecasters) for returns, are not the main drivers of our results.

5.4 Controlling for volatility

Ang et al. (2006) showed that stocks with high idiosyncratic volatility earn "abysmally" low excess returns. It is possible therefore that the reason negative sentiment forecasts low returns is because it is associated with high idiosyncratic or systematic volatility. We include $CAR^2_{0,0}$ (idiosyncratic volatility) and VIX (systematic volatility) in our regressions to control for this possibility. Table A16 in the Internet Appendix shows the results of the specification in (1) when we remove the volatility controls. Compared to the results in Table 4, the forecasting ability of $Sent$ for both excess returns and CARs is slightly *lower* in the absence of the volatility controls. Why does this happen?

We first note that both $CAR^2_{0,0}$ and VIX are associated with a positive though mostly not significant one-day risk premium, as can be seen in the coefficient estimates from Tables 1 and A7 in the Internet Appendix.[68] Second, idiosyncratic and systematic volatility are both negatively correlated with sentiment. To see how this can explain our finding, consider that if sentiment positively forecasts one-day returns, then at times of negative sentiment expected returns should be low. However, if sentiment is also negatively correlated with volatility and if volatility commands a risk premium, then the latter effect will slightly increase the low expected return. By not including volatility controls in the

[67] We drop both days because we are uncertain whether the earnings announcement takes place before or after the market close on the announcement day.

[68] Ang et al. (2006) find that idiosyncratic volatility over the prior month negatively forecasts one-month ahead returns. However we look at daily idiosyncratic volatility and daily returns.

regressions we then expect to find a smaller coefficient associated with lagged sentiment.

6 Conclusion

We have studied time variation in the news-returns relationship to shed light on the apparent underreaction of stock prices to news. Previous work has emphasized behavioral explanations based on investor inattention to news or constraints on information processing capacity. Our paper provides evidence for the importance of strategic trading by institutions in producing the underreaction.

The time-varying news-returns relationship presents a puzzle because we often see a stronger response to lagged news together with a stronger contemporaneous response. If the time variation were driven by information processing capacity (in the form of increasing use of automated computer analysis of news text), a stronger contemporaneous response would produce a weaker lagged response. Increased institutional trading can account for a stronger contemporaneous response and (because of strategic trading) a stronger lagged response.

We support this interpretation by interacting news sentiment with measures of intermediary risk bearing capacity and active mutual fund management, both of which proxy for the level of news-driven institutional trading. Greater intermediary risk bearing capacity is indeed associated with a strong contemporaneous response to news and a greater lagged response. Similarly, we find that greater passive ownership is associated with weaker contemporaneous and lagged responses to news. When we control for institutional ownership and short interest, the widely observed underreaction of prices to news is eliminated, and we are left with an overreaction to news.

Our paper also introduces a novel approach to controlling for time variation in the informativeness of news. As in earlier work, we check the ability of news to forecast earnings. But we also apply an entropy measure to quantify the informativeness of news. We confirm that the predictability of earnings from news correlates with entropy. We find that the predictability of returns from news also correlates with entropy, but this correlation vanishes once we control of institutional trading motives. In other words, once we control for microstructure effects, the news-returns relationship is no longer related to the informativeness of news. This finding provides further support for the hypothesis that the market's underreaction to news is driven by strategic trading rather than information processing constraints.

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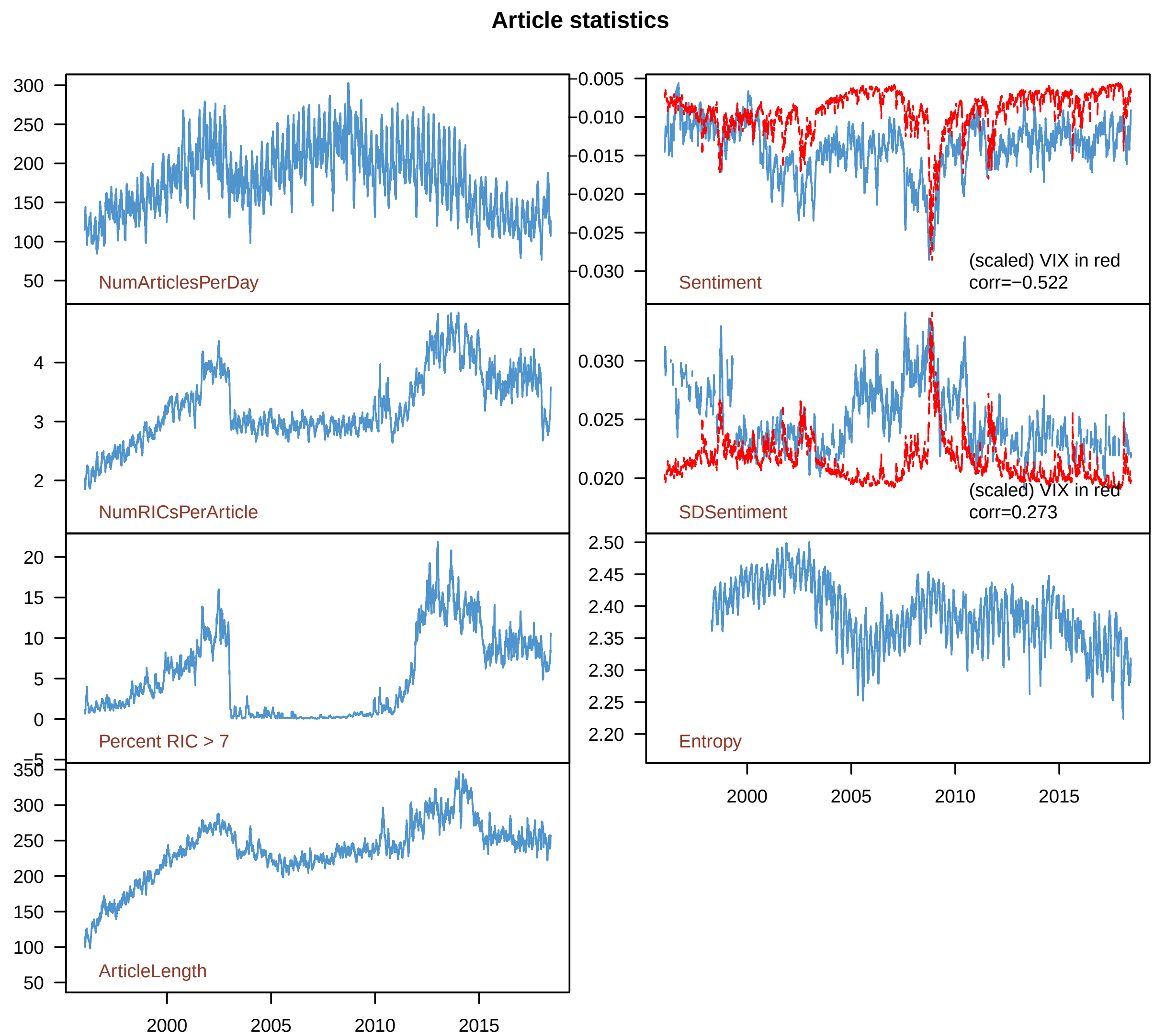

Fig. 4. This figure shows the number articles per day, the number of RICs per article, the percent of daily articles mentioning more than 5 RICs, the average article length (in number of words), daily average of article sentiment, and the daily standard deviation of article sentiment. Data are daily. The VIX (scaled to match the series in question) is shown in red.

Quarterly cross-sectional standard deviation of SUE and SAFE

Fig. 5. The top panel shows the quarterly cross-sectionasl standard deviation of SUE. The bottom panel shows the quarterly cross-sectional standard deviation of $SAFE$.

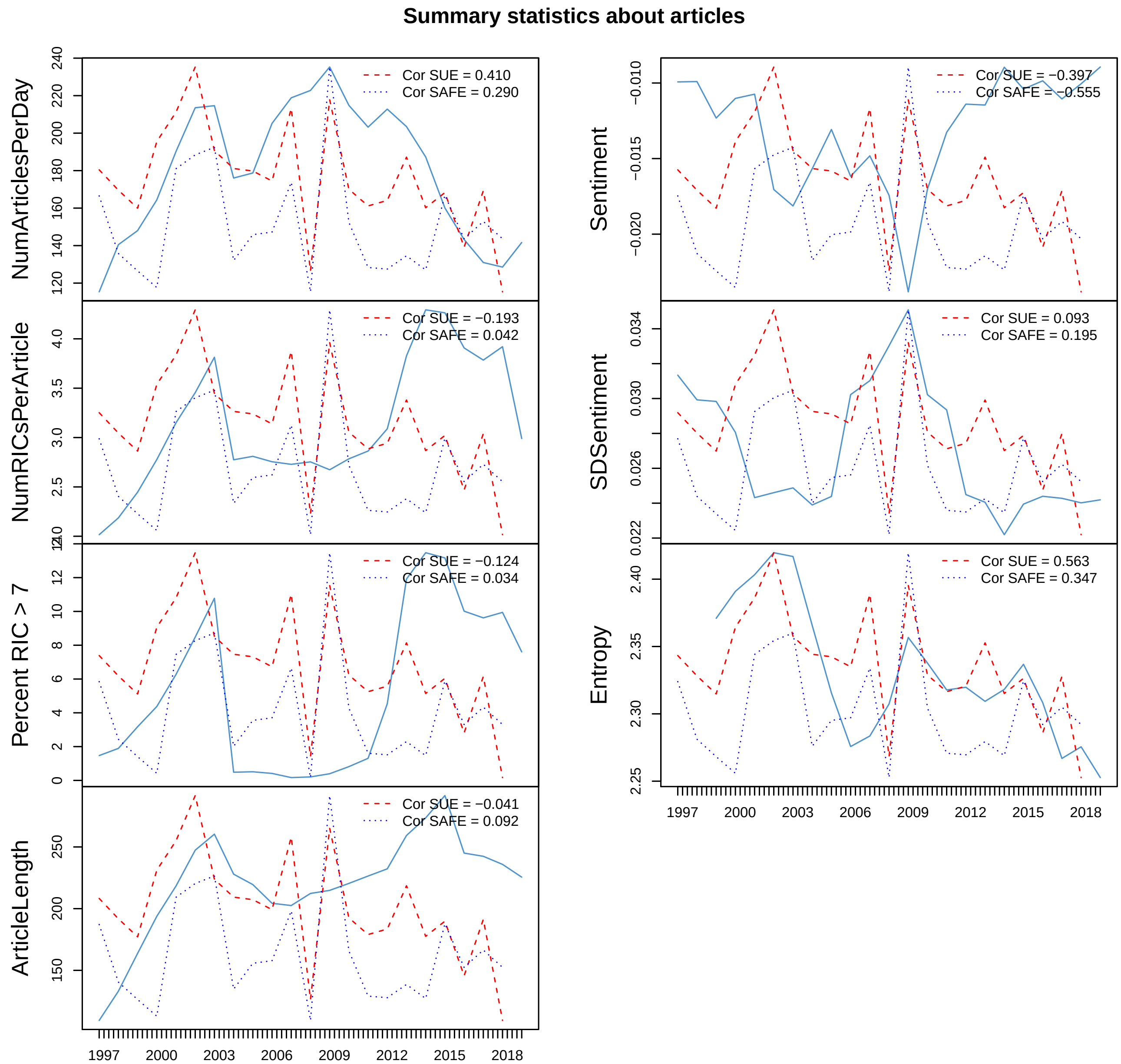

Fig. 6. This figure shows the number articles per day, the number of RICs per article, the percent of daily articles mentioning more than 5 RICs, the average article length (in number of words), daily average of article sentiment, and the daily standard deviation of article sentiment. Also shown is the average article entropy within each year of the sample. The other data are aggregated at an annual frequency. Superimposed on all the plots are the annual, scaled sentiment coefficients from the SUE and SAFE regressions whose subperiod results are shown in Table 8.

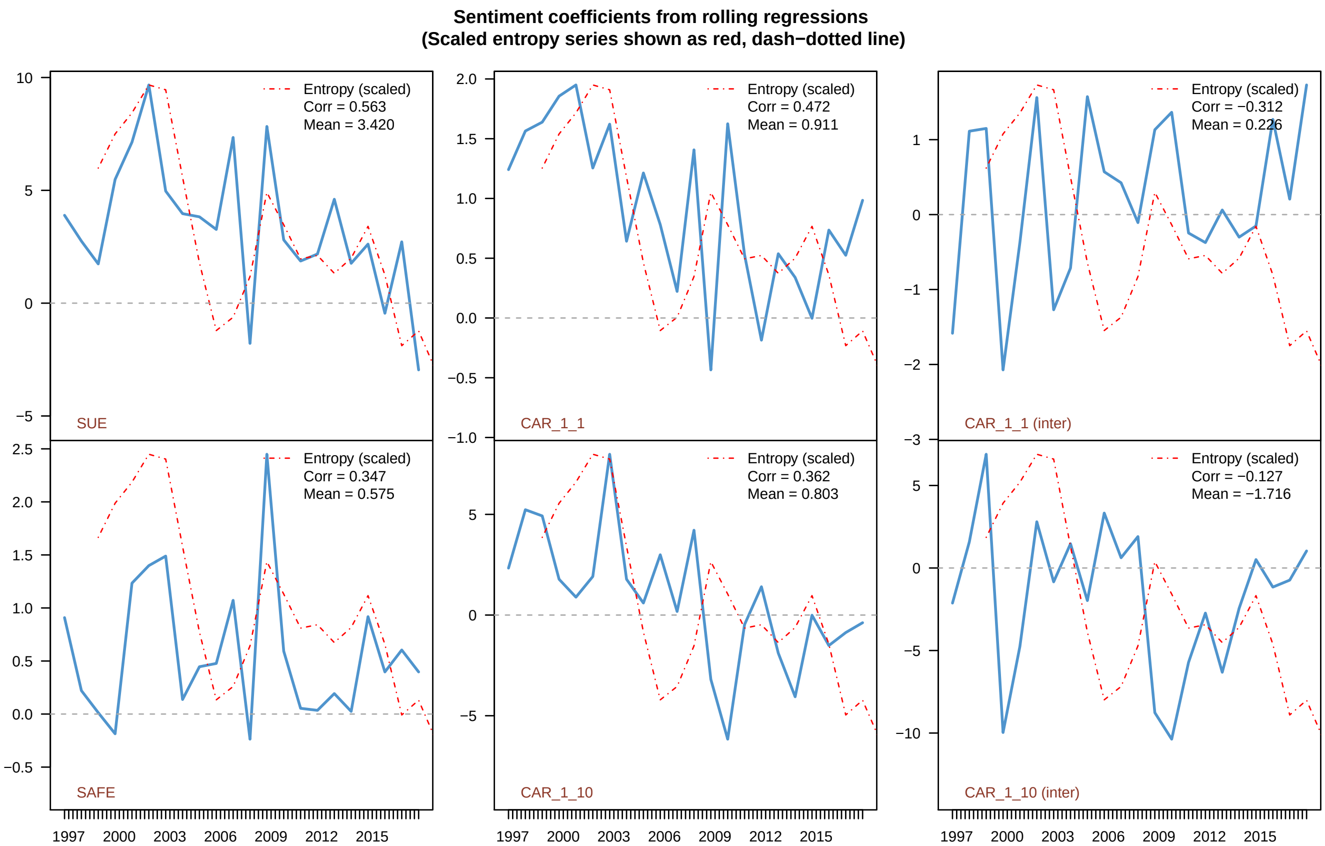

Fig. 7. Plots of *Sent* coefficients from the SUE, SAFE, and CAR regresions, with the annual entropy measure, scaled to fit the range of each series, superimposed. The horizontal line indicates the x-axis. The correlation of the two series, and the mean of the rolling *Sent* coefficient series are shown in the upper-right hand cornder of each plot. The entropy series is calculated as the average article entropy within a year for articles satisfying our filtering criteria.

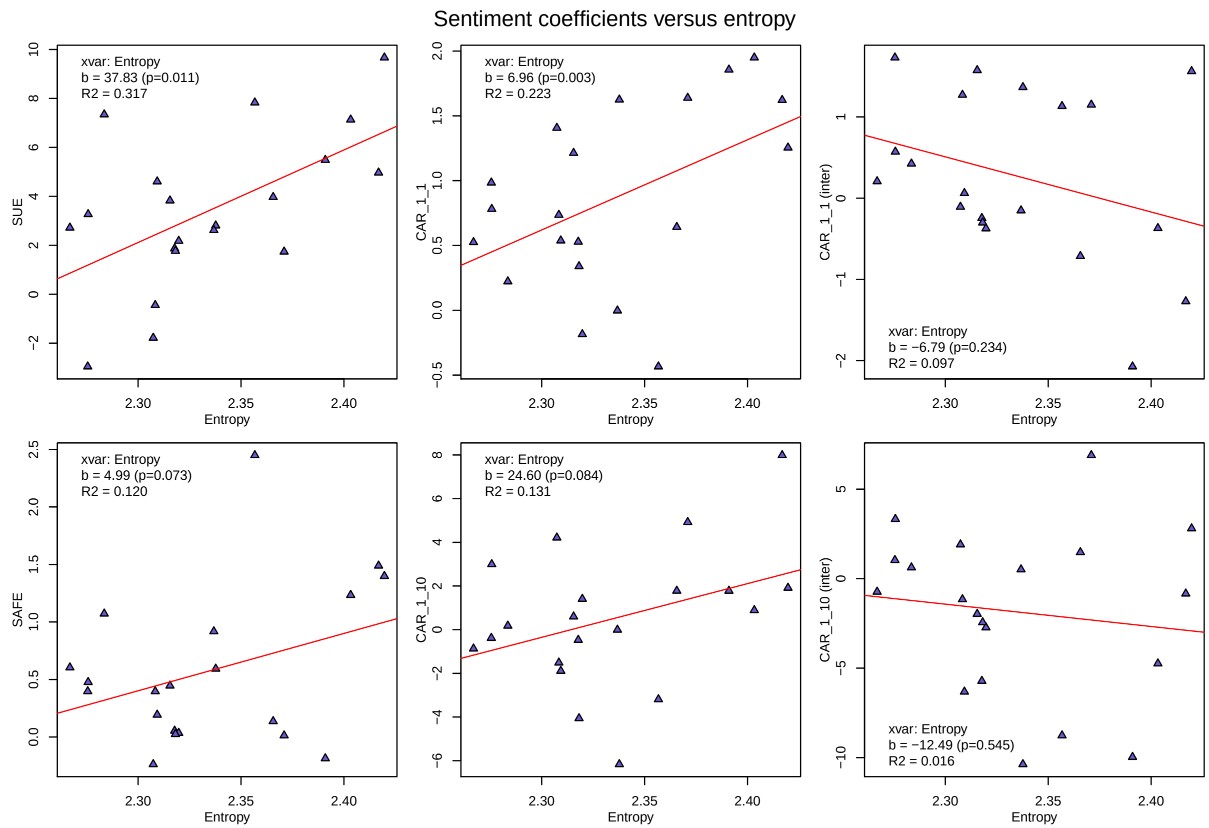

Fig. 8. Regression of year t sentiment coefficient from SUE, SAFE, and CAR forecasting regressions on year t entropy. The entropy series is calculated as the average article entropy within a year for articles satisfying our filtering criteria. Standard errors are calculated using White's heteroscedasticity correction.

Table 1
1-day ahead forecasting regressions. $Retrf_{i,j}$ ($CAR_{i,j}$) refers to the return (abnormal return) that includes days $t+i, \dots, t+j$ where t is the event date.

One-day ahead return regressions

	Dependent variable:													
	$\text{Retrf}_{1,1}$	$\text{CAR}_{1,1}$	$\text{Retrf}_{1,1}$	$\text{CAR}_{1,1}$	$\text{Retrf}_{1,1}$	$\text{CAR}_{1,1}$	$\text{Retrf}_{1,1}$	$\text{CAR}_{1,1}$	$\text{Retrf}_{1,1}$	$\text{CAR}_{1,1}$	$\text{Retrf}_{1,1}$	$\text{CAR}_{1,1}$	$\text{Retrf}_{1,1}$	$\text{CAR}_{1,1}$
	1996-2018		1996-2000		2001		2002-2006		2007-2009		2010-2014		2015-2018	
Constant	0.129	0.136	-0.141	0.212	1.080^{*}	0.859^{*}	0.164	0.243	1.005	0.376	-0.033	0.096	-0.382	-0.284
Sent	1.168^{***}	0.884^{***}	2.168^{***}	1.595^{***}	0.400	1.255	1.111^{***}	0.861^{***}	1.046	0.963^{*}	0.619^{**}	0.244	0.477	0.733^{***}
$\text{CAR}_{0,0}$	0.001	0.00003	-0.001	0.002	0.017	0.020	0.010	0.007	-0.017	-0.018	0.006	0.005	0.004	-0.002
$\text{CAR}_{-1,-1}$	-0.004	-0.008	-0.027^{***}	-0.024^{***}	0.003	0.001	-0.012	-0.012	0.016	-0.0001	0.002	-0.0001	-0.00002	-0.004
$\text{CAR}_{-2,-2}$	-0.009^{*}	-0.006	-0.010^{*}	-0.006	0.003	-0.00004	-0.005	-0.006	-0.015	-0.007	-0.004	-0.003	-0.006	-0.008
$\text{CAR}_{-30,-3}$	-0.001	-0.001	-0.0003	-0.0001	0.0001	0.001	-0.004^{**}	-0.003^{**}	0.001	-0.001	-0.001	-0.001	-0.002^{*}	-0.003^{**}
$\text{CAR}^2_{0,0}$	0.0005	0.0005	-0.001	-0.0005	-0.003^{*}	-0.003^{*}	0.0001	0.0001	0.001^{**}	0.001^{**}	-0.001^{*}	-0.001^{*}	0.001	0.0002
VIX	0.006	0.001	0.016^{*}	0.004^{**}	0.022	0.006	0.002	0.001	0.012	0.002	0.007	0.00001	0.011	-0.0003
SUE	0.011^{*}	0.007^{***}	0.001	0.003	0.021	0.008	0.003	0.003	0.006	0.010	0.008	0.009^{**}	0.016^{***}	0.011^{***}
Short Interest (%)	-0.006^{*}	-0.004^{*}	-0.004	-0.007	-0.014	-0.006	-0.007	-0.004	-0.015	-0.007	-0.0002	-0.001	-0.00004	0.001
IO (%)	-0.0002	-0.0002	0.001	0.0004	-0.001	-0.002	0.001	-0.0001	-0.005^{**}	-0.002^{*}	0.0002	-0.00001	0.001^{*}	0.001^{*}
log(Market Cap)	-0.033	-0.014^{*}	0.025	0.008	-0.036	-0.081	-0.023	-0.013	-0.171^{*}	-0.012	0.016	-0.033^{**}	-0.021	-0.010
IHS(Book/Market)	0.024	0.0001	0.021	0.010	-0.028	0.003	0.073^{**}	0.017	-0.0001	-0.075^{*}	0.031	0.008	0.013	0.022
log(Illiquidity)	-0.026	-0.009	0.035	0.022	0.029	-0.049	-0.015	-0.004	-0.134	-0.004	0.019	-0.030^{**}	-0.031	-0.021^{*}
α	-0.003	0.057	0.262^{**}	0.224^{**}	0.118	0.230	0.045	0.045	-0.333	-0.134	0.133	0.052	-0.044	0.055
Observations	610,504	610,504	110,141	110,141	25,980	25,980	142,093	142,093	96,082	96,082	152,908	152,908	83,300	83,300
Adjusted R^2	0.001	0.0004	0.002	0.001	0.006	0.007	0.001	0.001	0.003	0.003	0.001	0.0003	0.001	0.0005

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2
Summary statistics for the returns regressions. All statistics are calculated by pooling single-name data across all companies in our sample. This includes only the time periods during which these companies were members of the S&P 500 index.

Summary statistics for returns regressions

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
$\text{Retrf}_{1,1}$	703,994	0.036	2.696	−94.254	−1.037	1.082	102.358
$\text{CAR}_{1,1}$	703,981	0.004	2.239	−100.028	−0.849	0.819	96.015
Sent	706,545	−0.011	0.021	−0.283	−0.021	0.000	0.231
Sent (4pm-9:30am)	519,011	−0.012	0.021	−0.250	−0.022	0.000	0.147
$\overline{\text{Sent}}_D$	706,545	−0.011	0.004	−0.123	−0.014	−0.009	0.005
$\text{Sent} - \overline{\text{Sent}}_D$	706,545	−0.000	0.021	−0.272	−0.010	0.012	0.239
$\left(\text{Sent} - \overline{\text{Sent}}_D\right)^+$	706,545	0.008	0.010	0	0	0.01	0
$\left(\text{Sent} - \overline{\text{Sent}}_D\right)^-$	706,545	−0.008	0.014	−0.272	−0.010	0.000	0.000
Capital Ratio (daily)	595,325	8.045	3.666	1.459	4.878	10.882	17.355
Capital Ratio (monthly)	706,545	7.497	2.625	2.230	5.120	8.950	13.400
Capital Ratio (quarterly)	706,545	7.454	2.599	2.600	5.108	8.950	13.150
Leverage (quarterly)	706,545	23.222	5.625	13.931	18.957	27.089	36.482
Active/Market (%)	704,405	15.565	7.014	0.00004	10.864	19.892	74.202
Passive/Market (%)	704,448	5.492	3.614	0.00000	2.694	7.608	28.889
Passive/Fund Total (%)	704,388	26.215	14.466	0.001	15.300	34.676	99.984
VIX	706,338	20.639	8.584	9.140	14.530	24.180	80.860
SUE (5% Win)	639,112	−0.057	1.473	−4.644	−0.540	0.577	3.386
Short Interest (%)	669,804	2.846	3.522	0.000	1.021	3.176	77.916
Institutional Ownership (%, 1% Win)	700,560	67.545	18.906	0.936	57.997	80.317	108.205
log(Market Cap)	660,337	23.795	1.299	19.079	22.862	24.731	27.481
IHS(Book/Market) (1% Win)	704,320	0.450	0.296	−0.065	0.245	0.596	1.578
log(Share Turnover)	705,979	−4.983	0.731	−7.803	−5.499	−4.527	−1.061
log(Illiquidity)	705,957	−23.034	1.430	−27.683	−24.001	−22.105	−13.853
α	704,320	0.014	0.122	−1.132	−0.048	0.069	1.268
$\beta_{\text{Mktrf}} \times \text{Mktrf}_{1,1}$	704,199	0.029	1.353	−20.549	−0.490	0.597	22.407
$\beta_{\text{SMB}} \times \text{SMB}_{1,1}$	704,199	−0.00005	0.267	−8.707	−0.069	0.068	9.733
$\beta_{\text{HML}} \times \text{HML}_{1,1}$	704,199	0.002	0.534	−16.333	−0.107	0.108	23.447
$\beta_{\text{RMW}} \times \text{RMW}_{1,1}$	704,199	−0.0004	0.388	−11.422	−0.088	0.088	9.519
$\beta_{\text{CMA}} \times \text{CMA}_{1,1}$	704,199	0.002	0.438	−9.746	−0.095	0.097	13.263
$\beta_{\text{UMD}} \times \text{UMD}_{1,1}$	704,199	−0.001	0.532	−13.796	−0.100	0.096	22.156

Table 3
Summary statistics for the returns regressions.

Summary statistics for earnings regressions

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
SUE (5% Win)	40,000	−0.042	1.397	−4.320	−0.508	0.564	3.271
SAFE (5% Win)	36,812	0.097	0.281	−0.568	−0.007	0.177	0.991
Sent	35,839	−0.011	0.016	−0.250	−0.019	0.000	0.111
Forecast Dispersion (1% Win)	40,053	0.146	0.172	0.000	0.040	0.185	1.217
Forecast Revisions (1% Win)	40,289	−0.001	0.003	−0.028	−0.0003	0.000	0.007
$\text{CAR}_{-2,-2}$	40,478	0.029	1.918	−37.216	−0.803	0.806	55.365
$\text{CAR}_{-30,-3}$	40,477	−0.061	9.234	−82.174	−4.477	4.198	209.534
Short Interest (%)	38,817	3.188	3.575	0.000	1.193	3.776	77.120
Institutional Ownership (%, 1% Win)	40,320	71.423	19.075	0.962	61.612	84.583	111.719
log(Market Cap)	40,425	23.152	1.162	19.079	22.377	23.831	27.481
IHS(Book/Market) (1% Win)	38,274	0.448	0.303	−0.109	0.227	0.612	1.583
log(Illiquidity)	40,468	−22.466	1.387	−27.596	−23.361	−21.589	−13.853
α	40,467	0.015	0.116	−0.976	−0.046	0.069	1.222

Table 4
These regressions include as controls: constant, $CAR_{0,0}$, $CAR_{-1,-1}$, $CAR_{-2,-2}$, $CAR_{-30,-3}$, SUE, $SI(\%)$, $IO(\%)$, $\log(Market\ Cap)$, $IHS(Book/Market)$, $log(Illiquidity)$, lagged α, $CAR^2_{0,0}$ and VIX. The row labeled (4pm-9:30am) indicates that *Sent* has been measured from the prior day's close to the event day's market open. Standard errors are clustered by time. The $\text{Retrf}_{0,0}$ and $\text{CAR}_{0,0}$ regressions omit the $\text{CAR}_{0,0}$ control.

Return predictability

		1996-2018	1996-2000	2001	2002-2006	2007-2009	2010-2014	2015-2018
$\text{Retrf}_{0,0}$	Sent	9.181***	9.893***	12.624***	9.605***	12.649***	5.143***	9.103***
$\text{Retrf}_{0,0}$	Sent (4pm-9:30am)	6.193***	6.022***	8.806***	7.438***	7.059***	3.939***	5.961***
$\text{Retrf}_{1,1}$	Sent	1.168***	2.168***	0.4	1.111***	1.046	0.619**	0.477
$\text{Retrf}_{1,10}$	Sent	2.667***	4.621***	-0.859	2.961***	3.465	1.36	-1.861*
$\text{CAR}_{0,0}$	Sent	8.087***	9.303***	10.525***	8.999***	9.655***	4.416***	8.323***
$\text{CAR}_{0,0}$	Sent (4pm-9:30am)	5.949***	5.756***	7.538***	7.405***	6.924***	3.966***	5.557***
$\text{CAR}_{1,1}$	Sent	0.884***	1.595***	1.255	0.861***	0.963*	0.244	0.733***
$\text{CAR}_{1,10}$	Sent	0.722	2.856***	1.915	2.624***	-0.683	-0.869	-0.983

Table 5

These regressions include as controls: constant, $CAR_{0,0}$, $CAR_{-1,-1}$, $CAR_{-2,-2}$, $CAR_{-30,-3}$, SUE, $SI(\%)$, $IO(\%)$, $\log(Market\ Cap)$, $IHS(Book/Market)$, $log(Illiquidity)$, lagged α, $CAR^2_{0,0}$ and VIX. The row labeled (4pm-9:30am) indicates that *Sent* has been measured from the prior day's close to the event day's market open. Standard errors are clustered by time. The $\text{Retrf}_{0,0}$ and $\text{CAR}_{0,0}$ regressions omit the $\text{CAR}_{0,0}$ control.

Intermediary effects on sentiment predictability

Return regressions

		Capacity			
		CR (daily)	CR (monthly)	CR (quarterly)	Lev (quarterly)
$\text{Retrf}_{0,0}$	Sent	9.257***	9.184***	9.18***	9.225***
	Sent×Capacity	0.363***	0.453***	0.515***	0.221***
$\text{Retrf}_{0,0}$	Sent (4pm-9:30am)	6.209***	6.152***	6.153***	6.246***
	Sent (4pm-9:30am)×Capacity	0.369***	0.435***	0.453***	0.132**
$\text{Retrf}_{1,1}$	Sent	0.969***	1.174***	1.173***	1.107***
	Sent×Capacity	0.134	0.214*	0.197	0.047
$\text{Retrf}_{1,10}$	Sent	1.701**	2.671***	2.653***	2.181***
	Sent×Capacity	0.479	0.803**	0.681*	0.601***

CAR regressions

		Capacity			
		CR (daily)	CR (monthly)	CR (quarterly)	Lev (quarterly)
$\text{CAR}_{0,0}$	Sent	8.204***	8.1***	8.103***	8.121***
	Sent×Capacity	0.448***	0.512***	0.551***	0.152***
$\text{CAR}_{0,0}$	Sent (4pm-9:30am)	6.163***	5.981***	5.981***	6.002***
	Sent (4pm-9:30am)×Capacity	0.33***	0.305***	0.322***	0.124***
$\text{CAR}_{1,1}$	Sent	0.797***	0.89***	0.891***	0.881***
	Sent×Capacity	0.137**	0.206***	0.198***	0.013
$\text{CAR}_{1,10}$	Sent	0.4	0.747*	0.751*	0.699
	Sent×Capacity	0.687***	0.898***	0.833***	0.171**

Table 6
These regressions include as controls: constant, $CAR_{0,0}$, $CAR_{-1,-1}$, $CAR_{-2,-2}$, $CAR_{-30,-3}$, SUE, $SI(\%)$, $IO(\%)$, $\log(Market\ Cap)$, $IHS(Book/Market)$, $log(Illiquidity)$, lagged α, $CAR^2_{0,0}$ and VIX. The row labeled (4pm-9:30am) indicates that $Sent$ has been measured from the prior day's close to the event day's market open. Standard errors are clustered by time. The $\text{Retrf}_{0,0}$ and $\text{CAR}_{0,0}$ regressions omit the $\text{CAR}_{0,0}$ control.

Mutual fund ownership effects on sentiment predicatibility

Return regressions

		Mutual Fund Ownership (%)		
		Passive/Market	Active/Market	Passive/Fund Total
$\text{Retrf}_{0,0}$	Sent	9.197***	9.117***	9.174***
	Sent×Ownership	-0.043	0.212***	-0.051***
$\text{Retrf}_{0,0}$	Sent (4pm-9:30am)	6.219***	6.183***	6.223***
	Sent (4pm-9:30am)×Ownership	-0.043	0.201***	-0.052***
$\text{Retrf}_{1,1}$	Sent	1.149***	1.161***	1.157***
	Sent×Ownership	-0.084	0.012	-0.015
$\text{Retrf}_{1,10}$	Sent	2.464***	2.562***	2.564***
	Sent×Ownership	-0.412**	0.244***	-0.122***

CAR regressions

		Mutual Fund Ownership (%)		
		Passive/Market	Active/Market	Passive/Fund Total
$\text{CAR}_{0,0}$	Sent	8.096***	8.03***	8.082***
	Sent×Ownership	-0.031	0.187***	-0.045***
$\text{CAR}_{0,0}$	Sent (4pm-9:30am)	5.958***	5.937***	5.968***
	Sent (4pm-9:30am)×Ownership	0.005	0.174***	-0.033**
$\text{CAR}_{1,1}$	Sent	0.885***	0.874***	0.88***
	Sent×Ownership	-0.049	0.031	-0.017*
$\text{CAR}_{1,10}$	Sent	0.714	0.668	0.69
	Sent×Ownership	-0.298***	0.175***	-0.106***

Table 7

1-day ahead forecasting regressions. $Retrf_{i,j}$ ($CAR_{i,j}$) refers to the return (abnormal return) that includes days $t+i, \ldots, t+j$ where t is the event date. The results of these regressions by subperiod are shown in Tables A10 and A11 of the Internet Appendix.

Sentiment predictability with interaction effects

	Dependent variable:			
	$\text{Retrf}_{1,1}$	$\text{CAR}_{1,1}$	$\text{Retrf}_{1,10}$	$\text{CAR}_{1,10}$
Constant	0.188	0.178^{*}	3.563^{***}	2.174^{***}
Sent	0.384	0.262	-0.190	-1.684^{**}
Sent $\times\ \mathbf{1}_{\text{SI}=H}^{\text{Sent}=H}$	0.476	0.523	5.368^{*}	4.326^{*}
Sent $\times\ \mathbf{1}_{\text{SI}=L}^{\text{Sent}=H}$	1.031	-0.126	6.506^{***}	2.406
Sent $\times\ \mathbf{1}_{\text{SI}=H}^{\text{Sent}=L}$	1.376^{***}	0.931^{**}	3.200^{**}	3.017^{***}
Sent $\times\ \mathbf{1}_{\text{SI}=L}^{\text{Sent}=L}$	-0.379	-0.043	-2.006^{*}	-1.020
Sent $\times\ \mathbf{1}_{\text{IO}=H}^{\text{Sent}=H}$	0.752	0.149	3.001	0.476
Sent $\times\ \mathbf{1}_{\text{IO}=L}^{\text{Sent}=H}$	-0.044	0.463	2.369	1.077
Sent $\times\ \mathbf{1}_{\text{IO}=H}^{\text{Sent}=L}$	0.536	0.794^{**}	3.327^{***}	3.760^{***}
Sent $\times\ \mathbf{1}_{\text{IO}=L}^{\text{Sent}=L}$	0.828^{*}	0.339	1.959	0.980
$\text{CAR}_{0,0}$	0.001	-0.0001	-0.042^{***}	-0.040^{***}
$\text{CAR}_{-1,-1}$	-0.004	-0.008	-0.051^{***}	-0.049^{***}
$\text{CAR}_{-2,-2}$	-0.009^{*}	-0.006	-0.066^{***}	-0.060^{***}
$\text{CAR}_{-30,-3}$	-0.001	-0.001	-0.005^{*}	-0.007^{**}
$\text{CAR}_{0,0}^{2}$	0.0005	0.0005	0.002	0.003^{***}
VIX	0.006	0.001	0.020	0.002
SUE	0.011^{*}	0.007^{***}	0.039^{**}	0.023^{***}
Short Interest (%)	-0.005	-0.003	-0.023^{**}	-0.007
IO (%)	-0.0003	-0.0001	-0.002^{*}	-0.002^{***}
log(Market Cap)	-0.036	-0.016^{**}	-0.236^{***}	-0.134^{***}
IHS(Book/Market)	0.022	-0.002	0.209^{***}	-0.004
log(Illiquidity)	-0.027	-0.009	-0.094	-0.050^{**}
α	-0.007	0.055	-0.364^{*}	-0.055
Observations	610,504	610,504	610,506	610,506
Adjusted R^2	0.001	0.0005	0.002	0.002
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 8
These regressions include as controls: lagged SUE or SAFE, analyst forecast dispersion, analyst forecast revisions, lagged abnormal returns $CAR_{-2,-2}$ and $CAR_{-30,-3}$, short interest, institutional ownership, log market capitalization, the IHS transform of book to market, log illiquidity, and the past year's alpha from our six factor model. Standard errors are clustered by time.

SUE **and** $SAFE$ **forecastability by** $SENT$

	1996-2018	1996-2000	2001	2002-2006	2007-2009	2010-2014	2015-2018
SUE	3.733***	3.971***	9.67***	4.323***	3.182**	3.144***	0.015
SAFE	0.557***	0.369	1.399***	0.743***	0.967**	0.379*	0.557**

Table 9

These regressions include as controls: constant, $CAR_{0,0}$, $CAR_{-1,-1}$, $CAR_{-2,-2}$, $CAR_{-30,-3}$, SUE, $SI(\%)$, $IO(\%)$, log($Market\ Cap$), $IHS(Book/Market)$, $log(Illiquidity)$, lagged α, $CAR^2_{0,0}$ and VIX. The row labeled (4pm-9:30am) indicates that $Sent$ has been measured from the prior day's close to the event day's market open. Standard errors are clustered by time. The $\text{Retrf}_{0,0}$ and $\text{CAR}_{0,0}$ regressions omit the $\text{CAR}_{0,0}$ as a control.

Return predicatibility with cross-sectional sentiment

		1996-2018	1996-2000	2001	2002-2006	2007-2009	2010-2014	2015-2018
$\text{Retrf}_{0,0}$	(Sent - $\overline{\text{Sent}}_t$)+	11.429***	10.403***	15.492***	11.912***	13.738***	8.688***	15.119***
	$(\text{Sent} - \overline{\text{Sent}}_t)^-$	6.996***	9.407***	9.699***	7.842***	8.67***	2.523***	5.194***
	$\overline{\text{Sent}}_t$	28.587***	15.646*	43.027*	19.457*	97.825***	28.96***	17.374
$\text{Retrf}_{0,0}$	(Sent - $\overline{\text{Sent}}_t$)+ (4pm-9:30am)	8.838***	6.888***	11.063***	9.958***	10.816***	8.36***	8.465***
	$(\text{Sent} - \overline{\text{Sent}}_t)^-$ (4pm-9:30am)	4.763***	5.963***	6.913***	6.368***	5.066***	1.563***	4.204***
	$\overline{\text{Sent}}_t$ (4pm-9:30am)	3.84	-3.439	17.057	-3.93	-1.572	4.454	11.717
$\text{Retrf}_{1,1}$	(Sent - $\overline{\text{Sent}}_t$)+	1.219***	1.924**	-0.87	1.643**	0.892	0.3	1.483**
	$(\text{Sent} - \overline{\text{Sent}}_t)^-$	0.876***	2.115***	1.474	0.556	0.823	0.447	0.145
	$\overline{\text{Sent}}_t$	7.188	8.333	-5.928	7.903	9.387	12.222	-7.462
$\text{Retrf}_{1,10}$	(Sent - $\overline{\text{Sent}}_t$)+	2.288**	3.43	10.668*	4.799**	-8.982*	4.565**	-1.832
	$(\text{Sent} - \overline{\text{Sent}}_t)^-$	1.014	4.927***	-7.975	2.633	4.374	-2.441**	-1.074
	$\overline{\text{Sent}}_t$	45.977***	17.142	-27.768	-21.859	184.589**	71.216**	-25.34
$\text{CAR}_{0,0}$	(Sent - $\overline{\text{Sent}}_t$)+	10.789***	10.232***	11.596***	11.371***	11.095***	8.917***	13.869***
	$(\text{Sent} - \overline{\text{Sent}}_t)^-$	6.452***	8.73***	10.122***	7.499***	8.403***	2.068***	5.048***
	$\overline{\text{Sent}}_t$	8.574***	9.983***	-0.327	9.647***	18.447***	1.653	6.374**
$\text{CAR}_{0,0}$	(Sent - $\overline{\text{Sent}}_t$)+ (4pm-9:30am)	8.466***	7.176***	8.316***	10.046***	8.838***	8.281***	8.366***
	$(\text{Sent} - \overline{\text{Sent}}_t)^-$ (4pm-9:30am)	4.502***	5.122***	7.701***	5.776***	5.488***	1.685***	4.08***
	$\overline{\text{Sent}}_t$ (4pm-9:30am)	5.354***	1.802	-8.523	7.916***	12.325**	3.456**	-0.025
$\text{CAR}_{1,1}$	(Sent - $\overline{\text{Sent}}_t$)+	0.992***	1.129	-0.014	1.121*	2.47**	-0.096	1.231**
	$(\text{Sent} - \overline{\text{Sent}}_t)^-$	0.812***	1.887***	2.2	0.784*	-0.162	0.311	0.377
	$\overline{\text{Sent}}_t$	1.054	1.104	-0.986	-1.702	5.415	4.169***	2.395
$\text{CAR}_{1,10}$	(Sent - $\overline{\text{Sent}}_t$)+	0.353	-1.82	7.618	2.44	-0.797	1.763	-0.944
	$(\text{Sent} - \overline{\text{Sent}}_t)^-$	1.254*	6.115***	-0.835	2.996**	-1.127	-2.621***	-0.957
	$\overline{\text{Sent}}_t$	-6.469*	-12.432	-36.073	-5.241	12.709	10.351**	-2.424