Time Variation in the News-Returns Relationship*

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Abstract

The well-documented underreaction of stock prices to news exhibits substantial time variation. Higher risk-bearing capacity of financial intermediaries, lower passive ownership of stocks, and more informative news increase price responses to contemporaneous news; surprisingly, they also increase price responses to lagged news (underreaction). Our findings are not driven by short-sale constraints, serial correlation in news flow, or improved information processing capacity. We discuss possible mechanisms based on investor behavior and strategic order-splitting by institutions. A simple model with limited attention and three investor types – institutional, non-institutional, passive – predicts the varying response to news we observe.

Keywords: Price efficiency, news media, textual analysis, institutional trading

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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 is quite large.[1] To understand the nature of the underreaction, we investigate time variation in the news-returns relationship. We find substantial time variation in the extent of underreaction, and we find evidence of an important role for institutional trading in determining the contemporaneous and future response of prices to news. The evidence is based on time variation in intermediary risk-bearing capacity, passive fund ownership, and the information content of news.

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 on day $t+1$ in the same direction as the news. 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.[2] In our sample, a one standard deviation news sentiment shock on day t forecasts a 1.9 basis point abnormal return on day $t+1$.[3]

However, the full-sample result masks substantial time variation in stock price underreaction. In the most recent period, 2015–2018, the degree of underreaction is roughly half as large as in the earliest part of the sample, 1996–2000. One might expect such a decline if the return predictability from news articles has been traded away, as natural language processing techniques coupled with faster computers and larger data sets have become more widely used by practitioners. In other words, one might argue that the market has become more informationally efficient as more investors have learned to extract trading signals from news sentiment. This conjecture would be consistent with other evidence (as in Bai, Philippon, and Savav 2016) of increasing price efficiency in financial markets.

Figure 1 shows that the time variation in return predictability follows a more complex pattern. The figure repeats the analysis above in annual regressions for every year of our sample and plots the coefficients on our news sentiment measure. The left panel shows the impact of contemporaneous news sentiment on returns for each year. The right panel shows the impact of news sentiment on next-day returns. Returns are measured relative

[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 (2021) reach similar conclusions. Using conservative assumptions, we estimate the size of the effect to be roughly 10% per annum in certain market conditions, or higher if more leverage is employed (see Sections 5.1 and 5.2).

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

[3] When we exclude several controls variables that are absent in TSM, our results are even closer.

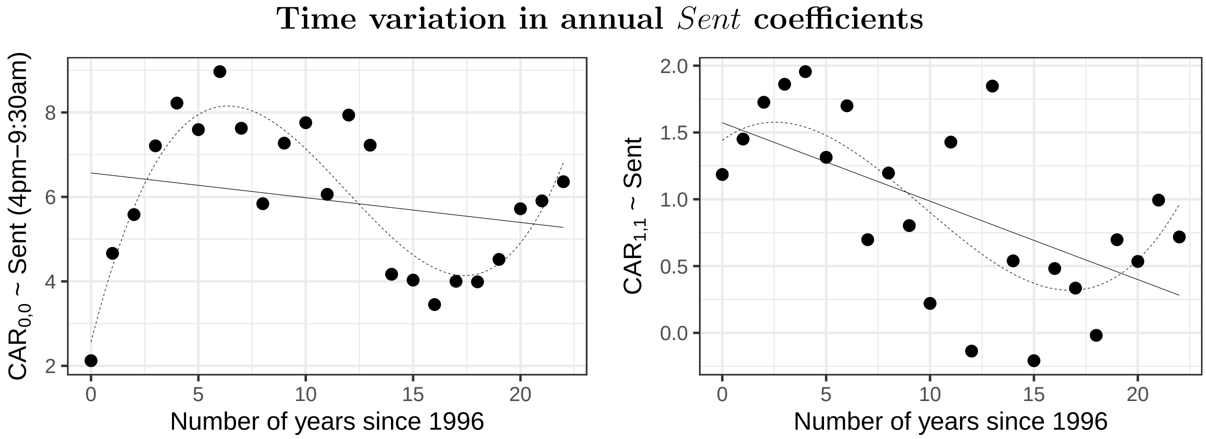

Fig. 1. This figure shows annual *Sent* coefficients from regressions of abnormal returns on either contemporaneous news (left) or news lagged by one day (right). The coefficients are fitted with a trendline and a third-degree polynomial in time to show cyclical variation. The contemporaneous regressions use pre-9:30AM news to calculate day t sentiment.

to a six factor model. The data used in this analysis and the exact regression specification are explained in Sections 2 and 3. Each panel shows a trend line for the coefficients on our sentiment variable *Sent*, as well as the fit from a third-degree polynomial in time.

Two patterns emerge from the figure. First, the magnitude of the response of contemporaneous *and* future returns to news sentiment shocks has been declining over time. Second, this trend decline exhibits cyclical variation that is similar for return responses to contemporaneous and lagged news.

If the time variation in the underreaction to news were simply driven by growing information processing capacity, we would expect to see a consistent decline in magnitude of the next-day reaction in the right panel. We would also expect to see an *increase* in the contemporaneous reaction of prices to news. 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. Instead, we see the coefficients in the two panels fluctuating over time, and often moving in the same direction. These patterns cannot be explained by faster information processing alone.

We hypothesize that the time variation in Figure 1 is influenced by time variation in three other variables: the risk-bearing capacity of financial intermediaries, the fraction of passive ownership of stocks, and the informativeness of news. We develop these hypotheses in the context of a simple model with institutional investors, passive investors, and non-institutional investors. We then test the hypotheses by interacting each of the three variables with news sentiment in regressions of contemporaneous and next-day responses of stock prices to news. The empirical tests support our hypotheses: intermediary capacity and news informativeness both increase the impact of sentiment on same-day and next-day returns, while passive ownership decreases this impact.

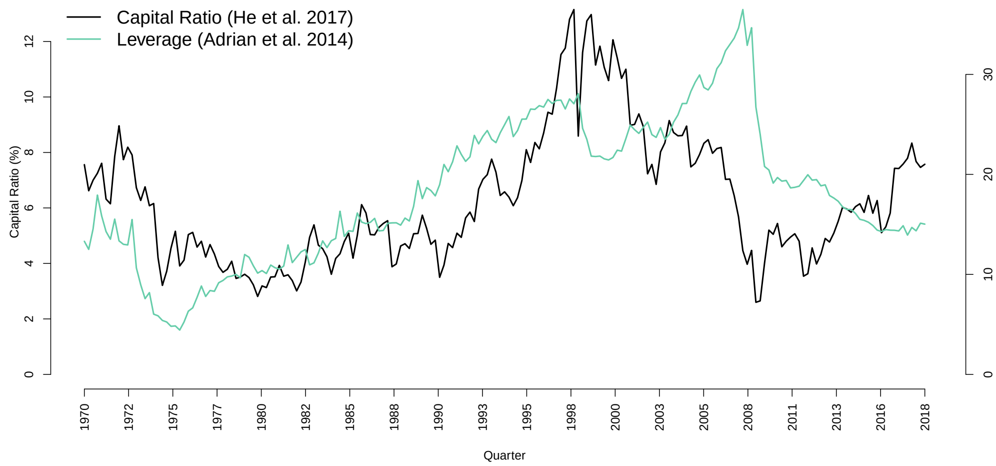

Fig. 2. This chart shows the quarterly intermediary capital ratio and leverage. These series are defined in Section 5.1.

The reaction of market prices to news should depend in part on the availability of investment capital to trade on news. Figure 2 shows the time variation in intermediary risk-bearing capacity, as indicated by the *capital ratio* measure of He, Kelly, and Manela (2017) (and the leverage ratio of Adrian, Etula, and Muir 2014, though our focus is on the former). The 1996–2006 part of our sample was characterized by high intermediary capital ratios, which fell dramatically during the financial crisis, but which 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 forty 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 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.

Along with changes in the risk-bearing capacity of the intermediation sector, the last two decades have witnessed a move towards passive investing, and away from actively

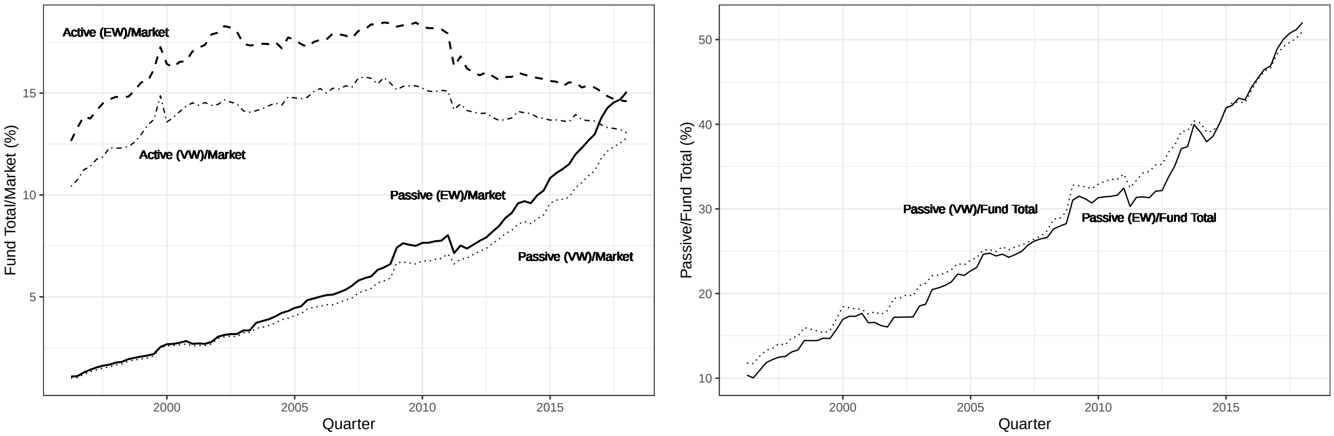

Fig. 3. The left chart shows the fraction of S&P 500 firms' market capitalization that is owned by either active or passive mutual funds. The right chart shows the ratio of passive mutual fund assets invested in S&P 500 firms to total mutual fund assets invested in those firms. EW (VW) refers to equal- (value-) weighted versions of the calculation.

managed mutual funds. Passive investors should be less responsive to news. Figure 3 shows that the fraction of all S&P 500 stocks that are owned by passive funds has steadily grown over the past several decades.[4] 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. Furthermore, stocks with greater passive ownership experience *less* one- to forty-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 future prices to news.

The market's response to news should also depend on the informativeness of the news, and some periods may be richer in news than others. Our third interacting variable is therefore *entropy*, a measure of news informativeness which we explain in Section 2.1. Panel G of Figure 5 shows that average daily entropy exhibits substantial time variation over our sample. As suggested by our model, we find that contemporaneous and future stock price responses to news are higher in time periods of higher entropy.

Our empirical findings on the effects of intermediary capital, passive ownership, and news informativeness suggest a role for institutional trading in producing underreaction to news. We therefore investigate channels through which institutional trading could affect the news-returns relationship. We begin with two channels suggested by the literature — short sale constraints and serial correlation in news flow. Though we find a

[4] 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.

role for each of these channels, they cannot fully account for our findings. We therefore discuss other mechanisms that are difficult to test, based on investor behavior or strategic order-splitting by institutions. A behavioral explanation based on Daniel, Hirshleifer, and Subrahmanyam (1998) argues that overconfidence and self-attribution bias prevent institutional investors from responding immediately and fully to new information. Investors may also simply have limited attention capacity to trade quickly on all news. The strategic order-splitting explanation posits that institutions, aware of the price impact of their trades, rationally delay some of their trading to balance immediacy versus price impact.

Our analysis does not identify the fundamental source of underreaction. Instead, we focus on understanding, theoretically and empirically, how interactions with the capacity and mix of different types of investors produces time-variation in the degree of underreaction and the strength of the contemporaneous reaction to news.

Our paper contributes to a growing literature on the use natural language processing techniques in finance. Early work in this area is due to Antweiler and Frank (2005) and Das and Chen (2007), who propose measures of information and sentiment in text from internet message boards. 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 (2021), Garcia, Hu, and Rohrer (2020), and others also find return predictability using various measures of sentiment and news events. Our work extends the literature by exploiting time variation in the news-returns relationship to investigate factors that affect predictability.[5] 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 (2019).

We also contribute 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. We contrast their

[5]Garcia (2013) also exploits such time variation and finds return predictability at the index level is greatest in recessions.

results with ours in Section 7.

The rest of the paper proceeds as follows. Section 2 describes the data and the methodology used to construct our sentiment and news informativeness measures. Section 3 presents the regression results documenting the time variation depicted in Figure 1. Section 4 uses a simple model to formulate hypotheses on how intermediary capital, passive ownership, and news informativeness should affect the price response to news. Section 5 tests the predictions of Section 4. Section 6 discusses several channels that may give rise to the news-returns relationship we document. Section 7 presents robustness checks, including the effects of earnings news and volatility controls. Section 8 concludes. Internet and Model Appendixes contain further technical details and supporting results.[6]

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 on days when it was part of the S&P 500 index.

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 occurring news events (e.g., an hourly snapshot of market developments). 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

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

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.[7] This rule tries to avoid duplication of articles from type (1) chains and while retaining relevant articles from type (2) chains.

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).[8] This leaves us with 1.36 million articles. The left panel of Figure 4 shows the distribution of

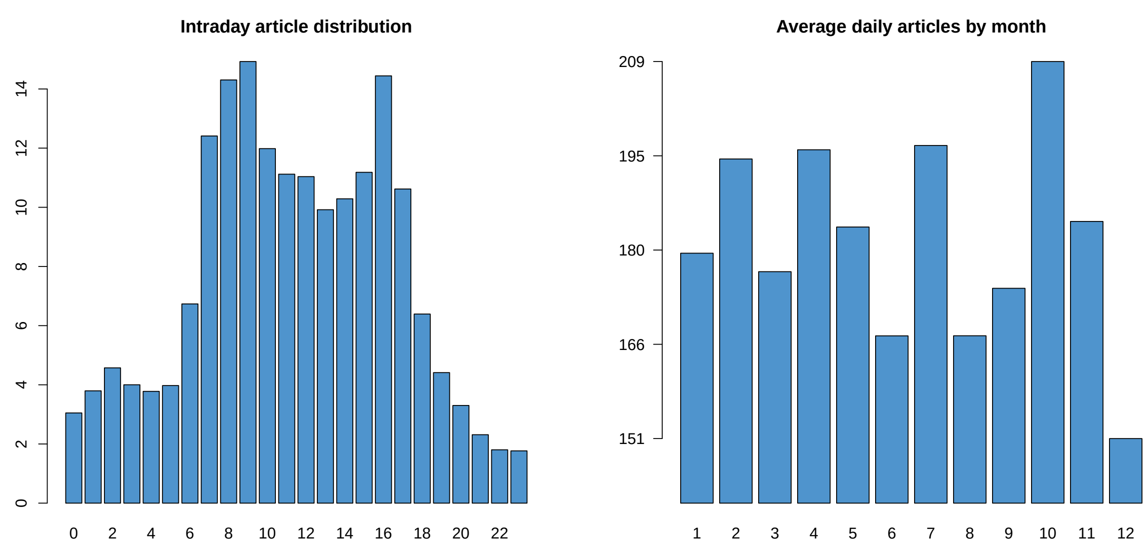

Fig. 4. The left panel shows the average number of articles in each hour of the day. The right panel shows the average number of daily articles within each month.

articles throughout the day. The majority of articles about S&P 500 firms are released

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

[8]We identify a RIC by the occurrence of the string "R:" in the article's `subjects` field. As can be seen from Figure 5 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.

from 7am to 5pm. The right panel of Figure 4 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.

We next 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 i on business day t is the equally-weighted average sentiment of articles for firm i 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.[9]

To measure informativeness, we use an article's entropy, which quantifies the "unusualness" of the article relative to an earlier training corpus of text. As in Calomiris and Mamaysky (2019) and Glasserman and Mamaysky (2019), 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.[10] This entropy measure is

[9]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 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.

[10]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 occurrence 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

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 2 shows headlines of some sample articles from our corpus, sorted by entropy. For example, in June of 2005, the lowest entropy article (that satisfied our selection 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." The relationship between the headlines of the sample articles and their entropy scores suggests that entropy is a useful proxy for the information content of news.

Figure 5 shows the time-series behavior of some summary statistics about the text archive. The average number of daily articles (panel A), on top of having seasonal patterns, also exhibits lower frequency fluctuations which may be related to the business cycle. The average number of RICs per article (panel B) and the number of articles with more than seven RICs (panel C) are highly correlated, with peaks around 2002 and 2013. The average number of words per articles (after stopwords have been excluded, panel D) 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 (panel E) 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, panel F) is strongly countercyclical, exhibiting peaks during times of market stress. Panel G of Figure 5 shows that average daily entropy exhbits substantial time variation.[11]

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) 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 (2019).

[11] Average entropy is calculated using the set of articles described in Section 2.1. Furthermore we drop all articles containing the string "RESEARCH ALERT-" in their headline (using case insensitive match). Such articles are brief summaries of sell-side research reports, 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.

2.2 Financial data

We run all of our specifications with either raw excess returns ($Retrf$) or with cumulative abnormal returns (CAR) relative to our six factor model, which uses the five factors from Fama and French (2015) augmented with momentum. We estimate the six factor model using daily data in the twelve month period preceding day t, but following TSM we exclude 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 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.[12]

We also construct an extensive set of control variables. 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 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).

We obtain mid-month short interest (SI) from Compustat, and use the most recently available SI value for day t. 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.[13] In our regressions, we time stamp IO with the data date from the 13F

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

[13]Institutions with over $100 million in assets, including mutual funds, hedge funds, insurance compa-

filing, though this information is not yet available to market participants.[14] To control for effects of post-earnings announcement drift,[15] we 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

$$\begin{aligned} SUE_q &= \frac{UE_q - \mu_q}{\sigma_q} \\ UE_q &= E_q - E_{q-4} \end{aligned} \tag{1}$$

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 winsorize SUE at the 5% level and IO at the 1% level.[16] Tables 3 shows summary statistics for all the variables. All return variables are in percentage points.

3 Time variation in the news-returns relationship

In this section, we explain the regression specifications for the time variation in return predictability results in Figure 1. We also present additional full-sample results, and show that the magnitudes in our sample are consistent with the previous literature.

3.1 Lagged responses

The right panel of Figure 1 summarizes the results of regressing abnormal returns on lagged news, in each year of our sample. Following TSM, our main specification is

$$Y^i_{t,u,v} = s \times Sent^i_t + \boldsymbol{\beta}' \boldsymbol{X}^i_t + \epsilon^i_{t,u,v} \tag{2}$$

where $Y^i_{t,u,v}$ is the abnormal return variable, $Sent^i_t$ is lagged sentiment and $\boldsymbol{X}^i_t$ is a vector of lagged control variables including a constant. Stock i enters our analysis on day t if that stock was a member of the S&P 500 index on day t, and if a news article about that stock appeared in our news sample from 4pm on business day $t-1$ to 4pm on day t.[17]

nies, banks, trusts, pension funds and others, must file 13Fs. Short sales are not included in 13Fs.

[14] In our regressions, we are interested in whether institutional ownership 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.

[15] In Sec. 7.2 we show removing earnings announcements from our sample does not change the results.

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

[17] TSM use a 3:30pm cutoff. Our results are qualitatively similar when using a 3:30pm cutoff.

We refer to such days as event days. As in TSM, we run a pooled regression, with no firm fixed effects. And we cluster standard errors by trading day in the above and in all subsequent variants of the returns regressions.

The response variable $Y^i_{t,u,v}$ is either the excess return or CAR (relative to the six factor model described in Section 2.2) 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 $v = 10$). We sometimes refer to this effect as a *lagged response*, which means a future stock price move in response to lagged (past) news.

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.[18] These controls are analogous to those used by TSM.[19] In addition, we control for short interest and institutional ownership, because these will be important interaction terms in our analysis in Sections 5 and 6. Finally, to ensure that the effect of sentiment on returns 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.[20]

To interpret the magnitude of the results in Figure 1 and compare with TSM, we present the full-sample results for one- and ten-day ahead returns in Table 1 columns 5-8. Over the full sample, the $Sent$ coefficient for one-day ahead CAR is 0.914. From Table 3, 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 (0.914×0.021) 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. Table 1 also shows that $Sent$ has a large and significant effect on ten-day ahead excess returns, while the effect on ten-day ahead abnormal returns is positive and significant but of a smaller magnitude. We discuss this result further Section 5.1, where we analyze the dynamics of return responses to news shocks in more detail.

[18]We include four CARs as controls: $CAR_{0,0}$, $CAR_{-1,-1}$, $CAR_{-2,-2}$ and $CAR_{-30,-3}$, where $CAR_{u,v}$ on day t is the cumulative abnormal return over trading days $[t+u, t+v]$. For $i \in \{0, -1, -2\}$, $CAR_{i,i}$ is calculated using coefficient estimates from the 6-factor model over the trading days $[t-251+i, t-21+i]$. $CAR_{-30,-3}$, $CAR_{1,1}$ 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.

[19]TSM use stock turnover rather than the Amihud (2002) illiquidity measure. We replicate TSM's exact specification in Table A8 of the Internet Appendix and find the results are similar to ours.

[20]We discuss the volatility controls further in Section 7.3, but note that the inclusion of these controls has little effect on the $Sent$ coefficients in our regressions.

The 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 reasons for such high annualized returns 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 (2021) report frictionless long/short returns in the 20%-30% range (their Table 3). We discuss the economic magnitude of the underreaction effect further in Section 5.

3.2 Contemporaneous responses

The left panel of Figure 1 shows the sentiment coefficient in annual regresions of abnormal returns on contemporaneous news in each year of our sample. The specification is a contemporaneous version of equation (2) given by

$$Y_t^i = s \times Sent_t^i + \boldsymbol{\beta}' \boldsymbol{X}_t^i + \epsilon_t^i. \tag{3}$$

$\boldsymbol{X}_t^i$ is the same set of controls as in (2) with the exception of $CAR_{0,0}$, which is now dropped; the remaining controls in $\boldsymbol{X}_t^i$ are already measured prior to day t.

While the timing in (3) is the same as the $FFCAR_{+0,+0}$ specification in Table VI of TSM, there is a potential endogeneity problem between the day t return measures and day t news, since the news may on occasion be written in response to a large stock price movement. 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 individual stock 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 greatly reduces the likelihood that after-hours news stories about individual stocks are written solely in response to after-hours individual stock price movements. In fact we are not aware of any such news stories. We refer to this sentiment measure as “pre-9:30am news”.

The left panel of Figure 1 shows the *Sent* coefficients s from annual regression in (3) with pre-9:30am news. The full-sample results for both sentiment measures are shown in the first four columns of Table 1. Not surprisingly, for the full sample, the s coefficient in the contemporaneous news regressions is much larger than the s coefficient in the lagged news regressions. For example, the same-day stock reaction to news is 5-6 times larger than the next-day reaction. In addition, the s coefficient from the pre-9:30am news regression is almost as large as that from the full-day news regression.

4 Hypothesis development

Motivated by Figure 1, we now develop hypotheses to explain the time-variation in the news-returns relationship. We first consider a one-period model in Section 4.1 to illustrate how this relationship depends on investor composition, intermediary constraints, and the information content of news. In Section 4.2 we extend the model to two periods to study stock price *underreaction*. The model predictions are investigated empirically in subsequent sections. Proofs and further model details are available in a Model Appendix.

4.1 A one-period model with three types of agents

To support our hypothesis formulation, we start with a simple one-period model with three types of agents (indexed by i): financial intermediaries, passive institutional investors, and all other investors, whom we call non-institutional. Type i agents represent fraction ϕ_i of all investors, with $\sum_{i=1}^{3} \phi_i = 1, \phi_i > 0$. Agents invest in N securities (indexed by j) that pay liquidating dividends at the end of the period. Security j has an exogenous supply of S_j shares, and $S \in \mathbb{R}^N$ denotes the vector of the number of shares supplied.

A type i agent solves the following static mean-variance portfolio problem with a possible benchmarking penalty,

$$\max_{w} w^\top (\mu_i - P) - \frac{\gamma_i}{2} w^\top \Sigma w - \frac{1}{2} (w - x)^\top \Lambda_i (w - x) \tag{4}$$

for $w, x, \mu_i, P \in \mathbb{R}^N$. Here, P is a vector of prices, μ_i is agent i's expectations about end-of-period security values, w is the portfolio, and Σ is the covariance matrix of dividend payouts, which we take to be common to all investors for simplicity. The benchmark target is given by x, and $\Lambda_i \in \mathbb{R}^{N \times N}$ determines the penalty for deviating from x.

The three types of agents differ in their beliefs (expectations about end-of-period security values), their risk aversion, and their benchmarking constraints.

- For non-institutional investors ($i = 1$), $\Lambda_1 = diag\,(\lambda_1)\,, \lambda_1 = 0$. Then (4) reduces to a standard mean-variance problem. We normalize risk-aversion γ_1 to 1.

- For the intermediaries ($i = 2$), we again assume $\Lambda_2 = diag\left(\lambda_2\right), \lambda_2 = 0$. Intermediaries are risk-neutral, but they are subject to capital requirements in the form of a value-at-risk (VaR) constraint. As detailed in Section 3.4 of Shin (2010), the VaR constraint leads to an objective of the form (4) (without the last term), with γ_2 introduced as a Lagrange multiplier. We emphasize this interpretation of the objective because capital constraints are important for the intermediary leverage and capital measures discussed in the introduction; see in particular Adrian et al. (2014). We assume that $\gamma_2 < 1$, so that the effective risk aversion of intermediaries is less than that of non-institutional investors.

- Passive investors ($i = 3$), which we think of as index funds, have $\gamma_3 = 0$, but they are constrained by the last term in (4), which penalizes deviations from a target portfolio vector x. For simplicity, we take $\Lambda_3 = diag\left(\lambda_3\right)$ with $\lambda_3 > 1$.

The key features of the three types of agents can be summarized as follows:

Investor	Weight	Risk Aversion	Benchmarking	Constrained
Non-institutional	ϕ_1	$\gamma_1 = 1$	$\lambda_1 = 0$	Medium
Intermediaries	ϕ_2	$\gamma_2 < 1$	$\lambda_2 = 0$	Least
Passive	ϕ_3	$\gamma_3 = 0$	$\lambda_3 > 1$	Most

The ranking of agents' constraints will become clear from their investment choices, which we discuss next.

From (4), we can solve for type i investors' demand for the securities

$$w_i = \left(\gamma_i \Sigma + \Lambda_i\right)^{-1} \left(\mu_i - P + \Lambda_i x\right). \tag{5}$$

To solve for the equilibrium prices,we impose the market clearing condition $\sum_i \phi_i w_i = S$ As the risk premium in the prices is not central to our analysis, we set $S_j = x_j = 0, \forall j$. For simplicity, we assume that Σ is a diagonal matrix with all entries equal to σ^2. With these conditions, substituting (5) in the market clearing condition and solving for P_j yields.

$$P_j = \left(\sum_i \frac{\phi_i}{\gamma_i \sigma^2 + \lambda_i}\right)^{-1} \sum_i \frac{\phi_i}{\gamma_i \sigma^2 + \lambda_i} \mu_{ij}. \tag{6}$$

We interpret P_j as the end-of-period price, where the start-of-period price is zero.[21] Notice that γ_i and λ_i have similar effects here and also in (5). We take $\lambda_3 > 1$ and $0 < \sigma < 1$

[21] This follows from $S_j = x_j = 0$ and the assumption that unconditional dividend expectations are zero.

to support our interpretation of the passive investors as the most constrained investors in (5), which we believe properly reflects institutional constraints faced by indexers.

The beliefs reflected in the conditional means μ_{ij} may depend on many factors. We do not model belief formation but simply capture the idea that these expectations respond to news. Let I_j denote public news about stock j, and let τ denote the informativeness of the news, which is homogeneous across securities and investors. For example, I_j could be a noisy signal of a stock's dividend, and τ could be the precision of the signal; for now, it is assumed I_j is seen immediately by all investors. Larger values of I_j reflect more favorable news for stock j. We assume that

$$\frac{\partial \mu_{1j}}{\partial I_j} = \frac{\partial \mu_{2j}}{\partial I_j} = f(\tau) \quad \text{and} \quad \frac{\partial \mu_{3j}}{\partial I_j} = 0, \tag{7}$$

where $f(\tau) > 0$ and is increasing in τ. In other words, passive investors ($i = 3$) do not respond to news, but all other investors do and their response is greater for more informative news. We further assume that the variance $\sigma^2 = \sigma^2(\tau)$ is decreasing in τ to reflect that investors face less uncertainy in markets with more informative news.

Using (7) and the price from (6), we find that the sensitivity of the price P_j to news is

$$\frac{\partial P_j}{\partial I_j} = \frac{\frac{\phi_1}{\sigma^2(\tau)} + \frac{\phi_2}{\gamma_2 \sigma^2(\tau)}}{\frac{\phi_1}{\sigma^2(\tau)} + \frac{\phi_2}{\gamma_2 \sigma^2(\tau)} + \frac{\phi_3}{\lambda_3}} f(\tau). \tag{8}$$

Under the assumptions of the model, it has the following properties, all of which can be verified by taking derivatives in (8) and simplifying:

Proposition 1 *The price sensitivity to news $\partial P_j / \partial I_j$,*

(a) increases with more intermediaries (ϕ_2) and decreases with more passive investors (ϕ_3);

(b) increases when intermediaries are less constrained, i.e., have lower γ_2;

(c) increases as the information content τ of news grows.

It is worth emphasizing two frictions in the model that are key for the above results. The first is that passive investors do not update their beliefs about dividends in response to news. This means there is no term in the numerator of (8) that reflects ϕ_3. The second is that passive investors (indexers) are institutionally constrained to track a portfolio target x, and given our assumption that $\lambda_3 > 1$ this constraint makes their share demands less price elastic than the demands of intermediaries or of non-institutional investors. This feature of the model is reminiscent of Gabaix and Koijen (2021).

4.2 A two-period extension

We extend the model to two periods, which allows us to make predictions on price *underreaction* to news, conditional on investor composition, intermediary constraints, and news informativeness. We first show that price underreaction to news depend on these factors in a similar way as in Proposition 1: future price changes are more responsive to news when the fraction of intermediaries increases, or the fraction of passive investors decreases, or intermediaries become less financially constrained, or news becomes more informative. Then we study how technological innovation impacts price reactions to public news. We introduce a parameter that can be interpreted as the aggregate technological capacity constraint in the economy. And we establish a direct mapping from this technological constraint to investors' information acquisition and market participation decisions.

The above predictions crucially depend on the assumption that non-institutional investors and intermediaries behave like *newswatchers*, in the sense of Hong and Stein (1999): they "formulate their asset demands based on the static-optimization notion that they buy and hold until the liquidating dividend" and they do not make inferences about dividends from prices. We view this as a simple, yet intuitively appealing, mechanism to generate price underreaction to news. We discuss alternative mechanisms that lead to price underreaction in Section 6.3.

In this extended model, we divide the single period in Section 4.1 into subperiods 0 and 1. Each security pays a one-time liquidating dividend at the end of period 1. In what follows, we explain the information set of the agents and their decision to participate in trading in each period. The ultimate goal is to derive the equilibrium stock prices in each period, and then study the price (under-)reaction to news.

Information set, market participation, and delayed trading

In period 0, a fraction $\theta \in [0, 1]$ of the non-institutional and intermediary investors pays attention to stock j and trades that security, while the remaining fraction $1 - \theta$ does not pay attention and stays out of the market (until period 1). We interpret θ as the technological capacity constraint faced by investors. As technology improves, investors are able to follow more stocks and a greater fraction of investors is able to follow each stock in period 0. All investors who pay attention to stock j receive the same public signal

I_j about stock j's liquidating dividend.

Conditional on the signal received (I_j), the θ fraction of non-institutional and intermediary investors solve the "myopic" portfolio problem in (4). They are "myopic" in the sense that they do not hedge against changing investment opportunities as information is revealed to more agents over time, and they employ a buy-and-hold strategy until the end of period 1, not realizing that they will trade again at the start of period 1.

In period 1, the remaining $1-\theta$ fraction of non-institutional and intermediary investors now also have access to the signal I_j, and now all non-institutional and intermediary investors are fully attentive to stock j with the same information set. The $1-\theta$ fraction of non-institutional and intermediary investors who did not participate in period 0 trading do so now, as do the θ fraction of traders who did – myopically – participate in period 0 trading. In period 1, therefore, all investors see I_j and solve the static problemx in (4).

All other assumptions remain the same as in the one-period model. In particular, the passive institutional investors behave as before – their demand does not respond to news and they submit the same demand curve in both periods 0 and 1.

The present model is characterized by delayed trading in the following sense. Assume there is now a positive supply of each stock j, and let $X_{2j}(\theta)$ denote the equilibrium holdings of stock j by the intermediary sector when only θ fraction of non-institutional and intermediary investors pay attention to j. We show in the Model Appendix, that $\partial X_{2j}(\theta)/\partial\theta > 0$, which means that $X_{2j}(1)-X_{2j}(\theta) > 0$ assuming that $\theta < 1$. Since $X_{2j}(1)$ is the equilibrium holdings of stock j by financial intermediaries in period 1 (when $\theta = 1$), the financial intermediation sector must add to its holdings of j over time. Furthermore, we show that $\partial(X_{2j}(1) - X_{2j}(\theta))/\partial I_j > 0$, which means that with positive news about the stock, the financial intermediation sector will need to buy even more stock in period 1 relative to period 0. With slow diffusion of information, institutional investors (the intermediaries in our model) trade gradually.

Equilibrium prices

Given the above assumptions and setting $\mu_{3j} = 0$ for simplicity, the period 1 price P_{1j} is the same as the price in the one-period model given by (6), i.e.,

$$P_{1j} = \frac{\frac{\phi_1}{\sigma^2}\mu_{1j} + \frac{\phi_2}{\gamma_2\sigma^2}\mu_{2j}}{\frac{\phi_1}{\sigma^2} + \frac{\phi_2}{\gamma_2\sigma^2} + \frac{\phi_3}{\lambda_3}} = \frac{\phi_1\mu_{1j} + \frac{\phi_2}{\gamma_2}\mu_{2j}}{\phi_1 + \frac{\phi_2}{\gamma_2} + \frac{\phi_3}{\lambda_3}\sigma^2} \tag{9}$$

The period 1 price reflects information acquisition by *all* investors.

Given our newswatchers assumption, the period 0 equilibrium is identical to the period 1 equilibrium, except the fraction of non-institutional and intermediary investors is given by $\theta\phi_1$ and $\theta\phi_2$. The period 0 price is therefore

$$P_{0j} = \frac{\phi_1 \mu_{1j} + \frac{\phi_2}{\gamma_2}\mu_{2j}}{\phi_1 + \frac{\phi_2}{\gamma_2} + \frac{\phi_3}{\lambda_3}\frac{\sigma^2}{\theta}} \tag{10}$$

It follows that

$$P_{0j} = \alpha(\theta) P_{1j} \qquad \text{and} \qquad P_{1j} - P_{0j} = (1 - \alpha(\theta)) P_{1j} \tag{11}$$

where

$$\alpha(\theta) = \frac{\phi_1 + \frac{\phi_2}{\gamma_2} + \frac{\phi_3}{\lambda_3}\sigma^2}{\phi_1 + \frac{\phi_2}{\gamma_2} + \frac{\phi_3}{\lambda_3}\frac{\sigma^2}{\theta}} \in [0, 1].$$

Therefore, when news I_j arrives, the period 0 price reaction will be smaller than the full (period 1) price reaction, and the price change from period 0 to period 1, $P_{1j} - P_{0j}$, will be nonzero and will go in the same direction as the period 0 price response:

$$\frac{\partial}{\partial I_j}(P_{1j} - P_{0j}) > 0.$$

In light of (11) the following proposition is immediate:

Proposition 2 *Proposition 1 (a)–(c) all apply to the period 0 price response to news, $\partial P_{0j}/\partial I_j$, and to the period 1 price change in response to news, $\partial(P_{1j} - P_{0j})/\partial I_j$.*

To study the effect of technological innovation, note that $\alpha(\theta)$ is increasing in θ. Hence, according to (11), if technology improves, i.e., as θ increases, the model makes an unambiguous prediction:

Proposition 3 *As θ increases, the period 0 price response to news $\partial P_{0j}/\partial I_j$ increases, and the period 1 price change in response to news $\partial(P_{1j} - P_{0j})/\partial I_j$ decreases.*

As already mentioned, we interpret P_{0j} as the period 0 price change, relative to a start-of-period price of zero (see footnote 21). Proposition 2 thus says that the contemporaneous price response to news, $\partial P_{0j}/\partial I_j$, and the price response to lagged news, $\partial(P_{1j} - P_{0j})/\partial I_j$, both increase when: there are more intermediaries (higher ϕ_2); fewer passive investors (lower ϕ_3); less constrained intermediaries (lower γ_2); or more informative news (higher τ). Consider the impact of having a less constrained intermediary sector. Less constrained intermediaries trade more aggressively in period 0 when news arrives, thus causing P_{0j} to be more responsive to news. These intermediaries are newswatchers in that they only consider the final dividend, and not the period 1 price, in formulating their demands. Now a fraction $1 - \theta$ of intermediaries was not in the market in period 0, and enters the market in period 1. These agents did not have the capacity to response to period 0 news when it arrived (perhaps because they were in a meeting with the head of the trading desk or with a client, or because they were focused on news about other securities). The less constrained intermediaries are, the *more* period 1 trading there will be in response to period 0 news. Thus higher contemporaneous and higher future price responses to news occur together. We have not sought to explain the fundamental source of this newswatcher underreaction; instead, we have focused on how the underreaction to news (and the contemporaneous response) interact with the capacity and mix of institutional investors and the informativeness of news.

Proposition 3, on the other hand, says that the contemporaneous price response to news and the next period price response to lagged news should move in opposite directions as the technological constraint in the economy changes. With fewer inattentive agents (higher θ), there is a larger contemporaneous price response to news, and there is less underreaction. This prediction is very intuitive: as markets become more efficient the contemporaneous price response to news increases, while the price response to lagged news decreases. Yet, as we discuss next, this prediction cannot account for the empirical patterns we document.

4.3 Model predictions

We now formulate testable hypotheses based on the implications of the model. We interpret $\partial P_{0j}/\partial I_j$ as the contemporaneous response to news and $\partial(P_{1j} - P_{0j})/\partial I_j$ as the lagged response (i.e., stock price response to past news). We start with a naive prediction based on Proposition 3, considering only the change in technology over time:

Prediction 1 (Faster technology). With technology accelerating the dissemination and processing of news, the contemporaneous price response to news should grow stronger and the lagged response to news should weaken.

We have already seen in Figure 1 that this prediction is contradicted by the data: the strength of the contemporaneous response varies nonmonotonically over time, and the strength of the lagged response often moves in the same direction as the strength of the contemporaneous response. Although information processing technology has unquestionably improved over the period we study, faster technology cannot explain the patterns in Figure 1. We therefore consider other predictions of the model, starting with parts (a) and (b) of Propositions 1 and 2.

Prediction 2 (Changing intermediary capacity). An increase in the capacity of financial intermediaries should strengthen both the contemporaneous price response to news and the lagged response to news. Tightening of their capacity should have the opposite effects.

Prediction 3 (Growth in passive investing). An increase in passive investing should weaken both the contemporaneous price response to news and the lagged response to news.

As intermediary capacity has fluctuated over time, Prediction 2 predicts cycles in the strength of the news-returns relationship. Passive investing has generally grown over the period we study, so Prediction 3 predicts a growing underreaction, partly offsetting the trend resulting from faster technology. Both Prediction 2 and Prediction 3 imply comovement in the contemporaneous and lagged response to news, which Prediction 1 cannot explain.

Our final prediction is based on part (c) of Propositions 1 and 2. Translating this result from the model to our empirical setting requires time variation in the informativeness of news (the parameter τ in the model). We will use the entropy measure discussed in Section 2.1 for this purpose.

Prediction 4 (Varying news informativeness). In periods of greater news informativeness, both the contemporaneous price response to news and the lagged response to news should be stronger.

We follow a common framework for testing Predictions 2–4, using the passive ownership, intermediary capital, and entropy measures introduced in Section 2. Building on the basic specification in (2), we regress same-day and next-day returns on news sentiment and controls, adding an interaction term for each prediction. The interaction term interacts sentiment with one of the following: a measure of intermediary capacity, a measure of passive ownership, or a measure of news informativness (entropy). Our predictions imply the following hypotheses for the signs of the interaction coeffecients:

Return	Intermediary Capacity	Passive Owernship	Entropy
Contemporaneous	+	−	+
Lagged	+	−	+

As already noted, Prediction 1 – that technological change is the primary driver of the news-returns relationship – is contradicted by Figure 1, so we do not address it further, but we expect that improving technology over the period we study would generally lead to a diminished lagged response to news as the contemporaneous response strengthens.

5 Testing drivers of the news-returns relationship

In Section 4 we argued that the dynamics of intermediary capital, passive ownership, and news informativeness are important drivers of price responses to contemporaneous and lagged news. This section empirically tests these predictions.

5.1 Intermediary capital

We have argued in Section 4 that less capital constrained intermediaries should increase stock price responses to contemporaneous and lagged news. The intermediary capacity measures we consider can be seen as proxies for $1/\gamma_2$, where $\gamma_2 > 0$ in Section 4 measures the degree to which intermediaries are financially constrained. 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

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

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 2 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

$$CR_t = \frac{\sum_i Market\ Equity_{i,t}}{\sum_i (Market\ Equity_{i,t} + Book\ Debt_{i,t})}$$

where the sum is taken over all New York Fed primary dealers as of time t, and $Market\ Equity_{i,t}$

is the market capitalization of the i^{th} primary dealer's parent bank holding company. 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 is procyclical, as can be seen from Figure 2. As discussed in the appendix of He et al. (2017), procyclical leverage describes hedge funds whereas countercyclical leverage is more representative of commercial banks and thus less relevant to our setting. 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:

$$Y_{t,u,v}^i = s_0 \times Sent_t^i + s_1 \times Capacity_t + s_2 \times Sent_t^i \times Capacity_t + \boldsymbol{\beta}' \boldsymbol{X}_t^i + \epsilon_{t,u,v}^i, \tag{12}$$

where $Capacity_t$ is the most recently available level of either $Leverage_t^{BD}$ or CR_t as of event day t.[22] 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. Table 4 shows the results of this specification. The first three columns use CR_t measured at either the daily, monthly or quarterly frequency and the last column uses $Leverage_t^{BD}$ measured quarterly.[23]

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 (0.302×10 for the monthly specification against $s_0 = 5.978$). 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 $10\% \times 0.84 = 8.4\%$. This is the same order of magnitude as the contemporaneous stock price reaction to news. A 10% increase in CR_t also leads to a $0.194 \times 10\% = 1.94\%$ increase in $CAR_{1,1}$. Indeed this amount of variation is enough to capture the entire sample range of both annual $CAR_{1,1}$ sentiment coefficients in Figure 1.

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

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

These results are consistent with Prediction 2 in Section 4.3 that an increase in intermediary capacity results in larger price responses to contemporaneous and lagged news.

Dynamics of the sentiment effect

To better understand the impact of intermediary capital on the news-returns relationship over longer horizons, we construct the impulse responses of stock returns to a sentiment shock under different levels of intermediary capital. Specifically, we ask what happens to a \$100 investment in a hypothetical stock in response to a one standard deviation increase in $Sent_t^i$, under the following two assumptions about intermediary capital:

- Case 1: intermediary capacity equals its long-term average (the baseline case).
- Case 2: intermediary capacity is one standard deviation above its long-term average.

We calculate the impulse responses of excess and abnormal returns to the sentiment shock using the local projection method of Jorda (2005). This approach allows us to examine the effects over longer horizons. Figure 7 shows the results of this analysis. Section A5 of the Internet Appendix details the methodology.

Panel A of Figure 7 plots the impulse response of excess returns. The solid line in the panel is the baseline case where intermediary capacity is equal to its long-term mean (Case 1 above). On the news day (day zero), a one standard deviation positive sentiment shock increases the value of a \$100 portfolio to just under \$100.15. The value of the portfolio continues to increase for the next 25 trading days, and peaks at a level of just over \$100.20. It then stays constant at this level until day 40. Hence, the underreaction to a sentiment shock persists for roughly one month.

The dashed line in the panel corresponds to Case 2, where intermediary capacity is one standard deviation above its long-term mean. The initial news-day response is a little larger than in the baseline case, but the subsequent responses are substantially higher. By day 25, the portfolio has appreciated to \$100.30, and it continues to appreciate to \$100.35 over the ensuing 15 trading days. These results are consistent with the importance of institutional trading in generating an underreaction to news. The contemporaneous response to news is larger when intermediary capacity is higher; and the subsequent responses are much larger at times of high intermediary capacity. Conditional on high intermediary capacity, the underreaction to sentiment shocks persists for at least 40 trading days.

Panel B of Figure 7 shows the same analysis, but for cumulative abnormal returns. The difference between the baseline response (solid line) and the response conditional on high intermediary capacity (dashed line) is similar to the case of excess returns. Interestingly, at horizons longer than the 10-day post-event window of TSM (and our analysis thus far), cumulative abnormal returns in the baseline case show evidence of reversal, suggesting a day 0 overreaction to news. The impulse response conditional on a one standard deviation positive intermediary capacity shock remains very persistent even out to 40 days. This difference between excess and abnormal returns is an interesting topic for future research.

For our purposes, we note that the cumulative return response to news conditional on high intermediary capacity is considerably more persistent than the baseline case for *both* excess returns and CARs. In fact, the impact of high intermediary capacity increases over time. Cumulative abnormal returns drift in the direction of news for up to 25 trading days post the news event, and do not reverse after 40 trading days following the news event; for excess returns with high intermediary capacity, the impulse response continues to increase through all 40 trading days. The evidence is consistent with Prediction 2 in Section 4.3 – a pronounced news underreaction when an informationally constrained intermediary sector becomes less financially constrained.

Economic magnitude

From the end of day zero to the end of trading day 40, we see a 20-basis-point increase in excess return for a stock experiencing a one standard deviation positive sentiment shock, conditional on intermediary capacity being one standard deviation above its long-run mean. In response to a two-standard-deviation sentiment shock, which occurs in 5.25% of our firm-day observations, the effect doubles to 40 basis points. This effect is economically large in terms of portfolio returns. Consider a trading strategy where we hold a $200 long position in two-standard-deviation positive news stocks and a $200 short position in two-standard-deviation negative news stock. The above results imply a 40-trading-day portfolio excess return of 1.6%, or roughly 10% per annum for a 3-times levered portfolio (i.e. $100 in capital, $100 additional long, and $200 short). Admittedly, such opportunities are available only during times of high intermediary capacity.

5.2 Mutual fund ownership

We turn next to testing the effect of passive ownership in Prediction 3 of Section 4.3. Mutual fund ownership provides rich time-series (as shown in Figure 3) 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. A greater share of passive ownership corresponds to a larger value of ϕ_3 in Section 4.

For each stock, we employ three quarterly measures of the ownership mix:[24]

- $Passive/Market$ – the fraction of shares outstanding of a given stock that are held by passively managed mutual funds;

- $Active/Market$ – the fraction of shares outstanding held by actively managed mutual funds;

- $Passive/Fund\,Total$ – the fraction of shares outstanding held by passively managed mutual funds divided by the fraction of shares held by all mutual funds.

Table 5 shows the results of estimating the following modification of equation (2),

$$Y^i_{t,u,v} = s_0 \times Sent^i_t + s_1 \times Ownership^i_t + s_2 \times Sent^i_t \times Ownership^i_t + \boldsymbol{\beta}'\boldsymbol{X}^i_t + \epsilon^i_{t,u,v}, \quad (13)$$

where $Ownership^i_t$ is one of the three aforementioned measures of passive and active ownership for stock i.[25] All these measures are constructed at a quarterly frequency and merged to daily stock returns using the most recently available observation. The top panel of the table shows results for the excess returns, and the bottom panel shows the results for CARs.

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 0.167 (significant at the 1% level) interaction coefficient for 4pm-9:30am sentiment. However, higher active ownership of a stock marginally increases the degree of the underreaction to news one-day ahead,[26] and meaningfully increases the degree of underreaction to news ten days ahead with a coefficient of 0.176 (significant at the 1% level).

The third column in the table shows that a higher $Passive/Fund\,Total$ ratio decreases the contemporaneous stock price response to news with a $Sent \times Ownership$ coefficient of -0.031 (5% level). At the same time, a higher passive share of mutual fund ownership also decreases the price response to lagged news with a -0.015 coefficient for one-day responses and a coefficient of -0.1 (significant at the 1% level) for ten-day responses.

The size of the effect is large. When a stock's passive share ($Passive/Fund\ Total$) goes from 40% to 60% (a 1.4 standard deviation move according to Table 3), its $CAR_{0,0}$

[24]These mutual fund classification are explained in Section 2.

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

[26]The sentiment-ownership interaction for one-day ahead CARs and $Active/Market$ is 0.034, as can be seen from the bottom panel of Table 5. The p-value of this coefficient is 0.14.

response to contemporaneous news falls by 10%, its $CAR_{1,1}$ response to lagged news is cut by 30% (the 0.909 coefficient is decreased by 0.015×20), and its $CAR_{1,10}$ response to lagged news switches signs from strongly positive to strongly negative. The results for $Passive/Market$ are qualitatively similar to those for $Passive/Fund\ Total$. These results are consistent with Prediction 3 from Section 4.3 that greater passive ownership results in weaker price responses to contemporaneous and lagged news.

Dynamics and magnitude of the sentiment effect

We also calculate the impulse response of excess and cumulative abnormal returns to a sentiment shock in the context of regression (13), where the interacting variable is $Passive/Fund\ Total$. The results are qualitatively similar to those of Section 5.1 where the interacting variable is intermediary capacity. Conditional on a one standard deviation decrease in $Passive/Fund\ Total$, the contemporaneous response to news is higher, and the post-news price drift is considerably higher than in the baseline case. These impulse responses are shown in Figure A4 in the Internet Appendix.

We can also consider a levered portfolio going long positive-news stocks and short negative-news stocks, conditional on those stocks having low passive ownership. The return of that portfolio is quite large. The argument mirrors that of Section 5.1. Because this strategy exploits cross-sectional variation in stocks' mutual fund ownership, such opportunities may exist even in times of low intermediary capacity.

5.3 The informativeness of news

As we argued in Section 4.3 Prediction 4, returns should be more responsive to contemporaneous and lagged news when news flow is more informative. We use average entropy across all articles in a given time period as our measure of news informativeness. Panel G of Figure 5 shows that average cross-sectional entropy exhibits large time series variation, suggesting that some economic environments are richer in news than others. This variation should be related to the magnitude of return responses to contemporaneous and lagged news. As a robustness check for our entropy measure, in the Internet Appendix, we show that in years with higher entropy, news sentiment is a better forecaster of future earnings surprises, as measured by SUE in (1). Hence, entropy, a purely text-based measure of news informativeness, is consistent with an earnings-based measure of informativeness, namely the ability of news sentiment to forecast earnings. Sections A8, A9, and Figure A6 of the Internet Appendix give details of this analysis.

Figure 6 shows the correlation between quarterly average entropy, quarterly average ownership ratios from Section 5.2, and quarterly intermediary capacity. Entropy is negatively correlated with the time-series average of our two passive ownership measures, and positively correlated with the time-series average of the active ownership measure and with intermediary capacity. We now analyze a version of the regressions in (12) and (13) where intermediary capacity and ownership ratios are replaced with daily, monthly, quarterly, or annual average entropy:

$$Y^i_{t,u,v} = s_0 \times Sent^i_t + s_1 \times Entropy_t + s_2 \times Sent^i_t \times Entropy_t + \boldsymbol{\beta}'\boldsymbol{X}^i_t + \epsilon^i_{t,u,v}. \qquad (14)$$

Daily $Entropy_t$ is calculated as the average of all article-level entropies in day t. Monthly $Entropy_t$ is the average of all daily entropies within the $[t-30, t]$ window leading up to day t. Quarterly and annual entropies are calculated by averaging daily entropies in the $[t-91, t]$ and $[t-365, t]$ day windows.[27] The results of this regression are shown in Table 6. The top panel of the table shows results for excess returns as the dependent variable, and the bottom panel shows the results for CAR. We focus on the CAR results in our discussion, though the excess return results are qualitatively similar.

For the contemporaneous regressions, the sentiment-entropy interactions are significant in seven out of eight cases, and the economic magnitude of the effect is very large. For example, for quarterly entropy and 4pm-9:30am news, the s_0 coefficient in (14) is 6.22 and the interaction coefficient with entropy is 23.183; both are highly significant. Given the standard deviation of quarterly entropy from Table 3 of 0.048, a one standard deviation increase in entropy increases the return responsiveness to contemporaneous sentiment by $23.183 \times 0.048 = 1.113$, which is a large effect. For the one-day ahead CAR regression with quarterly entropy, the s_0 coefficient is 0.893 and the interaction term for quarterly entropy is 7.916; again both are highly siginficant. So a one standard deviation increase in quarterly entropy increases the effect of news on one-day ahead returns by $7.916 \times 0.048 = 0.380$, which is a very large effect relative to s_0. The impact for one-day ahead returns with annual entropy is similarly large. For ten-day ahead returns, the interaction term for quarterly and annual entropy is positive and larger than the interaction term for one-day ahead returns, but is not significant. However, the interaction terms for daily and monthly entropy for ten-day ahead returns are large, positive, and significant – for example, the sentiment-monthly entropy interaction term for ten-day ahead returns is 20.05 and significant at the 5% level.

[27] We demean all entropy measures in (14) using their full-sample means.

The results are consistent with Prediction 4 from Section 4.3 that more informative news flow results in larger price responses to contemporaneous and lagged news.

Dynamics and magnitude of the sentiment effect

We also calculate the impulse response of excess and abnormal returns to a sentiment shock in the context of regression (14), where the interacting variable is monthly entropy. The results are qualitatively similar to those of Sections 5.1 and 5.2 where the interacting variables are intermediary capacity and $Passive/Fund\ Total$. Conditional on a one standard deviation increase in monthly entropy, the contemporaneous response to news is higher, and the post-news price drift is considerably higher, than in the baseline case. These impulse response results are shown in Figure A5 in the Internet Appendix. The magnitude of the return response to a news shock, conditional on a one standard deviation increase in monthly entropy, does not appear to increase over time relative to the baseline case (of entropy at its long-term average).

6 Channels

In Section 5 we presented evidence consistent with our hypotheses that variation in intermediary capital, passive ownership, and news informativeness impacts the news-returns relationship. However, our evidence argues against purely technological drivers of the relationship because price responses to contemporaneous and lagged news generally increase or decrease together, which is the opposite of the implication from the technological constraint channel. Two other potential drivers for stock underreaction to news are short-sale constraints and serial correlation in news flow. In Section 6.1, we test the former and find that short-sale constraints alone cannot fully explain stock price underreaction. Section 6.2 rules out serial correlation in news flow as the channel for underreaction. Section 6.3 discusses three other mechanisms that could potentially explain our findings: slow diffusion of information, overconfidence with self-attribution bias, and strategic order-splitting by institutions. All result in delayed trading by institutional investors.

6.1 Short-selling constraints

When a company experiences surprisingly bad news, some market participants may short its stock, anticipating and contributing to a decline in the stock price. However, in a mechanism described by Miller (1977), they may not be able to sell short the desired amount of stock if doing so is costly, and this constraint may slow the process by which bad news gets incorporated in the stock price, causing an underreaction. If short-sale constraints fully explain the underreaction, we should (1) observe more underreaction in stocks with more binding short-sale constraints, and (2) only observe underreaction when bad news comes out. Since short-sale constraints are plausibly related to intermediary capital and to the presence of institutional owners in a stock, such constraints are a tempting explanation for our finding of a systematic relationship between intermediary capital and institutional ownership and underreaction.

To test these two hypotheses, we group stocks by the tightness of their short-sale constraints and the tone of the news, then examine which group exhibits more underreaction. We use measures of short interest and institutional ownership to proxy for the short-sale constraints. Asquith, Pathak and Ritter (2005) posit that short interest captures the short-sale demand, and institutional ownership is a proxy for the supply of lendable shares. Stocks with the highest short interest and the lowest institutional ownership will have the most binding short-sale constraints. The short interest variable (SI) is defined in Section 2.2. For institutional ownership, we use the residual measure (RI) introduced by Nagel (2005), which adjusts for size. We first perform a logit transformation on the institutional ownership variable (IO) from Section 2.2. Then for each quarter, we regress the transformed variable on log market cap and squared log market cap. The RI measure is defined as the residual from this regression. Nagel (2005) argues that, because institutional ownership and firm size are highly correlated, sorting on IO is akin to sorting on size. To capture the effect of IO on short-sale constraints, it is therefore necessary to take out the firm size effect.[28]

The first hypothesis implies that stocks with higher SI and lower RI should exhibit more underreaction. So we first sort stocks by SI and RI. Specifically, for each month, we obtain the median SI and the median RI across all stock-day observations within that month. Using these cutoffs, we double sort the stocks by SI and RI independently. In each bucket, we run the main specification in equation (2). We are interested in the coefficient s, which captures the stock price underreaction to news.

Table 7 panel A shows the coefficient estimates. We focus on the responses of cumulative abnormal returns, though the excess return results are similar. Over both the one-day horizon and the ten-day horizon, stocks with high SI and *high* RI exhibit the largest magnitude of underreaction, and the underreaction is highly significant at the 1%

[28]In unreported results, we use IO instead of RI in the double and triple sorts below, and also try dependent sorts instead of independent sorts. The results remain qualitatively the same.

level. These stocks have less binding short-sale constraints than those with high SI and low RI, yet they show more underreaction. In fact, low SI and low RI stocks, again not the short-sale constrained group, also show more underreaction than the high SI and low RI ones. This contradicts the first prediction of the short-sale constraint story.

We then test the second prediction on the asymmetric response to good news versus bad news. To that end, we obtain the median sentiment, across all stock-day observations within a month. Using this sentiment cutoff and the SI and RI cutoffs from above, we triple sort stocks by sentiment, SI, and RI independently, and run the main specification in equation (2) for each bucket. In Table 8, panel A shows the coefficient estimates for the low sentiment buckets, and panel B shows the results for the the high sentiment buckets.

Over a one-day horizon, we observe a highly significant coefficient of 0.976 for cumulative abnormal returns in the low sentiment, high SI, low RI bucket, which is the bucket with the most binding short-sale constraint, as well as bad news. This is consistent with the prediction that stocks with tight short-sale constraints underreact to bad news, but not to good news. But we also see evidence of underreaction in the low sentiment, low SI, low RI grouping, and this effect is unlikely to be caused by short-sale constraints since these stocks are not heavily shorted.

Furthermore, the triple sort results are not robust to different return horizons. At the ten-day horizon, we observe the strongest $CAR_{1,10}$ response in the high sentiment, high SI, high RI bucket, with a coefficient of 4.149 (significant at the 10% level). And we observe a similar response in the low sentiment, high SI, high RI bucket, which is not short-sale constrained. For other groups where short sale constraints are most binding (those with high SI and low RI), we do not observe significant underreaction nor asymmetric responses across different news tone. These results argue against the second hypothesis.

6.2 Serial correlation of news flow

Market participants may underreact to news because they do not fully understand the data generating process. In this section, we consider a particular aspect of the data generating process – the autocorrelation of news. Wang, Zhang, and Zhu (2018) document news sentiment momentum at a monthly frequency, and Huang, Tan, and Wermers (2020) show that news tone is highly persistent within-day and across consecutive days. Suppose market participants are unaware of this positive autocorrelation and simply assume independence in news tone. Investors will then respond to today's news unaware that tomorrow's news will likely have a similar tone. When tomorrow's news arrives it will surprise investors and cause a stock price reaction, even though this should have been forecastable using news from today. There will appear to be "underreaction" of prices to news, but this underreaction will operate entirely through the forecastability of tomorrow's news by today's news. We refer to this as the *news autocorrelation hypothesis.*

To test this hypothesis, we start from the following two panel regressions,

$$\begin{aligned} Y^i_{t,u,v} &= s_0 \times Sent^i_t + s_1 \times Sent^i_t \times \xi^i_t + s_2 \times \xi^i_t + \boldsymbol{\gamma}'\boldsymbol{X}^i_t + \varepsilon^i_{t,u,v}, \\ Sent^i_{t,u,v} &= \beta_0 \times Sent^i_t + \beta_1 \times Sent^i_t \times \xi^i_t + \beta_2 \times \xi^i_t + \boldsymbol{\delta}'\boldsymbol{X}^i_t + \eta^i_{t+1}, \end{aligned} \tag{15}$$

where $Y^i_{t,u,v}$ is the excess or cumulative abnormal returns from day $t+u$ to $t+v$, $Sent^i_{t,u,v}$ is the average sentiment from day $t+u$ to $t+v$, ξ^i_t is either $Capacity_t$ or $Ownership^i_t$, and $\boldsymbol{X}_t$ is a vector of controls. With this notation, $Sent^i_t$ is the same as $Sent^i_{t,0,0}$. The β_0 coefficient in (15) is roughly 0.25 for one-day ahead sentiment and 0.18 for ten-day ahead sentiment, and is highly significant in both cases (see Table A18 in the Internet Appendix). We therefore would like to understand whether this predictability in news sentiment is responsible for the predictability in price underreaction.

If the predictability of $Y^i_{t,u,v}$ results from the predictability of $Sent^i_{t,u,v}$, then s_0 should be a multiple of β_0, and s_1 should be the same multiple of β_1. To see this, consider a return process where

$$Y^i_{t,u,v} = a + b \times Sent^i_{t,u,v} + e^i_{t,u,v}, \tag{16}$$

where the noise term is independent of $Sent^i_{t,u,v}$ and all time t information. Then the top equation in (15) would follow from the sentiment process in the bottom equation.[29] Given (16), news autocorrelation fully explains stock price underreaction, and thus the ratios of estimated coefficients $\hat{s}_0/\hat{s}_1$ and $\hat{\beta}_0/\hat{\beta}_1$ should be close to each other. In fact, this test has power against more general specifications than shown in (16).

With $\hat{\boldsymbol{\theta}} = (\hat{s}_0, \hat{s}_1, \hat{\beta}_0, \hat{\beta}_1)$, we thus arrive at the test statistic

$$g(\hat{\boldsymbol{\theta}}) \equiv \frac{\hat{s}_0}{\hat{s}_1} - \frac{\hat{\beta}_0}{\hat{\beta}_1}.$$

Under the news autocorrelation hypothesis, $g(\hat{\boldsymbol{\theta}}) \xrightarrow{p} 0$. If the ratios $\hat{s}_0/\hat{s}_1$ and $\hat{\beta}_0/\hat{\beta}_1$ are far from each other, then we can reject this hypothesis, and thus conclude that news autocorrelation does not fully explain the stock price underreaction.

Panel A of Table 9 shows the test statistics and the simulated p-values for the above regressions when ξ^i_t equals intermediary capacity. The details of the simulation are discussed in Section A6 of the Internet Appendix. Across different combinations of the CAR

[29]See Section A6 of the Internet Appendix for a precise derivation.

variables and the intermediary capacity measures, the test statistics are always significant at the 5% level. Hence, we can reject the null hypothesis that news autocorrelation is the only channel through which stock prices underreact to news. In Panel B of Table 9, we set ξ_t^i equal to our mutual fund ownership variables from Section 5.2 and redo the analysis. We reject the null for ten-day cumulative abnormal returns for all three ownership variables, and we reject the null hypothesis for one-day returns for the $Passive/Market$ ownership measure, and for $Active/Market$ measure for CAR (the one CAR non-rejection has a p-value of 0.1077).

These results indicate that news autocorrelation and market participants' lack of awareness of this correlation do not fully explain the dependence of stock price underreaction on our intermediary and ownership interaction variables.

6.3 Possible mechanisms for underreaction

Our hypothesis development in Section 4 uses Hong and Stein's (1999) newswatchers as a simple mechanism to generate investor underreaction, which then allows us to make predictions about the impact of investor composition and news informativeness on same-day and next-day price responses to news events. One behavioral explanation that is consistent with our empirical findings is that information diffuses slowly through a population of even informed agents.[30]

Another mechanism for underreaction involves overconfident investors and arbitrageurs. Daniel, Hirshleifer, and Subrahmanyam (1998) show that investor overconfidence and self-attribution bias (believing confirming signals, but ignoring disconfirming ones) can lead to short-term momentum in equilibrium.[31] The model of Kyle, Obizhaeva, and Wang (2018) is also noteworthy as it can generate autocorrelated returns from the perspective of an uninformed econometrician. That model relies on a form of disagreement in which all traders, who know their trades incur price impact, believe that their information is more precise than that of other traders. Interestingly, the return autocorrelation in Kyle,

[30]Hong, Lim, and Stein (2000) explain momentum via the slow diffusion of information. By exploiting differences in institutional ownership of Chinese A and B shares, Chui, Titman, and Subrahmanyam (2021) show "momentum is caused by informed investors who underreact to fundamental signals."

[31]A large literature offers models of investor underreaction and overreaction grounded in patterns of investor psychology. 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.

Obizhaeva, and Wang (2018) is stronger when market liquidity is greater, which aligns with our finding of a greater underreaction in periods of higher risk-bearing capacity. Daniel, Klos, and Rottke (2021) develop a model where short-term momentum and long-term reversals arise from the interaction of overconfident investors with Hong and Stein (1999) newswatchers, thus combining the two behavioral mechanisms we have in mind.

Periods of high intermediary capacity should be periods when large institutional investors are broadly active in markets. When a large institution observes news that it interprets as a surprisingly positive signal about a stock's prospects, it will buy that stock on the day of the news article's arrival. There is a large literature set in partial equilibrium on the optimal execution strategy for a trader who incurs price impact (Bertsimas and Lo 1998; Almgren and Chriss 2000; He and Mamaysky 2005; Obizhaeva and Wang 2012).[32] In all cases this involves splitting up a large trade into smaller components and trading the large order over time. If it is acting optimally, the large investor will split its order and trade on subsequent days after the news day. In a partial equilibrium setting, such order-splitting will create a contemporaneous price impact, as well as price moves in the same direction in subsequent days, thus leading to price underreaction. The greater the number of institutional investors who respond in the same way to the same piece of news, the larger will be the price response to contemporaneous news, and the larger will be the price response to lagged news.[33]

Extending this partial equilibrium logic to general equilibrium requires some market friction. In a frictionless market, rational arbitrageurs would realize the institution is

[32] There is ample empirical and anecdotal evidence of strategic trading by institutional investors concerned about revealing information through their trades. 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 more recent data from a large asset management firm, Frazzini, Israel, and Moskowitz (2018) report a mean target execution time of 2.7 days. Di Mascio, Lines, and Naik (2017), with detailed data on the trading activity of some institutional investors, report an average order execution time of 2 days, with a standard deviation of almost 3 days, suggesting a right-skewed distribution. Using the ANcerno trade execution data Brière et al. (2020) estimate that the average time to execute an institutional "parent" order (which is typically split into multiple "child" orders) varied between 1.5 days and 3 days between 1999 and 2015. Campbell, Ramadorai, and Schwartz (2009) report serial correlation in institutional trades consistent with strategic trading through order-splitting.

[33] Using ANcerno order data, Huang et al. (2020) find that institutional investors respond to news primarily within the first 30 minutes following the release of the news. However, they also find (in their Figure 3) abnormal trading consistent with an underreaction for a week following the news release. It is possible that the institutions most concerned with trading strategically are less likely to report their trades to ANcerno. Based on data from a large asset manager, Frazzini et al. (2018) report an average of 62 executed child orders for every parent order, typically executed within three days. This pattern is consistent with an underreaction driven by strategic trading.

executing a large trade in response to public news, and would trade in the same direction thereby accelerating the price response. One way to avoid the acceleration of price discovery is to assume arbitrageurs are capital constrained relative to the large institutional trading demand (Shleifer and Vishny 1997; Gromb and Vayanos 2010).

We believe that strategic trading by large, and potentially imperfectly rational, institutional investors is an important part of the story of the time variation in the news-returns relationship. A clean empirical demonstration of this hypothesis would require high-frequency investor trading data, which we do not have. A clean theoretical demonstration of this mechanism would require a model that produces predictable price impact from public signals that does not get arbitraged away. Kyle et al. (2018) comes closest. We hope future research will make headway in both of these areas.

7 Robustness checks

In Section 7.1 we examine how our analysis is related to prior work on the news-returns relationship. In Section 7.2 we check whether earnings announcements impact our results. Section 7.3 checks whether the effect of sentiment on future returns can be explained by either idiosyncratic or systematic volatility. Finally, Section 7.4 checks whether the effects of intermediary capital, ownership, and entropy on the news-returns relationship simply reflects economic uncertainty, as captured by the VIX.

7.1 Stock market reactions to shocks

In work related to ours, Frank and Sanati (2018, FS) find that stocks overreact to good news and underreact to bad news. They also find that both overreaction to good news and underreaction to bad news tend to occur only during times of scarce intermediary capital. These results contrast with ours in two important ways. As seen in Table 8, we do not find evidence of a strong asymmetry between good and bad news. In particular, there is underreaction in both cases. Furthermore, as our results in Table 4 show, an increase in intermediary capacity *increases* the degree of stock underreaction to news.

There are four important methodological differences between our study and FS. First, FS classify news articles as good or bad news based on whether the event day (i.e., the day of the news article release) abnormal return is positive or negative, and not by the tone of news article itself, as we do. Second, FS use only the firms that are in the S&P 500 as of October 2014 in their analysis. In our analysis, we only include firm-day observations if the firm was in the S&P 500 on the day in question. Third, while we use the level of intermediary capital as our interacting variable, FS use the quarterly growth rate of intermediary capital (their equation 10). We believe that the level of intermediary capital is a better reflection of the state of solvency of the financial system than the change: if the intermediary capital ratio falls slightly from a high level, it will still be the case that financial intermediaries are well capitalized and active in financial markets. Finally, our news sample consists of 1.36 million Reuters news articles about S&P 500 firms from 1996 to 2018, while the FS news sample consists of 61,170 Financial Times articles about S&P 500 firms from 1982 to 2013. While we cannot control for this last difference, we can control for the first three.

We replicate the FS methodology in our sample, and check whether we observe their results. We sort stock-day observations into quintiles (Q1 to Q5) based on the aggregate intermediary capital ratio growth rate. For each quintile, we split the observations by the sign of $CAR_{0,0}$, then compute the average cumulative abnormal returns for each subgroup over different subsequent holding periods. To be consistent with FS, we only use the list of S&P 500 firms as of October 2014 in this analysis. And we restrict the sample period to be January 1996–September 2013, which is the overlapping period between our full sample and the FS sample.

The top panel of Table 10 corresponds to the subsample with bad news ($CAR_{0,0} < 0$), and the bottom panel to the subsample with goods news ($CAR_{0,0} \geq 0$). This table should be compared to Table 8 from FS. We do not find an overreaction to good news. In fact, we find an overreaction to bad news, and an underreaction to good news (recalling that "news" is defined by $CAR_{0,0}$ for this comparison). The top panel of Table 10 shows the bad news firm-day observations bucketed by the innovation to the intermediary capital ratio. Across the five capital ratio buckets, we see a negative same day return, which is by construction, and positive returns over the subsequent one to 40 days. This indicates overreaction to bad news. On the other hand, the bottom panel of the table shows a positive contemporaneous return, again by construction, followed by positive subsequent returns. This is indicative of underreaction to good news. Furthermore, if anything, the degree of our effect increases with higher intermediary capital, as can be seen in the greater Q5 (high capital ratio growth) 40-day return relative to the Q1 (low capital ratio growth) 40-day return. This holds for both positive and negative news. This is consistent with our core results in Table 4.

The differences in our results in Table 10 and those in Table 8 of FS are likely due to our different news samples. Financial Times articles are much less frequent than Reuters articles and, when they are written, tend to cover weightier events. As Frank and Sanati write: "the Financial Times will tend to have a somewhat higher threshold for something to be considered 'newsworthy.' " We agree with this assessment. Thus it is likely that the set of news-day observations in FS and our set of observations represent very different types of underlying events. And markets appear to respond to these events differently.

There remains the question of why our replication of the FS methodology finds an asymmetry in the post-event reaction to positive and negative news, whereas our core results in Table 8 do not show this asymmetry. We believe this is because sorting on news-day returns and on the sentiment of news are fundamentally different sorts. In the Table 1 regressions of contemporaneous returns on news and all our control variables the R^2's are 1.1% or lower. Sorting by returns thus sorts on the 99% of return variation that is unexplained by our model; sorting on news sentiment, as we do in Table 8, identifies a different set of events than does sorting on returns.

7.2 The role of earnings announcements

TSM show that the sentiment of articles containing 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 (2) and (3) that drops all event days that take place either on earnings announcement days, or on the trading day following the earnings announcement.[34] Dropping these two-day announcement periods reduces the number of observations in our full-sample regression by roughly 10%.

Table A15 in the Internet Appendix is the analogue of Table A10 but after the two-day announcement windows are dropped. Table A10 shows the Table 1 results for the full sample, as well as results by subperiods as explained in Section A7 of the Internet Appendix. 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- and ten-day ahead returns are roughly comparable. The impact of news on future returns hardly changes when earnings days are excluded from the sample and, thus, earnings-related news are not the main drivers of our results.

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

7.3 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 variance) and VIX (systematic volatility) in all our regressions to control for this possibility. Table A16 in the Internet Appendix shows the results of the specification in (2) when we remove the volatility controls. Compared to the baseline results in Table A10, the forecasting ability of $Sent$ for both excess returns and CARs is basically unchanged in the absence of the volatility controls.

7.4 The VIX as an interaction variable

To control for the possibility that intermediary capacity, ownership, and entropy simply proxy for the impact of investor perceptions of risk on the sentiment coefficient in (12, 13, 14), we run a specification analogous to these but use the VIX as the interaction variable for sentiment. Table A17 of the Internet Appendix shows these results. In all cases, the VIX has a positive influence on the impact of sentiment on contemporaneous returns, and a negative (and usually insignificant) influence on the impact of sentiment on future returns. These results are fundamentally different from the intermediary capacity, ownership, and entropy interaction results in Tables 4, 5, and 6, where the impact of the interaction variable on the sentiment coefficient has the same sign for contemporaneous and future returns. The VIX, therefore, cannot be the underlying driver of our results.

8 Conclusion

The stock market's underreaction to news is surprising. The time variation in this underreaction is even more surprising. We might naively expect that the degree of underreaction would simply decline over time, as more investors learn to trade on news signals; for the same reason, we might also expect that the contemporaneous response to news would strengthen as the underreaction weakens. But both expectations are contradicted by the data. Moreover, we find that the degree of underreaction is positively associated with the level of intermediary capital, negatively associated with the level of passive ownership of stocks, and positively associated with the informativeness of news. These interactions help explain the time variation we observe in the news-returns relationship.

We have investigated channels through which these interactions may operate. Prior work suggests a role for short-sale constraints in slowing the response to news, and also a role for serial correlation in news that is unrecognized by investors. We test these mechanisms and conclude that neither can fully account for our findings. We do not find that the underreaction is strongest among the most tightly short-sale constrained stocks, nor do we find a consistently asymmetric response to good and bad news, as would be expected from limits on short selling. We do not find that predictability in news flow explains the underreaction in stock prices, nor are we aware of a plausible link between the persistence of news and our interaction variables, intermediary capital, passive ownership, and entropy.

These channels — short-sale constraints and news autocorrelation — may contribute to time variation in the news-returns relationship, but they do not fully account for it. We are left with two further channels: investor psychology, particularly slow response to information and overconfidence with self-attribution bias, and strategic order-splitting by institutions. Either channel generates delayed trading by institutions in response to news.

The behavioral explanations require a mechanism that associates slow responses to information or overconfidence with intermediary capital and active ownership of stocks, and such a link would presumably rely on not fully rational behavior by institutional, as well as retail, investors. We show that a model with these characteristics generates results consistent with our empirical findings, but the model is silent on the underlying cause (proxied by the assumption of newswatchers) of the underreaction effect.

Strategic order-splitting may provide a simple explanation for comovement in the contemporaneous and lagged response to news, as institutions respond to news quickly but not all at once. Greater intermediary capital, lower passive ownership of stocks, and more informative news are associated with greater institutional trading; to the extent that part of this trading is executed strategically, it is associated with both a stronger contemporaneous response to news and a more pronounced underreaction. Should such consequences of strategic trading be noteworthy? This mechanism offers a very different view of the market's underreaction to news than an explanation based on limited investor attention. It also poses several challenges to our theoretical understanding of market microstructure. Standard models of informed trading assume private signals; but the news signals we study are private only in the sense of Grossman's (1986) "costly private processing of public information." And standard models have a hard time explaining an observable underreaction, because prices are efficient by assumption.

Our investigation does not identify the fundamental source of underreaction, but it shows the importance of interactions with the capacity and size of different types of investors in producing time-variation in the market's response to news.

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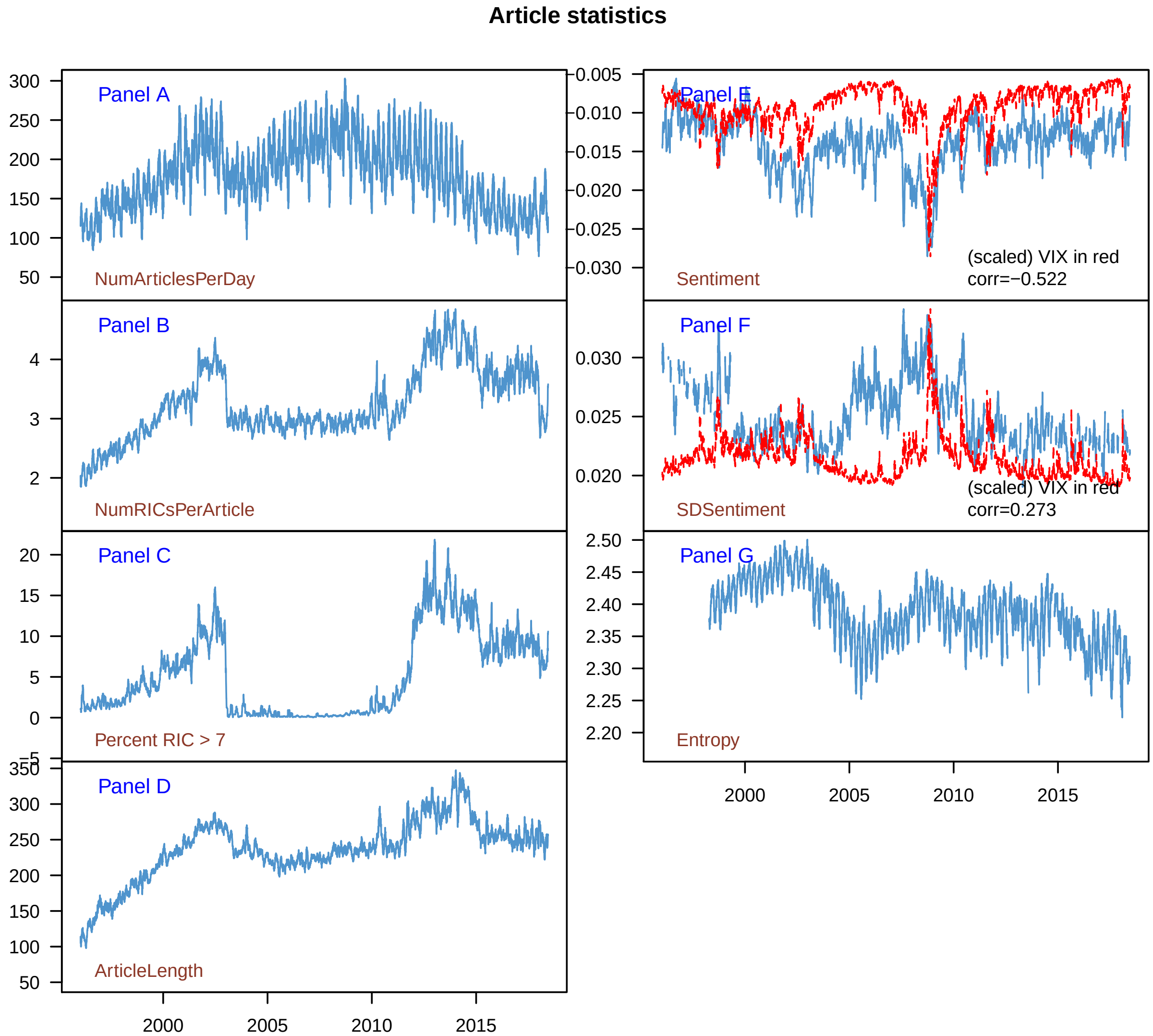


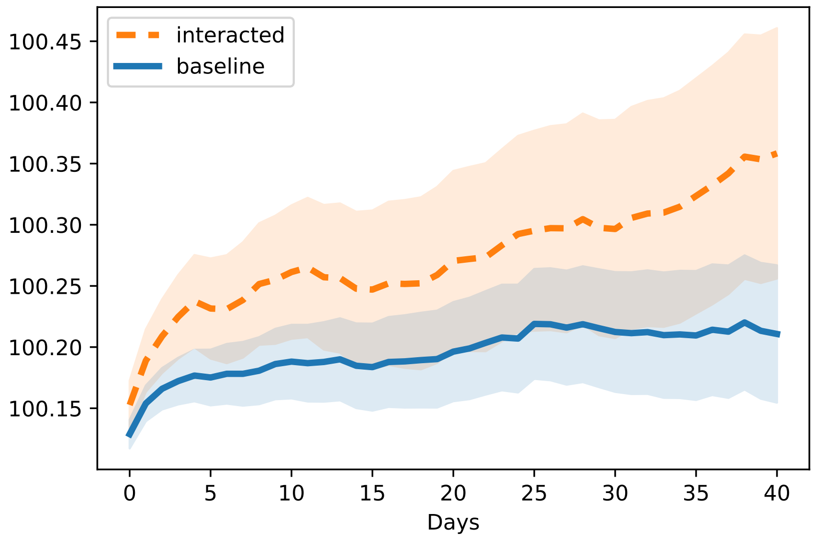
Fig. 5. This figure shows the number articles per day, the number of RICs per article, the percent of daily articles mentioning more than 5 RICs, the average article length (in number of words), daily average of article sentiment, the daily standard deviation of article sentiment, and the average daily entropy (defined in Section 5.3). Data are daily. The VIX (scaled to match the series in question) is shown in red.

Series correlations (quarterly)

Fig. 6. Correlations between quarterly entropy, intermediary capacity, and ownership measures. The entropy and ownership variables are within quarter averages. The intermediary capacity variable is a quarterly average of monthly observations from He et al. (2017). Active and Passive refer to the the Active/Market and Passive/Market variables. Passive_Total refer to Passive/Fund Total.

Impulse responses to {sentiment $\times$ monthly intermediary capacity} shocks

Panel A: Excess returns ($Retrfs$): response to shock



Panel B: Cumulative abnormal returns ($CARs$): response to shock

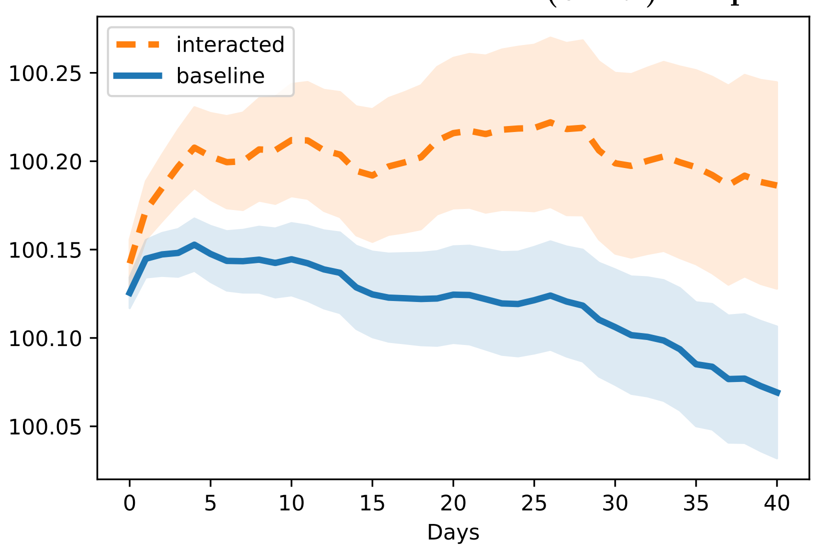


Fig. 7. Impulse response functions estimated using the local projection method of Jorda (2005). The figure shows the baseline response (labeled *baseline*) of future excess returns and cumulative abnormal returns ($CARs$) to a one standard deviation sentiment shock, as well as the response conditional on a one-standard deviation increase in monthly intermediary capacity (labeled *interacted*). The starting price level on day -1 is 100. Day 0 is the news event day. The x-axis is in number of days. The top panel shows cumulative excess returns, and the bottom panel shows $CARs$. The cumulative responses show the arithmetic sums of one-day returns; the geometric cumulative returns are almost identical. Standard errors are based off time-clustered panel regressions of one-day ahead future returns on lagged sentiment, and assume independence of one-day returns across time, and between the baseline and the conditinal responses. The shaded regions represent 2 standard error bands around the impulse response.

Table 1

Return regressions in the full sample, using specifications (2) and (3). $Retrf_{i,j}$ ($CAR_{i,j}$) refers to the return (abnormal return) that includes days $t+i,\dots,t+j$ where t is the event date. Standard errors are clustered by time. The *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Return regressions

	Dependent variable:							
	$\text{Retrf}_{0,0}$	$\text{CAR}_{0,0}$	$\text{Retrf}_{0,0}$	$\text{CAR}_{0,0}$	$\text{Retrf}_{1,1}$	$\text{CAR}_{1,1}$	$\text{Retrf}_{1,10}$	$\text{CAR}_{1,10}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sent	9.184***	8.086***			1.192***	0.914***	2.793***	0.821*
Sent (4pm-9:30am)			6.180***	5.949***				
$\text{CAR}_{0,0}$					0.001	0.001	−0.040***	−0.038***
$\text{CAR}_{-1,-1}$	0.001	−0.001	0.001	−0.001	−0.004	−0.008	−0.051***	−0.049***
$\text{CAR}_{-2,-2}$	−0.010	−0.015**	−0.008	−0.013*	−0.009*	−0.006	−0.065***	−0.059***
$\text{CAR}_{-30,-3}$	−0.001	−0.0005	0.001	0.001	−0.001	−0.001	−0.005*	−0.007***
$\text{CAR}^2_{0,0}$	0.003	0.002	0.003	0.002	0.0005	0.0005	0.002	0.003***
VIX	−0.021***	−0.0002	−0.021***	0.001	0.006	0.001	0.020	0.002
SUE	0.012*	0.018***	0.019***	0.026***	0.011*	0.007***	0.039**	0.021***
Short Interest (%)	−0.0003	−0.007***	−0.005	−0.010***	−0.006*	−0.004*	−0.027***	−0.010*
IO (%)	0.0002	−0.0003	0.0002	−0.0002	−0.0002	−0.0002	−0.002**	−0.002***
log(Market Cap)	0.046*	−0.028***	0.033	−0.036***	−0.033	−0.014*	−0.218***	−0.121***
IHS(Book/Market)	0.082***	0.031**	0.064**	0.022	0.024	0.0003	0.218***	−0.001
log(Illiquidity)	0.075***	−0.011	0.066**	−0.016*	−0.026	−0.009	−0.084	−0.046**
α	−0.031	−0.104*	−0.010	−0.119*	−0.015	0.048	−0.360*	−0.052
Constant	1.166***	0.541***	1.229***	0.582***	0.126	0.136	3.396***	1.975***
Observations	618,633	618,633	455,083	455,083	618,367	618,367	618,369	618,369
Adjusted R^2	0.011	0.007	0.008	0.005	0.001	0.0004	0.002	0.002
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 2
This table shows the headlines of the eight highest and lowest entropy articles in two months of our sample. Within each month we look for articles with greater than or equal to 25 words and fewer than or equal to seven RICs. Also we exclude any articles with the string “shh margin” in the headline. The “Total” column shows the number of words in the article, after stopwords have been removed.

Examples of article headlines sorted by entropy

Month	Headline	Entropy	Total
Jun 2005	AMEX Nabors Industries Ltd (us;NBR) MOC Buy Imbalance: 193,000 shrs. <NBR.A>	0.08	49
Jun 2005	AMEX Nabors Industries Ltd (us;NBR) No Imbalance <NBR.A>	0.12	46
Jun 2005	TEXT-Target <TGT.N> dividend	0.34	25
Jun 2005	TEXT-CVS Corp. <CVS.N> May sales	0.38	26
Jun 2005	UPDATE 1-Billionaire investor Kerkorian extends stake in	2.83	191
Jun 2005	RESEARCH ALERT-UBS cuts Tribune to ””neutral””	2.85	40
Jun 2005	FACTBOX-Citigroup, Merrill neck-and-neck in broker rankings	2.94	116
Jun 2005	FACTBOX-European aluminium smelters face energy threat	3.20	216
Feb 2018	Moody’s rates Travelers’ senior notes A2; outlook stable	0.36	36
Feb 2018	Moody’s assigns provisional ratings to John Deere Owner Trust 2018	0.42	37
Feb 2018	Moody’s affirms Amgen at Baa1; outlook stable	0.46	35
Feb 2018	Moody’s assigns provisional ratings to SBA Communications wireless tower-backed securities	0.47	39
Feb 2018	BRIEF-S&P Downgrades Wells Fargo To ’A-/A-2’ From ’A/A-1’	2.93	49
Feb 2018	BRIEF-Walmart Says Currently Expects Cash Benefit Of Around $2 Bln For Fiscal 2019 Due To U.S.Tax Reform	2.93	47
Feb 2018	BRIEF-Saudi Telecom Company And Cisco Sign Strategic MoU To Bring The Benefits Of 5G To Saudi Arabia	3.04	40
Feb 2018	UPDATE 1-Malaysia to export fewer Kimanis cargoes in April - sources	3.34	115

Table 3
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
Entropy	623,408	2.346	0.344	0.053	2.255	2.561	4.042
Entropy (daily)	648,557	0.000	0.075	−1.101	−0.046	0.054	0.214
Entropy (monthly)	648,557	−0.000	0.056	−0.196	−0.037	0.039	0.126
Entropy (quarterly)	648,557	−0.000	0.048	−0.141	−0.033	0.036	0.107
Entropy (annual)	648,557	−0.000	0.044	−0.095	−0.029	0.034	0.093
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)	650,310	−0.051	1.465	−4.596	−0.538	0.576	3.392
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	0.0003	0.014	−0.205	−0.005	0.006	0.224
$\beta_{\text{SMB}} \times \text{SMB}_{1,1}$	704,199	−0.00000	0.003	−0.087	−0.001	0.001	0.097
$\beta_{\text{HML}} \times \text{HML}_{1,1}$	704,199	0.00002	0.005	−0.163	−0.001	0.001	0.234
$\beta_{\text{RMW}} \times \text{RMW}_{1,1}$	704,199	−0.00000	0.004	−0.114	−0.001	0.001	0.095
$\beta_{\text{CMA}} \times \text{CMA}_{1,1}$	704,199	0.00002	0.004	−0.097	−0.001	0.001	0.133
$\beta_{\text{UMD}} \times \text{UMD}_{1,1}$	704,199	−0.00001	0.005	−0.138	−0.001	0.001	0.222

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 $Retrf_{0,0}$ and $CAR_{0,0}$ regressions omit the $CAR_{0,0}$ control. The row label (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 *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Intermediary capacity effects on sentiment predictability

Return regressions

		Capacity			
		CR (daily)	CR (monthly)	CR (quarterly)	Lev (quarterly)
$Retrf_{0,0}$	Sent	9.271***	9.186***	9.182***	9.227***
	Sent×Capacity	0.363***	0.443***	0.504***	0.227***
$Retrf_{0,0}$	Sent (4pm-9:30am)	6.197***	6.136***	6.137***	6.232***
	Sent (4pm-9:30am)×Capacity	0.371***	0.432***	0.448***	0.137**
$Retrf_{1,1}$	Sent	1.012***	1.197***	1.196***	1.132***
	Sent×Capacity	0.135	0.202	0.185	0.052
$Retrf_{1,10}$	Sent	1.877***	2.796***	2.779***	2.305***
	Sent×Capacity	0.474	0.778**	0.657*	0.622***

CAR regressions

		Capacity			
		CR (daily)	CR (monthly)	CR (quarterly)	Lev (quarterly)
$CAR_{0,0}$	Sent	8.215***	8.096***	8.099***	8.119***
	Sent×Capacity	0.447***	0.498***	0.537***	0.159***
$CAR_{0,0}$	Sent (4pm-9:30am)	6.168***	5.978***	5.979***	6.001***
	Sent (4pm-9:30am)×Capacity	0.332***	0.302***	0.318***	0.129***
$CAR_{1,1}$	Sent	0.833***	0.919***	0.92***	0.912***
	Sent×Capacity	0.13**	0.194***	0.186***	0.021
$CAR_{1,10}$	Sent	0.523	0.841*	0.844*	0.795*
	Sent×Capacity	0.64***	0.84***	0.769***	0.184**

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 $Retrf_{0,0}$ and $CAR_{0,0}$ regressions omit the $CAR_{0,0}$ control. The row label (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 *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Mutual fund ownership effects on sentiment predictability

Return regressions

		Mutual Fund Ownership (%)		
		Passive/Market	Active/Market	Passive/Fund Total
$Retrf_{0,0}$	Sent	9.197***	9.12***	9.175***
	Sent×Ownership	-0.035	0.205***	-0.047***
$Retrf_{0,0}$	Sent (4pm-9:30am)	6.204***	6.169***	6.207***
	Sent (4pm-9:30am)×Ownership	-0.039	0.193***	-0.05***
$Retrf_{1,1}$	Sent	1.171***	1.185***	1.182***
	Sent×Ownership	-0.078	0.015	-0.012
$Retrf_{1,10}$	Sent	2.586***	2.691***	2.691***
	Sent×Ownership	-0.41**	0.252***	-0.117***

CAR regressions

		Mutual Fund Ownership (%)		
		Passive/Market	Active/Market	Passive/Fund Total
$CAR_{0,0}$	Sent	8.093***	8.028***	8.078***
	Sent×Ownership	-0.022	0.181***	-0.042***
$CAR_{0,0}$	Sent (4pm-9:30am)	5.956***	5.936***	5.966***
	Sent (4pm-9:30am)×Ownership	0.008	0.167***	-0.031**
$CAR_{1,1}$	Sent	0.913***	0.903***	0.909***
	Sent×Ownership	-0.043	0.034	-0.015
$CAR_{1,10}$	Sent	0.804*	0.765*	0.786*
	Sent×Ownership	-0.285***	0.176***	-0.1***

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, $CAR_{0,0}^2$ and VIX. The $Retrf_{0,0}$ and $CAR_{0,0}$ regressions omit the $CAR_{0,0}$ control. The row label (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 *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Entropy effects on sentiment predictability

Return regressions

		Entropy			
		Daily	Monthly	Quarterly	Annual
$Retrf_{0,0}$	Sent	9.51***	9.623***	9.688***	9.696***
	Sent×Entropy	12.267***	37.742***	45.873***	49.938***
$Retrf_{0,0}$	Sent (4pm-9:30am)	6.392***	6.49***	6.526***	6.53***
	Sent (4pm-9:30am)×Entropy	5.645	25.973***	28.795***	31.679***
$Retrf_{1,1}$	Sent	1.015***	1.066***	1.044***	1.034***
	Sent×Entropy	7.386*	8.052	9.441	8.471
$Retrf_{1,10}$	Sent	1.878***	1.821***	1.648**	1.517**
	Sent×Entropy	13.835	30.828*	15.164	-1.924

CAR regressions

		Entropy			
		Daily	Monthly	Quarterly	Annual
$CAR_{0,0}$	Sent	8.349***	8.404***	8.453***	8.464***
	Sent×Entropy	8.299***	32.217***	38.1***	42.353***
$CAR_{0,0}$	Sent (4pm-9:30am)	6.166***	6.195***	6.22***	6.229***
	Sent (4pm-9:30am)×Entropy	1.74	20.348***	23.183***	26.066***
$CAR_{1,1}$	Sent	0.87***	0.882***	0.893***	0.893***
	Sent×Entropy	3.199	4.979	7.916**	7.542*
$CAR_{1,10}$	Sent	0.414	0.467	0.473	0.485
	Sent×Entropy	13.222**	20.05**	16.103	14.839

Table 7
We obtain the monthly median SI and median RI, and use these cutoffs to double sort stock-day observations by SI and RI (independently). For each bucket, we run the main specification in equation (2). The coefficient estimates $\hat{s}$ and standard errors are reported in panel A. The average SI and average RI for each bucket and the number of observations are shown in panel B. The *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Return predictability by SI and RI (residualized ownership)

Panel A

		Coefficients		Standard Errors	
		Low RI	High RI	Low RI	High RI
Low SI	$CAR_{0,0}$	6.377***	11.028***	(0.258)	(0.466)
	$CAR_{0,0}$ (4pm-9:30am)	5.193***	7.894***	(0.31)	(0.58)
	$CAR_{1,1}$	0.953***	0.563	(0.225)	(0.385)
	$CAR_{1,10}$	0.174	-0.533	(0.704)	(1.191)
High SI	$CAR_{0,0}$	5.666***	11.673***	(0.21)	(0.483)
	$CAR_{0,0}$ (4pm-9:30am)	3.81***	9.317***	(0.231)	(0.609)
	$CAR_{1,1}$	0.73***	1.577***	(0.181)	(0.369)
	$CAR_{1,10}$	0.416	4.109***	(0.529)	(1.075)

Panel B

	Average SI		Average RI		Nobs	
	Low RI	High RI	Low RI	High RI	Low RI	High RI
Low SI	0.013	0.013	-0.917	0.564	182826	242336
High SI	0.051	0.058	-1.061	1.21	122740	123514

Table 8
We obtain the monthly median sentiment, median SI and median RI, and use these cutoffs to triple sort stock-day observations by sentiment, SI and RI (independently). For each bucket, we run the main specification in equation (2). The coefficient estimates $\hat{s}$ are reported in panels A and B, where A includes the buckets with below median sentiment and B includes the buckets with above median sentiment. Panels A and B also report the corresponding standard errors. The average Sent, average SI and average RI, and number of observations for each bucket are reported in panel C. The *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Return predictability by Sent, SI and RI (residualized ownership)

Panel A: Low Sent

		Coefficients		Standard Errors	
		Low RI	High RI	Low RI	High RI
Low SI	$CAR_{0,0}$	3.959***	6.601***	(0.399)	(0.73)
	$CAR_{0,0}$ (4pm-9:30am)	2.12***	1.021	(0.474)	(0.893)
	$CAR_{1,1}$	0.689*	0.275	(0.362)	(0.629)
	$CAR_{1,10}$	0.326	2.609	(1.147)	(2.002)
High SI	$CAR_{0,0}$	3.572***	7.299***	(0.351)	(0.788)
	$CAR_{0,0}$ (4pm-9:30am)	0.832*	3.074***	(0.446)	(1.004)
	$CAR_{1,1}$	0.976***	0.444	(0.282)	(0.616)
	$CAR_{1,10}$	1.244	4.042**	(0.81)	(1.818)

Panel B: High Sent

		Coefficients		Standard Errors	
		Low RI	High RI	Low RI	High RI
Low SI	$CAR_{0,0}$	4.53***	8.761***	(0.657)	(1.147)
	$CAR_{0,0}$ (4pm-9:30am)	1.071	3.747***	(0.784)	(1.408)
	$CAR_{1,1}$	0.36	0.639	(0.631)	(0.986)
	$CAR_{1,10}$	-1.556	2.149	(1.798)	(2.819)
High SI	$CAR_{0,0}$	4.845***	9.427***	(0.56)	(0.967)
	$CAR_{0,0}$ (4pm-9:30am)	1.31**	3.875***	(0.581)	(1.245)
	$CAR_{1,1}$	0.674	0.802	(0.515)	(0.867)
	$CAR_{1,10}$	1.291	4.149*	(1.457)	(2.488)

Panel C

	Average Sent				Average SI			
	Low Sent		High Sent		Low Sent		High Sent	
	Low RI	High RI	Low RI	High RI	Low RI	High RI	Low RI	High RI
Low SI	-0.026	-0.025	0.004	0.003	0.013	0.013	0.014	0.013
High SI	-0.027	-0.028	0.004	0.004	0.053	0.06	0.05	0.056
	Average RI				Nobs			
	Low Sent		High Sent		Low Sent		High Sent	
	Low RI	High RI	Low RI	High RI	Low RI	High RI	Low RI	High RI
Low SI	-0.871	0.568	-0.963	0.561	91692	123648	91134	118688
High SI	-1.082	1.181	-1.038	1.236	62510	58076	60230	65438

Table 9
This table reports the test statistic $g(\hat{\boldsymbol{\theta}}) \equiv \frac{\hat{s}_0}{\hat{s}_1} - \frac{\hat{\beta}_0}{\hat{\beta}_1}$, where the coefficient estimates $(\hat{s}_0, \hat{s}_1, \hat{\beta}_0, \hat{\beta}_1)$ come from the specification in (15). These control vector $\boldsymbol{X}_t$ in these regressions contains: 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 *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Panel A: News autocorrelation channel conditional on intermediary capacity

Panel A: News autocorrelation channel conditional on intermediary capacity								
	Capacity							
	CR (daily)		CR (monthly)		CR (quarterly)		Lev (quarterly)	
	$g(\hat{\boldsymbol{\theta}})$	p-value	$g(\hat{\boldsymbol{\theta}})$	p-value	$g(\hat{\boldsymbol{\theta}})$	p-value	$g(\hat{\boldsymbol{\theta}})$	p-value
$\text{Retrf}_{1,1}$	-48.3473**	0.0127	-82.6166***	0.0024	-74.6312***	0.0031	-1237.6356	0.8358
$\text{Retrf}_{1,10}$	-54.8816***	0.0058	-135.7281***	0.0018	-114.6694***	0.005	310.9865***	8e-04
$\text{CAR}_{1,1}$	-46.5655**	0.0116	-81.4448***	0.0022	-73.3033***	0.0039	-3658.4688***	0.0042
$\text{CAR}_{1,10}$	-57.1644***	2e-04	-137.7646***	0	-117.1208***	1e-04	304.0765**	0.0109

Panel B: News autocorrelation channel conditional on mutual fund ownership

Panel B: News autocorrelation channel conditional on mutual fund ownership						
	Ownership					
	Passive/Market		Active/Market		Passive/Fund Total	
	$g(\hat{\boldsymbol{\theta}})$	p-value	$g(\hat{\boldsymbol{\theta}})$	p-value	$g(\hat{\boldsymbol{\theta}})$	p-value
$\text{Retrf}_{1,1}$	-922.3345***	0.0065	-14.8314	0.9493	268.3963*	0.0683
$\text{Retrf}_{1,10}$	-121.5613**	0.0111	-33.5105**	0.0276	264.3765**	0.0112
$\text{CAR}_{1,1}$	-947.6541**	0.0108	98.5824*	0.087	237.8326	0.1077
$\text{CAR}_{1,10}$	-116.6313***	0.0036	-41.4574***	0.0051	282.6225***	6e-04

Table 10

We sort stock-day observations into quintiles (Q1 to Q5) based on intermediary capital ratio growth rate. Q1 (Q5) corresponds to the quintile with the lowest (highest) intermediary capacity growth rate. For each quintile, we split the observations by the sign of $CAR_{0,0}$, and show the average cumulative abnormal returns for each subgroup. We only use the list of S&P 500 firms as of October 2014, and the sample period is restricted to January 1996–September 2013. The top panel corresponds to the sample with $CAR_{0,0} < 0$, and the bottom panel includes observations with $CAR_{0,0} \geq 0$. All returns are shown in basis points. The *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Replication of Table 8 in Frank and Sanati (2018)

Sort:			CAR							
Cap. ratio (growth rate)	Shock	Obs.	[0,0]	[1,1]	[1,10]	[1,21]	[1,40]	[2,10]	[2,21]	[2,40]
Q1	−	41377	-152.8099***	2.3293**	20.5039***	44.2214***	67.815***	19.1058***	41.8921***	65.4857***
			(-146.4684)	(2.0669)	(5.8175)	(9.2939)	(10.1386)	(5.6392)	(9.0177)	(9.8981)
Q2	−	42672	-145.9212***	3.252***	18.9798***	41.3721***	70.7905***	15.9824***	38.1201***	67.517***
			(-153.5724)	(3.1044)	(6.3201)	(10.0454)	(12.8527)	(5.6783)	(9.523)	(12.4117)
Q3	−	35192	-113.604***	1.3514	15.244***	28.4867***	51.851***	13.953***	27.1353***	50.4996***
			(-138.705)	(1.5399)	(5.8785)	(7.4846)	(10.0951)	(5.7245)	(7.3037)	(9.9626)
Q4	−	42456	-121.6098***	1.5853*	15.3238***	24.4575***	47.5778***	13.9539***	22.8689***	45.9731***
			(-149.7748)	(1.8837)	(6.2737)	(6.749)	(9.599)	(6.0266)	(6.4956)	(9.4114)
Q5	−	41892	-156.399***	2.6802**	19.7249***	39.1525***	97.7703***	17.8278***	36.6133***	95.2058***
			(-149.2317)	(2.2219)	(5.6609)	(7.974)	(14.9099)	(5.3193)	(7.6661)	(14.727)
Q5 − Q1	−		-3.5891**	0.3509	-0.779	-5.0689	29.9553***	-1.278	-5.2788	29.7201***
			(-2.427)	(0.2125)	(-0.1572)	(-0.7414)	(3.198)	(-0.2682)	(-0.7923)	(3.213)
Q1	+	40723	160.0009***	-1.3954	6.9452**	25.0699***	44.7105***	8.7901***	26.4653***	46.1059***
			(146.653)	(-1.2359)	(2.0879)	(5.4666)	(6.8123)	(2.8093)	(5.9274)	(7.1157)
Q2	+	42502	153.2461***	1.4825	4.8	23.9646***	42.9064***	3.9013	22.4821***	41.4261***
			(149.9041)	(1.4241)	(1.6442)	(5.9374)	(7.9122)	(1.4117)	(5.7364)	(7.7546)
Q3	+	34734	121.4074***	1.3127	12.0202***	26.6504***	42.1501***	10.5273***	25.3377***	40.8374***
			(149.7253)	(1.5447)	(4.5912)	(7.0125)	(8.0964)	(4.3031)	(6.8817)	(7.9686)
Q4	+	41897	126.7323***	0.7714	8.8938***	24.5628***	48.3411***	8.2233***	23.809***	47.5834***
			(166.3519)	(0.9732)	(3.7072)	(6.9936)	(9.8711)	(3.6138)	(6.9517)	(9.8406)
Q5	+	41196	169.1162***	3.174***	5.4465	34.5278***	70.9083***	2.3713	31.3676***	67.6712***
			(147.3312)	(2.6395)	(1.6313)	(7.2584)	(11.115)	(0.7603)	(6.7762)	(10.7608)
Q5 − Q1	+		9.1154***	4.5694***	-1.4987	9.4579	26.1978***	-6.4188	4.9023	21.5654**
			(5.756)	(2.7702)	(-0.318)	(1.4314)	(2.8623)	(-1.4529)	(0.7622)	(2.3883)

Internet Appendix: Time Variation in the News-Returns Relationship

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Contents

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A1 Map Thomson-Reuters articles to S&P 500 firms

To select Thomson Reuters (TR) articles that mention S&P 500 firms, we map CRSP PERMNO to Reuters Instrument Code (RIC), where RIC is the stock identifier from TR. Unfortunately, RICs are not unique identifiers, and we have not been able to obtain a historical RIC mapping from the company. This section gives the full details of our mapping from PERMNOs to RICs, and we summarize the process here: (1) Obtain the augmented article body by combining the headline and body text of an article; (2) Select articles that contain standardized S&P 500 company names (from the CRSP historical names table) in the augmented article body and associate these articles with S&P 500 PERMNOs; (3) For each PERMNO, find the top three most frequently occurring RICs in the selected articles, override unreliable RICs (i.e., those which do not occur sufficiently frequently) then fetch all articles tagged with these RICs; (4) Keep an article selected from (3) if it loosely mentions any S&P 500 company name. Steps (1)-(4) allow us to create a robust mapping from TR articles to S&P 500 firms.

A1.1 Create variants of company names

We create two variants of each S&P 500 company name, denoted as *Variant-1* and *Variant-2*. *Variant-1* is the pattern used in the first pass search and *Variant-2* is the pattern used in the second pass search. See Section A1.2 and Section A1.3 for the discussion of first and second pass search.

For each historical firm name, we perform steps 1-11 to get *Variant-1*, and steps 1-12 to get *Variant-2*. And we only keep unique *Variant-1* and *Variant-2* for each PERMNO.

1. Remove extra spaces between words.
2. Replace abbreviations in Table A1.
3. Replace ‘’ / - with space.
4. Replace & if it occurs between words while keep it if it occurs inside a word.
5. Remove all other punctuation marks and do not replace with space.

6. Remove the space which exists between two single word characters.
7. Remove all English stopwords except "under".[1]
8. Remove words in Table A2 directly (case-insensitive).
9. Remove words in Table A3 recursively (case-insensitive), i.e. starting from the last word in the company name, if it is in Table A3 then remove it. Loop until the last word is not in Table A3.
10. Convert all names to lower case.
11. Capitalize the first character of each word in company name.
12. Remove words in Table A4 recursively (case-insensitive).

A1.2 First Pass Search

We first clean Thomson Reuters news data before searching for company names in article body. We drop non-English language articles or those with urgency < 2. We keep the first article within each article chain. Two articles belong to the same article chain if they have the same PNAC and have timestamps within the same 6-hour window in a day (we divide a day into four 6-hour windows). And we augment the article body with article headline.

Then we search for *Variant-1* in the augmented article body following the steps below:

1. Tokenize *Variant-1*.
2. Process the augmented article body as follows:
   (a) Replace ‘’ / - with space.
   (b) Replace & with space if it appears between words.
   (c) Replace . with space.
   (d) Remove all other punctuation marks.
   (e) Tokenize augmented article body and only keep non-empty tokens.

[1] "Under Armour Inc" is an S&P 500 company in our sample, so we should not remove the stopword "under" from company names.

(f) Convert all tokens to lower case. If the first character of a token is capitalized, keep the first character capitalized and convert all other characters to lower case.

3. Search for tokens of *Variant-1* in the augmented article body. An article is matched with *Variant-1* if all the conditions below are satisfied:

   (a) All tokens in *Variant-1* can be found in the text.

   (b) In the text, the last matched token and the first matched token are within 5 words of each other.

   (c) The order of tokens in *Variant-1* is preserved in the text.

If an article is matched with a *Variant-1* name and the associated PERMNO, then we say that all the RICs from that article is matched to the PERMNO. We then compute the frequency of each unique (PERMNO, RIC) pair and extract the top three frequently occurring RICs for each PERMNO. For a few PERMNOs, the top three PERMNO-RIC mapping are not robust, so we override the top three RICs with more reasonable ones.

A1.3 Second Pass Search

For each (PERMNO, RIC) pair, we search for the corresponding *Variant-2* in the augmented article body and only keep the matched articles after performing the following steps:

1. Tokenize *Variant-2*.

2. Process the augmented article body as follows:

   (a) Replace ‘’ / - with space.

   (b) Replace & with space if it appears between words.

   (c) Replace . with space.

   (d) Remove all other punctuation.

   (e) Tokenize augmented article body and only keep non-empty tokens.

   (f) Convert all tokens to lower case. If the first character of a token is capitalized, keep the first character capitalized and convert all other characters to lower case.

3. Search for tokens of *Variant-2* in the augmented article body. An article is matched with *Variant-2* if all the conditions below are satisfied:

   (a) The article is tagged with a top three frequently occurring RIC in its subject.

   (b) All tokens in *Variant-2* can be found in the text.

   (c) In the text, the last matched token and the first matched token are within 5 words of each other.

   (d) The order of tokens in *Variant-2* is preserved in the text.

A2 Constructing text measures

We construct two article-level text measures, sentiment and entropy, from our news data. Sentiment involves counting positive and negative words in articles, and entropy involves counting n-grams in the training corpus and the new text.

A2.1 Sentiment

For an article j, we first clean the augmented body text following steps 1-3 and 5 below. Then we do a case-insensitive search for positive and negative words in the augmented body using the Loughran and McDonald (2011) sentiment dictionary, and count the number of positive words n_j^{pos} and the number of negative words n_j^{neg} in article j. We also count the total number of words n_j in article j after we apply steps 1-4 to the augmented article body.

1. Convert the augmented body text to lower case.

2. Replace non-alphabet characters with space.

3. Tokenize the text.

4. Drop English stopwords.

5. Mark negation using the Das and Chen (2007) method.

The sentiment of article j is defined as

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

A2.2 Entropy

We extract n-grams from each article following the steps below:

1. Convert the augmented body text to lower case.
2. Replace date strings, entity names, numerical strings and punctuation marks between sentences, as shown in Table A5 panel A-D.
3. Break the augmented body text into sentences by $***$.
4. Within each sentence, replace punctuation marks in Table A5 panel E.
5. Tokenize each sentence and stem the tokens.
6. Obtain the sequence of n-grams in the article, $n = 3, 4$.

We then count the frequency of each 3-gram and each 4-gram in articles of a given month. We define the training corpus for month t as articles in months $t-27, t-26, \cdots, t-4$, and calculate the frequency of each 3-grams (4-gram) in the training corpus for month t. The entropy of article j in month t is defined as

$$\begin{aligned} Entropy_j &= -\sum_{i \in \text{4-grams}_j} \hat{p}_{i,j} \log \hat{q}_{i,j} \\ \hat{p}_{i,j} &= \frac{n_{i,j}}{\sum_{i \in \text{4-grams}_j} n_{i,j}} \\ \hat{q}_{i,j} &= \frac{\hat{c}_{t-27,t-4}\left(w_{1,i}w_{2,i}w_{3,i}w_{4,i}\right) + 1}{\hat{c}_{t-27,t-4}\left(w_{1,i}w_{2,i}w_{3,i}\right) + 10} \end{aligned}$$

where 4-grams$_j$ is the set of distinct 4-grams in article j, $n_{i,j}$ is the count of 4-gram i in document j, $\hat{c}_{t-27,t-4}\left(w_{1,i}w_{2,i}w_{3,i}w_{4,i}\right)$ is the count of 4-gram i in the training corpus, $\hat{c}_{t-27,t-4}\left(w_{1,k}w_{2,k}w_{3,k}\right)$ is the count of the 3-gram associated with 4-gram i in the training corpus.

A3 Measuring passive and active ownership in stocks

We obtain mutual fund characteristics and holdings data from CRSP Survivor-Bias-Free US Mutual Fund database and Thomson Reuters (TR) Mutual Fund Holdings database. We identify index/passive mutual funds by searching for certain strings in CRSP fund names and supplement this information with the index fund indicator from CRSP.

We focus on US domestic equity mutual funds[2] from CRSP and classify them into passive, active or unclassified categories. For each CRSP fund, we do the following.

1. Fill in missing fund names using the most recently available one.
2. Replace the following characters in fund name with space: ` ˜! @ # $ % ˆ∗() _ + − = [ ] \{}|; : “ ” , . / <>?
3. Classify the fund based on the following criteria:
   (a) If the fund has a CRSP index fund indicator (index_fund_flag) in {B, D, E}, then it is a passive fund.
   (b) Otherwise,
      i. If the fund name includes a word/phase in {index, idx, indx, ind, russell, s␣&␣p, s␣and␣p, s&p, sandp, sp, dow, dj, msci, bloomberg, kbw, nasdaq, nyse, stoxx, ftse, wilshire, morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, 5000}[3], then the fund is passive.
      ii. Otherwise,
         A. If the fund has missing name and missing CRSP index fund indicator, then it is unclassified.
         B. In all other cases, the fund is active.

We then match CRSP funds to TR funds using the link tables from MFLINKS. MFLINKS maps CRSP funds and TR funds to a common Wharton Financial Institution Center Number (WFICN), which uniquely identifies a fund.[4] Finally, we map TR fund holdings to CRSP stocks by historical CUSIP, and construct the mutual fund holdings dataset at fund-stock level.

A4 Trim mutual fund ownership variables

Figure A1 depicts the cross-sectional correlations between the passive and active ownership series. The top panel shows the correlations using all available data. The three

[2]We focus on US domestic equity mutual funds because they have the most complete and reliable holdings data.

[3]␣ denotes a space character.

[4]CRSP mutual fund data is at the share-class level, so there could be multiple CRSP funds associated with the same WFICN and they all have the same holdings. We only keep one CRSP fund for each WFICN.

correlations spike in early 2011. For example, Corr(Passive/Market, Active/Market) increases from 0.2573455 to 0.5809107 in the first quarter of 2011. This pattern is caused by outliers in terms of Passive/Market and Active/Market values. From Q1 2011 onwards, we have stocks with very few mutual fund holders and their Passive/Market and Active/Market are close to zero, which drives up the correlations between the passive and active series. In the bottom panel of Figure A1, we exclude the bottom 2.5% observations of each series and recompute their correlations. We no longer see the spikes in the correlations.

To mitigate the concern that these outliers drive our ownership interaction results, we rerun the ownership interaction regressions in Table 5 but using the 2.5% trimmed ownership series, and confirm that the results are qualitatively unchanged, as can be seen in Table A11.

A5 Impulse response functions

We calculate impulse response functions to a sentiment shock using the local projection method of Jorda (2005). We run regressions (12) and (13) in the paper with the left hand side one-day returns or CARs on the event day t, day $t+1, t+2, \ldots, t+40$. The day t (contemporaneous) regression uses the 4pm–4pm sentiment, and excluded the contemporaneous abnormal return $CAR_{0,0}$ as an explanatory variable. We calculate the impulse response as the value of a hypothetical \$100 portfolio invested for each day at that day's forecasted incremental return due to a unit sentiment shock. This assumes the sentiment shock under consideration has been orthogonalized to all other contemporaneous influences.

To calculate the cumulative baseline response for day h we add up all single day $Sent$ coefficients up to and including $t+h$, scaled by a one standard deviation sentiment shock.[5] Standard errors are calculated assuming each one-day return is independent, and using the one-day return standard errors (clustered by time) from the panel regressions in (12) and (13).

To calculate the price response to a sentiment shock conditional on a one standard deviation increase in intermediary capital or decrease in passive ownership we add the $Sent \times Capacity$ or subtract the $Sent \times Ownership$ interaction, scaled by a one standard deviation change in $Sent$ times a one standard deviation change in the interacting

[5] Calculating the geometric return, i.e. $100 \times (1 + E[r_t]) \times (1 + E[r_{t+1}]) \times \cdots$ yields an almost identical result.

variable, to each day's forecasted marginal return. For calculating standard errors for conditional responses, we assume the marginal $Sent$ response and the interacted response are independent.

Figure A4 shows the impulse response function of future excess returns (panel A) and CARs (panel B) to a one standard deviation sentiment shock conditional on average passive/total ownership (solid line). Also shown is the impulse response conditional on a one standard deviation decrease in passive/total ownership (dashed line). Figure 7 in the main body of the paper shows the responses to sentiment and sentiment interacted with intermediary capacity.

A6 Tests of the news autocorrelation channel

We provide a formal derivation of the test statistic in Section 6.2. We start from a generic setting and derive a general argument, then apply the results to our setting.

A6.1 Derive the test statistic

Consider the following generic data generating process:

$$Y = \theta W + \xi \tag{A1}$$

$$W = \boldsymbol{\beta}' \boldsymbol{Z} + \eta \tag{A2}$$

Equations (A1) and (A2) imply that

$$Y = \boldsymbol{s}' \boldsymbol{Z} + \varepsilon, \boldsymbol{s} = \theta \boldsymbol{\beta}, \varepsilon = \theta \eta + \xi \tag{A3}$$

In what follows, assume that $\mathbb{E}[\eta|\boldsymbol{Z}] = 0$, $\theta \in \mathbb{R}, \boldsymbol{\beta} \in \mathbb{R}^k, k \geq 2$.

We want to test the null hypothesis $H_0 : \mathbb{E}[\xi|\boldsymbol{Z}] = 0$. The null hypothesis says that $\boldsymbol{Z}$ affects Y only through W, there are no other channels through which $\boldsymbol{Z}$ could affect Y. Under H_0 and given the assumption $\mathbb{E}[\eta|\boldsymbol{Z}] = 0$, we have $\mathbb{E}[\varepsilon|\boldsymbol{Z}] = 0$. Let $\hat{\boldsymbol{s}}$ and $\hat{\boldsymbol{\beta}}$ denote the consistent estimates of $\boldsymbol{s}$ and $\boldsymbol{\beta}$ from OLS regressions (A3) and (A2), respectively. Then

$$\begin{aligned} \hat{\boldsymbol{s}} &\xrightarrow{p} \boldsymbol{s} = \mathrm{Var}(\boldsymbol{Z})^{-1} \mathrm{Cov}(\boldsymbol{Z}, Y) = \theta \boldsymbol{\beta} \\ \hat{\boldsymbol{\beta}} &\xrightarrow{p} \boldsymbol{\beta} = \mathrm{Var}(\boldsymbol{Z})^{-1} \mathrm{Cov}(\boldsymbol{Z}, W) \end{aligned}$$

which implies

$$\frac{\hat{s}_0}{\hat{s}_1} - \frac{\hat{\beta}_0}{\hat{\beta}_1} \xrightarrow{p} \frac{s_0}{s_1} - \frac{\beta_0}{\beta_1} = 0$$

Hence,

$$H_0 : \mathbb{E}\left[\xi|\boldsymbol{Z}\right] = 0 \implies \frac{\hat{s}_0}{\hat{s}_1} - \frac{\hat{\beta}_0}{\hat{\beta}_1} \xrightarrow{p} 0$$

If we find that $\frac{\hat{s}_0}{\hat{s}_1} - \frac{\hat{\beta}_0}{\hat{\beta}_1}$ is far from 0, then we reject the $H_0 : \mathbb{E}\left[\xi|\boldsymbol{Z}\right] = 0$, and we conclude that there are other channels through which $\boldsymbol{Z}$ affects Y.

Now we map this generic setting to our paper. $Y = Y^i_{t,u,v}$ is the Retrf or CAR variable over horizon $[t+u, t+v]$ for stock i. $W = Sent^i_{t+1}$. $\boldsymbol{Z} = \left(Sent^i_t, Sent^i_t \times Capacity_t, Capacity_t, (\boldsymbol{X}^i_t)'\right)'$. If we find that $\frac{\hat{s}_0}{\hat{s}_1} - \frac{\hat{\beta}_0}{\hat{\beta}_1}$ is far from 0, we conclude that the news autocorrelation channel does not fully explain the stock price underreaction.

So we can run the following two regressions to obtain consistent estimates of $\boldsymbol{s}$ and $\boldsymbol{\beta}$. These two regressions correspond to equation (A3) and equation (A2), respectively.

$$Y^i_{t,u,v} = s_0 \times Sent^i_t + s_1 \times Sent^i_t \times Capacity_t + s_2 \times Capacity_t + \boldsymbol{\gamma}'\boldsymbol{X}^i_t + \varepsilon^i_{t,u,v} \quad \text{(A4)}$$

$$Sent^i_{t,u,v} = \beta_0 \times Sent^i_t + \beta_1 \times Sent^i_t \times Capacity_t + \beta_2 \times Capacity_t + \boldsymbol{\delta}'\boldsymbol{X}^i_t + \eta^i_{t+1} \quad \text{(A5)}$$

Let $\boldsymbol{\theta} = (s_0, s_1, \beta_0, \beta_1)'$, $\hat{\boldsymbol{\theta}} = \left(\hat{s}_0, \hat{s}_1, \hat{\beta}_0, \hat{\beta}_1\right)'$. Define $g(\boldsymbol{\theta}) = \frac{s_0}{s_1} - \frac{\beta_0}{\beta_1}$. Then the test statistic is $g\left(\hat{\boldsymbol{\theta}}\right)$. The null hypothesis is $H_0 : g\left(\hat{\boldsymbol{\theta}}\right) \xrightarrow{p} 0$.

To get a sense of the persistence in the $Sent^i_{t,u,v}$ variable, Table A18 shows the β_0 estimates from the regression in (A5).

A6.2 Derive the p-value

Instead of using the Delta method to get the p-values for the test statistics,we propose the following simulation method.[6]

1. For each year y, run regressions (A4) and (A5), keep the coefficient estimates $\left(\hat{s}_{0,y}, \hat{s}_{1,y}, \hat{\beta}_{0,y}, \hat{\beta}_{1,y}\right)$.
2. Compute the Pearson correlation matrix for $\left(\hat{s}_{0,y}, \hat{s}_{1,y}, \hat{\beta}_{0,y}, \hat{\beta}_{1,y}\right)$ using the annual coefficient estimates from Step 1.

[6]The Delta method does not work well because the test statistic is far from 0. See Table 9.

3. Run the full panel regressions (A4) and (A5), keep the coefficient estimates $\left(\hat{s}_0, \hat{s}_1, \hat{\beta}_0, \hat{\beta}_1\right)$. Also keep the estimated covariance matrix of the coefficients. Let $\hat{\boldsymbol{C}}_1$ denote the estimated covariance of $(\hat{s}_0, \hat{s}_1)$, and $\hat{\boldsymbol{C}}_2$ denote the estimated covariance of $\left(\hat{\beta}_0, \hat{\beta}_1\right)$.

4. Compute the covariance between $(\hat{s}_0, \hat{s}_1)$ and $\left(\hat{\beta}_0, \hat{\beta}_1\right)$, using the estimated correlation matrix from Step 2 and the standard errors of $\left(\hat{s}_0, \hat{s}_1, \hat{\beta}_0, \hat{\beta}_1\right)$ from Step 3. Let $\hat{\boldsymbol{C}}_3$ denote that covariance matrix.

5. Draw $J = 1,000,000$ observations from a multivariate normal distribution with mean $\left(\hat{s}_0, \hat{s}_1, \hat{\beta}_0, \frac{\hat{s}_1}{\hat{s}_0}\hat{\beta}_0\right)$ and covariance matrix $\begin{pmatrix} \hat{\boldsymbol{C}}_1 & \hat{\boldsymbol{C}}_3 \\ \hat{\boldsymbol{C}}_3' & \hat{\boldsymbol{C}}_2 \end{pmatrix}$. Let $\left(\hat{s}_{0,j}, \hat{s}_{1,j}, \hat{\beta}_{0,j}, \hat{\beta}_{1,j}\right)$ denote the j-th draw.

6. Compute the p-value of the test statistic as the fraction of draws that satisfy $\left|g_j^{sim} - \bar{g}^{sim}\right| > |\hat{g} - \bar{g}^{sim}|$, where $g_j^{sim} = \frac{\hat{s}_{0,j}}{\hat{s}_{1,j}} - \frac{\hat{\beta}_{0,j}}{\hat{\beta}_{1,j}}$, $\bar{g}^{sim} = \frac{1}{J}\sum_{j=1}^{J} g_j^{sim}$, $\hat{g} = \frac{\hat{s}_0}{\hat{s}_1} - \frac{\hat{\beta}_0}{\hat{\beta}_1}$.

A7 Return response to news

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. The subperiods were selected by first identifying NBER recessions, and then splitting the remaining data into equal-sized windows. We chose subperiods prior to running any regressions and did not change them subsequently. Table A7 shows the results of the regression in (2) over the full sample with $u = v = 1$, as well as over the different subperiods.

In Table A7, 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).[7] 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.[8] The magnitude of the underreaction in the

[7] 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.

[8] 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.

most recent time period is similar to the full-sample coefficient of 0.884.[9]

Table A8 shows the results of the specification in (2) run with the original TSM control variables augmented with our two volatility controls. Here we use share turnover instead of illiqudity as we do in our main specification. 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. The inclusion of IO, SI and log illiquidity as control variables in Table A7 slightly diminishes the role of *Sent* in most subperiods. Our full-sample results in Table A8 are even closer to TSM.

Table A9 shows the results for $Retrf$ and CAR of the ten-day ahead returns regressions. Table A10 is a summary of regression (2) for one- and ten-day ahead returns and of regression (3) for full-day and 4pm-9:30am sentiment. All four regressions are run over the full sample and over subperiods. The top panel shows results for $Retrf$ and the bottom panel shows results for CAR. A brief summary of the results: there is evidence of forecastability at the ten-day ahead horizon; the contemporaneous reactions of prices to news are much higher than the reaction of prices to lagged news, as has been documented in the prior literature (TSM, Heston and Sinha 2017 and Ke, Kelly, and Xiu 2018); the results of the contemporaneous 4pm-9:30am news regressions are very similar to the results of the full-day news regressions; there is no negative relationship over the subperiods between *Sent* coefficients in the lagged news regressions in (2) and the contemporaneous news regression in (3).

A8 Earnings forecastability by news

TSM argue that news informativeness can be measured by the degree to which earnings surprises are forecastable by lagged news sentiment. We use this insight as a check of robustness of entropy as an indicator of news informativeness. As in TSM, we use two measures of earnings surprise: standardized unexpected earnings (SUE) and standardized analysts' forecast errors (SAFE). Our construction of SUE is explained in Section 2.2. 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

[9]Murray, Xiao and Xia (2020) examine the degree to which a recurrent neural network can forecast stock returns using lagged returns. They examine the performance of their strategy in subperiods (e.g., 1995-2004, 2005-2014, 2015-2019) that are similar to ours. The profitability of their strategy is high in 1995-2004 and 2015-2019, and low in the middle period 2005-2014. And the profitability in the most recent period is not as high as in the initial period. The time variation in their forecastability results is very close to our findings in Table A7 suggesting that the phenomena we examine may impact a broad class of return patterns.

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 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.[10] We winsorize SUE and SAFE at the 5% level for the earnings regressions, as we winsorize forecast dispersion and forecast revisions at the 1% level.[11]

Figure A7 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 global financial crisis.[12] Table A6 shows summary statistics of the firm-quarter earnings regression variables.

For our earnings regressions, 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

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

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

[12]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 A12 (discussed below), as Table A13 in the Internet Appendix shows. Also, the results in Figure A6 (discussed in Section 5.3) are not impacted by the exclusion of these quarters.

[13]We also ran the analysis in Section 5.3 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.

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.

Our earnings regressions take the form

$$SUE^i_{t+1} \text{ or } SAFE^i_{t+1} = s_0 \times Sent^i_t + \boldsymbol{\beta}'\boldsymbol{X}^i_t + \epsilon^i_t, \tag{A6}$$

using quarterly data. The sentiment measure $Sent^i_t$ is stock i's average sentiment in the month preceding the announcement date of quarter $t+1$ earnings, as described in Section 2. 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 quarter $t+1$ earnings. The other controls and their summary statistics are shown in Table A6. Standard errors for the earnings regressions are clustered by quarter.

Table A12 summarizes the results of this analysis.[16] 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 into their forecasts.[17] The informativeness of news, as measured by the magnitudes and significance of the coefficients in Table A12, has varied over time. There is little evidence of either an upward or downward secular trend in the s_0 estimates.

As a robustness check of entropy as a measure of news informativeness, Panel D of Figure A6 shows the s_0 coefficient from annual versions of the SUE regression in (A6) plotted against annual average entropy. The two series are highly correlated, supporting our interpretation of both as measures of news informativeness.[18] Panel E shows the

[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.

[16] Table A14 of the Internet Appendix shows the complete full-sample regression results.

[17] Prior work has found evidence for both underreaction and overreaction to news by analysts; see Abarbanell and Bernard (1992) and Easterwood and Nutt (1999).

[18] The annual SAFE s_0 coefficient is also positively correlated with annual average entropy.

annual $CAR_{0,0}$ sensitivity to contemporaneous news plotted against the annual SUE-sentiment coefficient s_0 from (A6). In years when news is more informative about earnings surprises, stock prices have a stronger reaction to contemporaneous news. Together, Panels D and E support our interpretation that both entropy and the earnings coefficient s_0 from (A6) proxy for the information content of news.

To test whether news-earnings informativeness and the degree of stock-news underreaction are related, Panel F plots the sentiment coefficient from the $CAR_{1,1}$ regression in (2) against the sentiment coefficient s_0 from the earnings regression in (A6). There is no relationship between the informativeness of news for earnings and the degree of stock-news underreaction. Apparently, the portion of news that is informative about future earnings gets quickly absorbed into prices (Panel E) and there is little left for future prices to react to (Panel F). The correlation of entropy and s_0 (Panel D) suggests that entropy captures components of news flow that are relevant for near-term earnings. But entropy also captures other components of news flow, and these latter components seem to be related to price underreaction to news. A better understanding of the components of news flow is an interesting area for future study; Glasserman et al. (2020) is a step in this direction.

A9 Annual entropy analysis

Our basic mode of analysis is to compare the sentiment coefficient in annual regressions of one-day abnormal returns – for $CAR_{1,1}$ in equation (2) and for $CAR_{0,0}$ in equation (3) – against an annual measure of news informativeness.[19] Panel A of Figure A6 shows the s coefficient from an annual regression of $CAR_{0,0}$ on contemporaneous sentiment and control variables plotted against the average entropy of all articles that appeared in that year. There is an economically and statistically significant relationship between average article informativeness and the magnitude of the contemporaneous return response to news. This is strongly supportive of the news information hypothesis.

That more informative news flow has a larger contemporaneous price effect is not surprising. But how does this relate to stock underreaction to news? Sims (2003) and a large subsequent literature propose that investors have a limited capacity to process information. This information capacity constraint should become more binding when there is more information to process. With a more binding constraint, market participants take longer to react to value-relevant news, and stock prices should therefore react more to

[19]The results for $CAR_{1,10}$ are qualitatively similar to the results for $CAR_{1,1}$.

lagged news during high information periods. Panel B of Figure A6 shows the $CAR_{0,0}$ sentiment coefficient from Panel A, but this time plotted against the sentiment coefficient from the $CAR_{1,1}$ regression on lagged sentiment from (2). Years when prices have relatively large reactions to one-day lagged news are also years when stock prices are very responsive to contemporaneous news. This is indirect supportive of the limited capacity hypothesis.

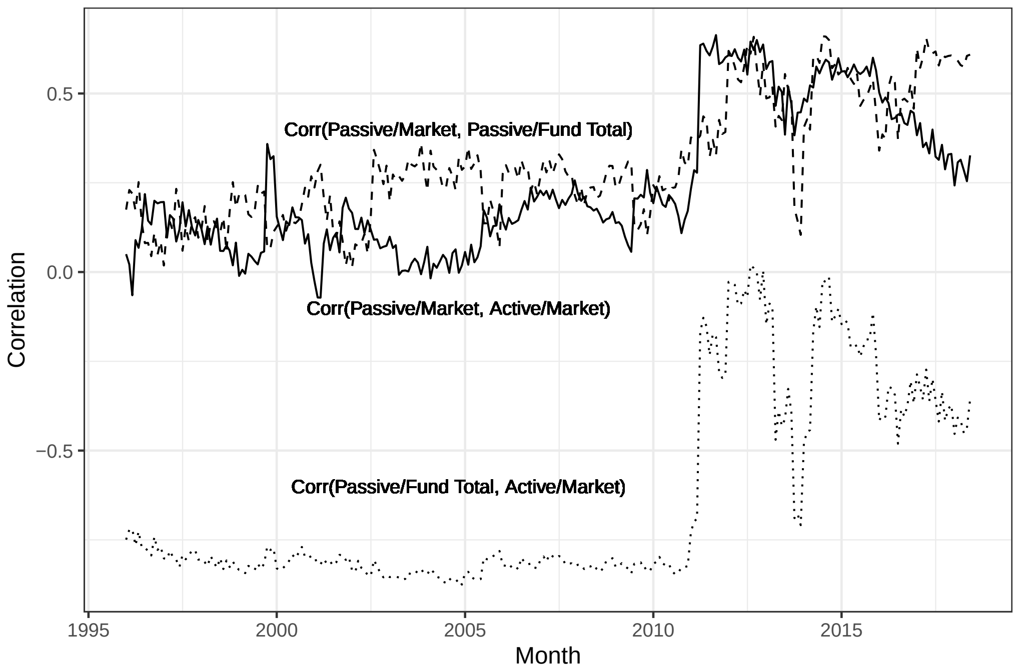
Panel C of Figure A6 offers further evidence for the hypothesis. It shows the sentiment coefficients from annual $CAR_{1,1}$ regressions plotted against annual average entropy. There is an economically and statistically significant relationship between the tendency of stocks to underreact to news (and thus for returns to load positively on one-day lagged news) and our entropy measure of informativeness. In time periods of more informative news flow, stocks have stronger reactions to contemporaneous news and also have stronger reactions to lagged news.

References

Jorda, O., 2005, "Estimation and inference of impulse responses by local projection," *American Economic Review*, 95 (1), 161–182.

Murray, S., H. Xiao, and Y. Xia, 2020, "Charting by machines," working paper.

Entire institutional ownership data set



Institutional ownership data set with outliers excluded

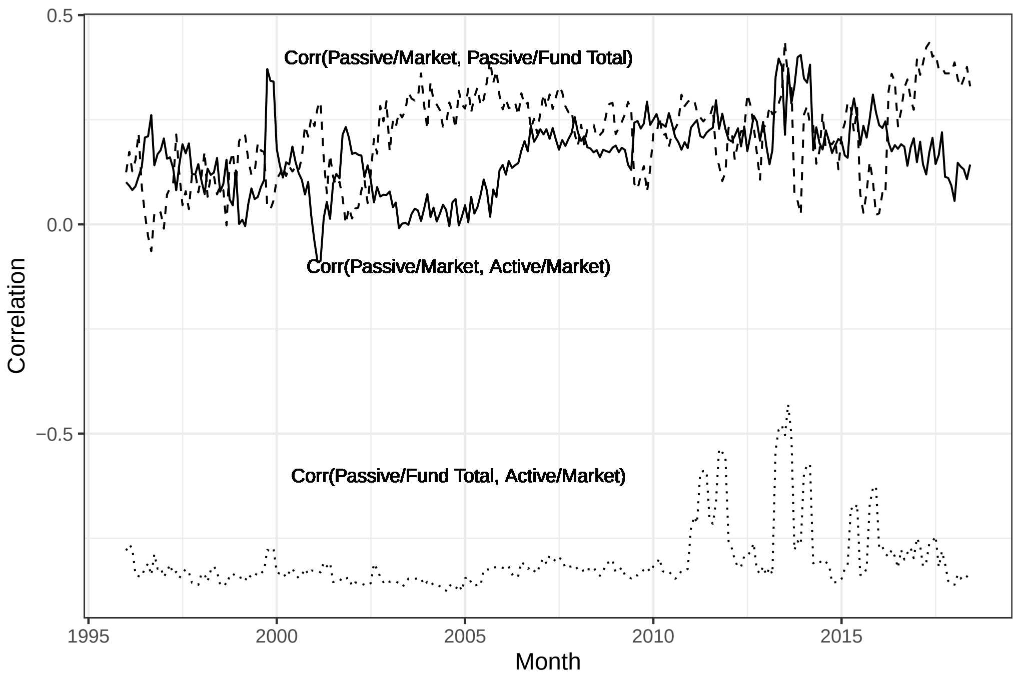


Fig. A1. Time series of cross-sectional ownership correlations. Within each month, this chart shows the cross-sectional correlations of our three ownership measures. The top panel shows the results for the full data set. The bottom panel shows the results when excluding the bottom 2.5% of each series within each month.

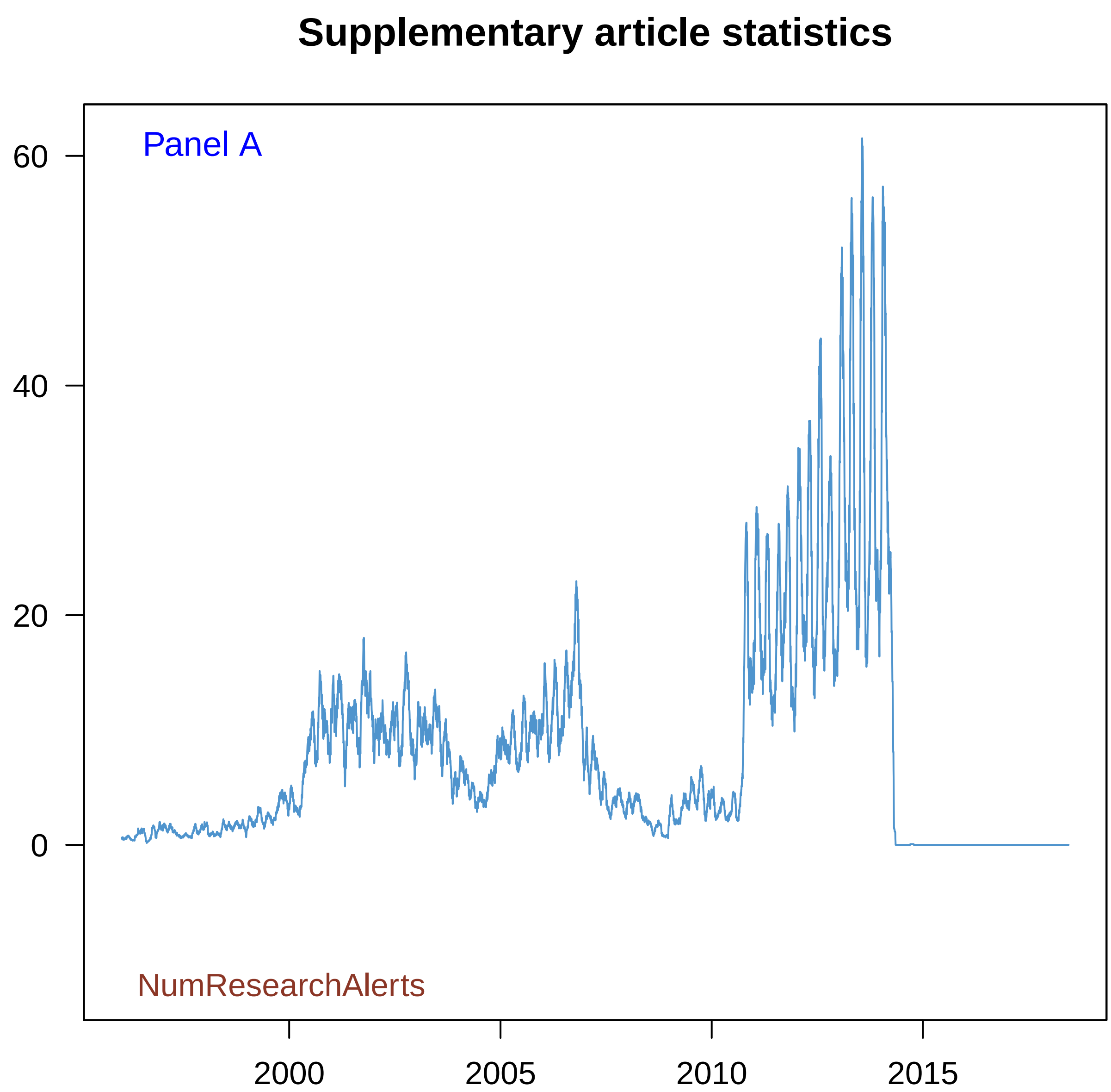


Fig. A2. This chart shows the daily number of articles with headlines containing "RESEARCH ALERT-" (case insensitive match).

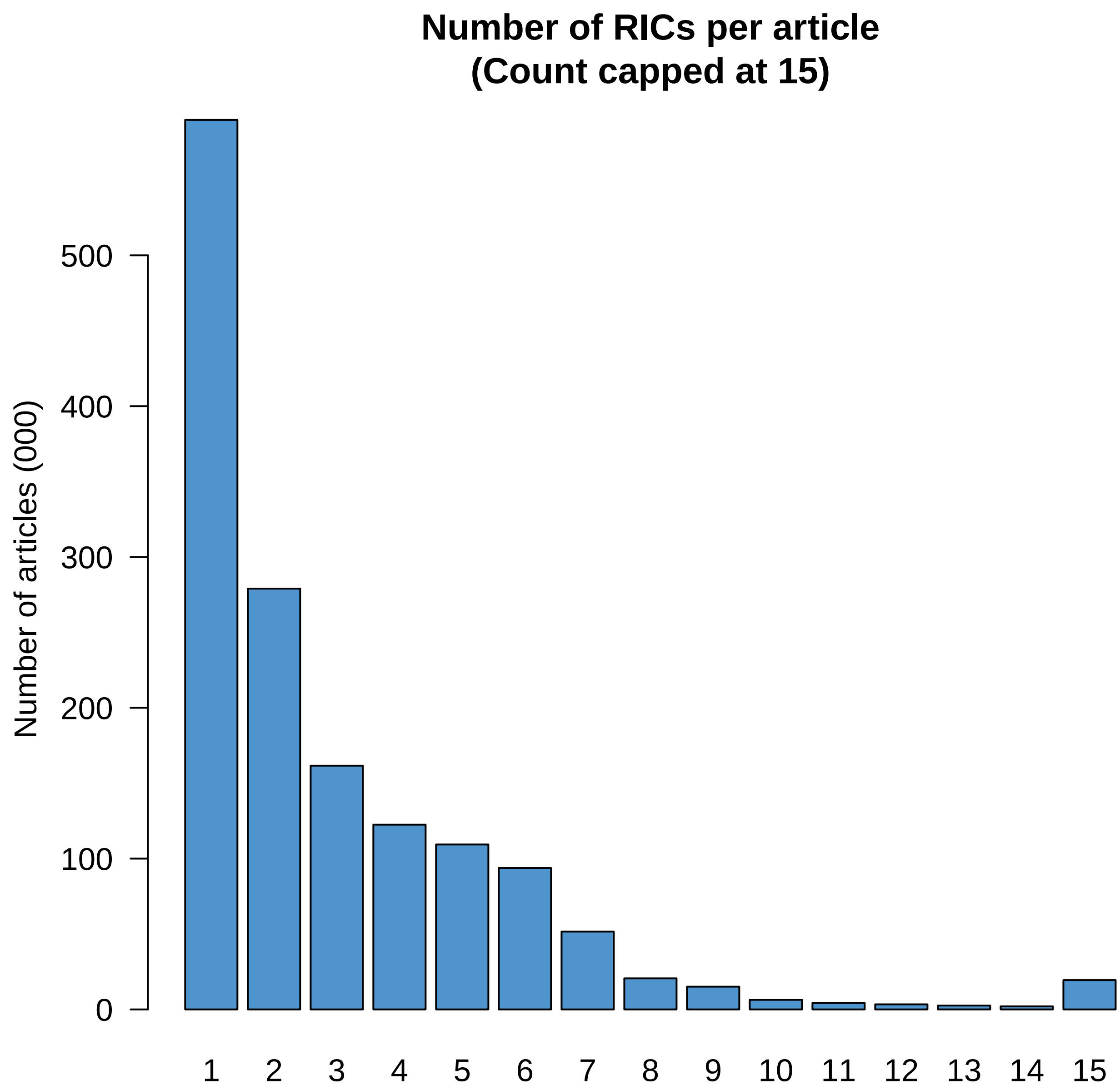
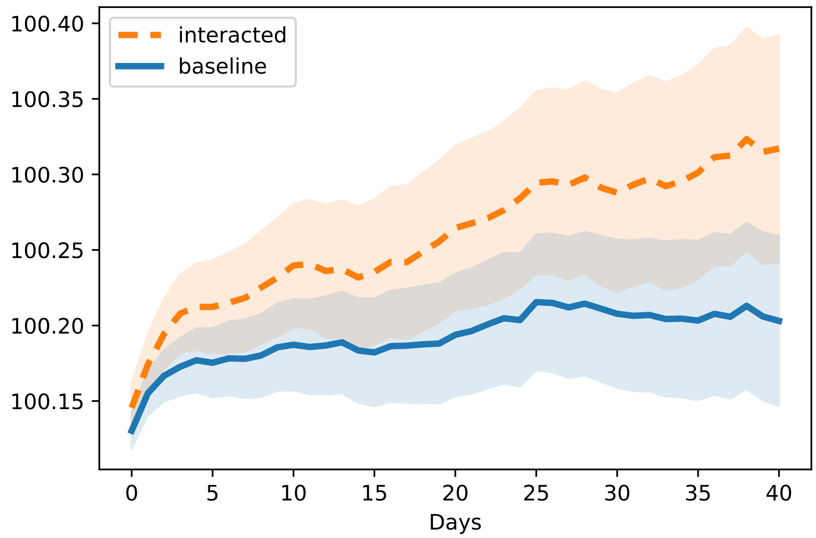


Fig. A3. This figure shows the histogram of the number of RICs (Reuters company identifier) per article. The y-axis is labeled with the number of articles in each RICs bucket, in thousands.

Impulse responses to {sentiment × passive/total ownership} shocks

Panel A: Excess returns ($Retrfs$): response to shock



Panel B: Cumulative abnormal returns ($CARs$): response to shock

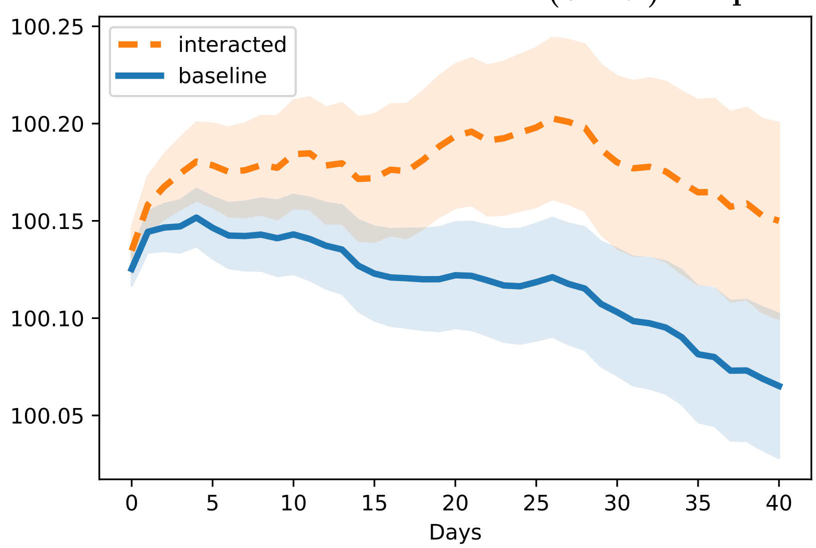
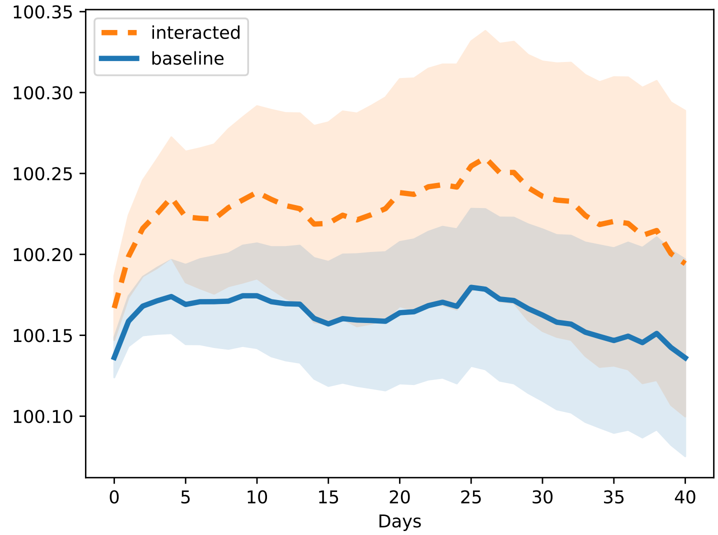


Fig. A4. Impulse response functions estimated using the local projection method of Jorda (2005). The figure shows the baseline response (labeled *baseline*) of future excess returns and cumulative abnormal returns (CARs) to a one standard deviation sentiment shock, as well as the response conditional on a one-standard deviation decrease in passive/total ownership (labeled *interacted*). The starting price level on day -1 is 100. Day 0 is the news event day. The x-axis is in number of days. The top panel shows cumulative excess returns, and the bottom panel shows CARs. The cumulative responses show the arithmetic sums of one-day returns; the geometric cumulative returns are almost identical. Standard errors are based off time-clustered panel regressions of one-day ahead future returns on lagged sentiment, and assume independence of one-day returns across time, and between the baseline and the conditinal responses. The shaded regions represent 2 standard error bands around the impulse response.

Impulse responses to {sentiment $\times$ monthly entropy} shocks

Panel A: Excess returns ($Retrfs$): response to shock



Panel B: Cumulative abnormal returns ($CARs$): response to shock

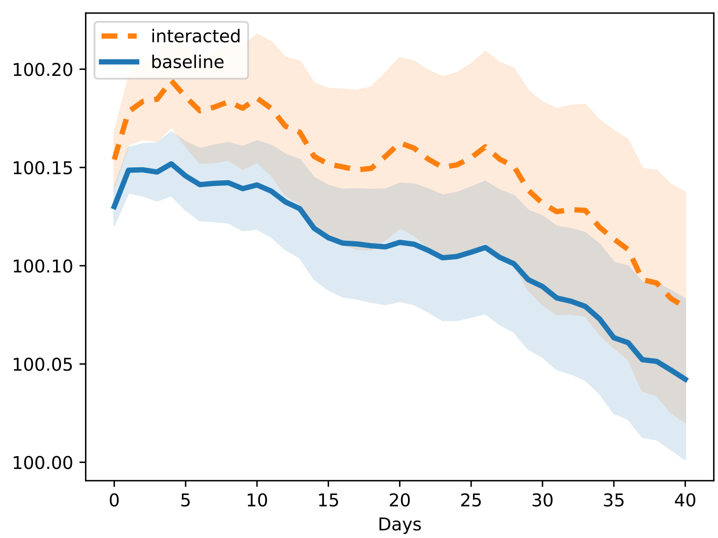


Fig. A5. Impulse response functions estimated using the local projection method of Jorda (2005). The figure shows the baseline response (labeled *baseline*) of future excess returns and cumulative abnormal returns (CARs) to a one standard deviation sentiment shock, as well as the response conditional on a one-standard deviation increase in monthly entropy (labeled *interacted*). The starting price level on day -1 is 100. Day 0 is the news event day. The x-axis is in number of days. The top panel shows cumulative excess returns, and the bottom panel shows CARs. The cumulative responses show the arithmetic sums of one-day returns; the geometric cumulative returns are almost identical. Standard errors are based off time-clustered panel regressions of one-day ahead future returns on lagged sentiment, and assume independence of one-day returns across time, and between the baseline and the conditinal responses. The shaded regions represent 2 standard error bands around the impulse response.

Sentiment coefficients and news informativeness

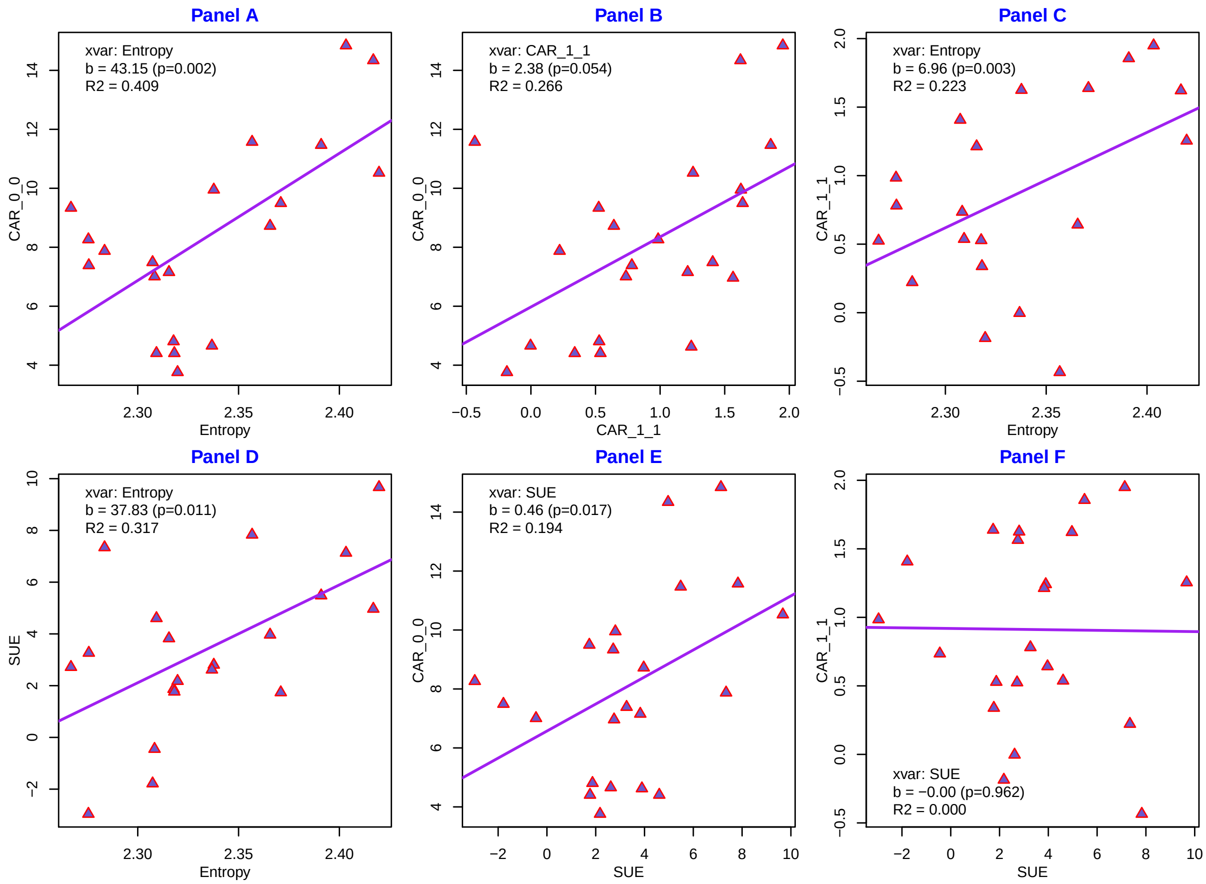


Fig. A6. Panel A shows the sentiment coefficients from annual regressions of returns $CAR_{0,0}$ on contemporaneous sentiment (eq. 3) plotted against annual average entropy. Panel B shows the sentiment coefficients from the $CAR_{0,0}$ regression plotted against the sentiment coefficients from an annual regression of returns $CAR_{1,1}$ on one-day lagged sentiment (eq. 2). Panel C shows the $CAR_{1,1}$ sentiment coefficients plotted against annual average entropy. Panel D plots the sentiment coefficient from annual regressions of SUE on lagged monthly sentiment (eq. A6) against annual average entropy. Panel E plots the annual $CAR_{0,0}$ sentiment coefficients against the annual SUE sentiment coefficients. Panel F plots the annual $CAR_{1,1}$ sentiment coefficients against the annual SUE sentiment coefficients. Each point in the table corresponds to a single year of the sample. Each chart also shows the R^2 of the best fitting regression line (shown in purple) between the y- and x-variables, as well as the slope coefficient and p-value of the regression, with standard errors calculated using White's heteroscedasticity correction.

Quarterly cross-sectional standard deviation of SUE and SAFE

Fig. A7. The top panel shows the quarterly cross-sectional standard deviation of SUE. The bottom panel shows the quarterly cross-sectional standard deviation of $SAFE$.

Table A1
Abbreviations.

Abbreviation	Replacement	Abbreviation	Replacement
SYS	SYSTEMS	UTILS	UTILITIES
MFG	MANUFACTURING	CHEM	CHEMICAL
WLDWD	WORLDWIDE	INTL	INTERNATIONAL
SVCS	SERVICES	INDS	INDUSTRIES
PPTY	PROPERTY	INVS	INVESTORS
RETRMENT	RETIREMENT	DEPT	DEPARTMENT
RLTY	REALTY	TR	TRUST
MGMT	MANAGEMENT	RES	RESOURCES
NETWRKS	NETWORKS	SOLS	SOLUTIONS
EXCH	EXCHANGE	HLDG	HOLDING
REST	RESORTS	MACHS	MACHINES
LTG	LIGHTING	LABS	LABORATORIES
RESH	RESEARCH	FRAG	FRAGRANCES
INFO	INFORMATION		

Table A2
Direct replacement.

Method	Words
Direct	INC, CORP, CO, GROUP, LTD, PLC, HOLDINGS, COMPANY, COMPANIES, COS, HLDGS, GRP, 2ND, COR, GP, LLC

Table A3
Recursive replacement: *Variant-1*.

Method	Words
Recursive	NEW, DEL, DE, NY, VA, WIS, GA, AG, MA, NC, NEV, NJ, OH, PA, TX, WA, NV, BRIDGEPORT, IND, AMER, LIMITED, KANSAS

Table A4
Recursive replacement: *Variant-2*.

Method	Words
Recursive	INTERNATIONAL, ENERGY, FINANCIAL, INDUSTRIES, L, SYSTEMS, RESOURCES, SERVICES, TECHNOLOGIES, TECHNOLOGY, INTL, POWER, ELECTRIC, HOLDING, SVCS, SERVICE, OF, INDS, UTILITIES, SYS, ENERGIES, UTILS, INSURANCE, LT, HLDG, RES

Table A5
Replaced patterns in augmented article body. X denotes a numerical character, ␣denotes a space character, and [␣]∗denotes zero or more space characters.

Pattern	Replacement	Pattern	Replacement
	Panel A: year and month		
19XX 19XX.XX 19XX-XX	␣␣y␣␣	20XX 20XX.XX 20XX-XX	␣␣y␣␣
	Panel B: entity names		
s&p	snp	s␣&␣p	snp
standard␣&␣poor's	snp	standard␣and␣poor's	snp
snp␣500	snp500	dow␣jones␣industrial␣average	djia
new␣york␣stock␣exchange	nyse	london␣stock␣exchange	ftse
stock␣exchange␣of␣hong␣kong␣	sehk	australian␣stock␣exchange␣	asx
fannie␣mae	fnma	freddie␣mac	fdmc
federal␣reserve	fed	securities␣and␣exchange␣commission	sec
chief␣executive␣officer␣	ceo	chief␣financial␣officer␣	cfo
chief␣operating␣officer␣	coo	chief␣investment␣officer␣	cio
vice␣president␣	vp	international␣monetary␣fund␣	imf
u.n.	un		
	Panel C: numerical strings		
XXXXXXXXXX	␣␣bn␣␣	XXXXXXX	␣␣mn␣␣
X[␣]∗billion	␣␣bn␣␣	X[␣]∗million	␣␣mn␣␣
	Panel D: punctuation marks between sentences		
? ! . : ;	∗∗∗		
	Panel E: punctuation marks within sentences		
“”# $ % & ‘’( ) ∗+ − \<= >@ [ ] ˆ`{|}˜	␣		

Table A6
Summary statistics for the earnings 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 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
$CAR_{-2,-2}$	40,478	0.029	1.918	−37.216	−0.803	0.806	55.365
$CAR_{-30,-3}$	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 A7

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. Standard errors are clustered by time. The *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

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	0.126	0.136	−0.150	0.194	1.107*	0.870*	0.187	0.266	1.013	0.396	−0.035	0.089	−0.400	−0.278
Sent	1.192***	0.914***	2.129***	1.584***	0.566	1.314	1.160***	0.899***	1.174	1.156**	0.598**	0.227	0.480	0.719***
$\text{CAR}_{0,0}$	0.001	0.001	−0.001	0.002	0.017	0.020	0.011	0.009	−0.015	−0.017	0.006	0.005	0.004	−0.002
$\text{CAR}_{-1,-1}$	−0.004	−0.008	−0.028***	−0.024***	0.003	0.001	−0.012	−0.011	0.016	0.0001	0.002	0.0005	0.001	−0.004
$\text{CAR}_{-2,-2}$	−0.009*	−0.006	−0.009*	−0.005	0.002	−0.0005	−0.004	−0.006	−0.016	−0.008	−0.004	−0.003	−0.007	−0.009
$\text{CAR}_{-30,-3}$	−0.001	−0.001	−0.0003	−0.0001	0.00002	0.001	−0.004**	−0.003**	0.001	−0.001	−0.001	−0.001	−0.003*	−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**	0.021	0.005	0.002	0.001	0.012	0.002	0.008	0.00000	0.012	−0.0004
SUE	0.011*	0.007***	0.0001	0.002	0.020	0.007	0.004	0.004	0.006	0.010	0.008	0.009**	0.016***	0.011***
Short Interest (%)	−0.006*	−0.004*	−0.005	−0.006	−0.015	−0.006	−0.007	−0.004	−0.015	−0.007	−0.0003	−0.001	0.0001	0.001
IO (%)	−0.0002	−0.0002	0.001	0.0004	−0.001	−0.002	0.001	−0.0002	−0.005**	−0.002*	0.0002	0.00003	0.001*	0.001*
log(Market Cap)	−0.033	−0.014*	0.026	0.008	−0.033	−0.079	−0.021	−0.013	−0.175*	−0.014	0.015	−0.033**	−0.022	−0.011
IHS(Book/Market)	0.024	0.0003	0.022	0.011	−0.029	0.006	0.072**	0.015	0.004	−0.072	0.030	0.007	0.014	0.022
log(Illiquidity)	−0.026	−0.009	0.036	0.022	0.033	−0.048	−0.013	−0.003	−0.138	−0.005	0.018	−0.029**	−0.031	−0.021*
α	−0.015	0.048	0.260**	0.226**	0.124	0.225	0.018	0.020	−0.349	−0.143	0.129	0.048	−0.049	0.050
Observations	618,367	618,367	111,817	111,817	26,383	26,383	144,277	144,277	97,376	97,376	154,433	154,433	84,081	84,081
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 A8

This table replicates the return forecastability results from Tetlock, Saar-Tsechansky, and Macskassy (2008). 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. Standard errors are clustered by time. The *, **, and *** indicate significance at the 10%, 5%, and 1% levels. 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 label (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 *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Replication of return results from Tetlock, Saar-Tsechansky, and Macskassy (2008)

	Dependent variable:													
	$Retrf_{1,1}$	$CAR_{1,1}$	$Retrf_{1,1}$	$CAR_{1,1}$	$Retrf_{1,1}$	$CAR_{1,1}$	$Retrf_{1,1}$	$CAR_{1,1}$	$Retrf_{1,1}$	$CAR_{1,1}$	$Retrf_{1,1}$	$CAR_{1,1}$	$Retrf_{1,1}$	$CAR_{1,1}$
	1996-2018		1996-2000		2001		2002-2006		2007-2009		2010-2014		2015-2018	
Constant	−0.045	0.080	0.039	0.384**	0.218	0.600	0.176	0.143	−0.090	−0.338	−0.053	0.123	−0.203	−0.080
Sent	1.258***	0.961***	2.125***	1.674***	0.228	1.140	1.424***	0.976***	1.407	1.316**	0.559**	0.224	0.464	0.696***
$CAR_{0,0}$	0.0001	−0.001	−0.003	0.0001	0.017	0.012	0.006	0.004	−0.016	−0.017	0.006	0.005	0.003	−0.002
$CAR_{-1,-1}$	−0.006	−0.010**	−0.025***	−0.024***	−0.028	−0.012	−0.012	−0.012	0.016	−0.00003	0.002	0.0004	0.002	−0.003
$CAR_{-2,-2}$	−0.011**	−0.007*	−0.013**	−0.008	0.001	−0.001	−0.008	−0.009	−0.017	−0.009	−0.004	−0.003	−0.007	−0.009
$CAR_{-30,-3}$	−0.001	−0.001	−0.0004	−0.0004	−0.002	−0.001	−0.004**	−0.003**	0.001	−0.0004	−0.001	−0.001	−0.003*	−0.003**
$CAR^2_{0,0}$	0.0004	0.0004	−0.001*	−0.001	−0.003**	−0.003**	0.0001	0.0001	0.001**	0.001**	−0.001	−0.001*	0.0005	0.0001
VIX	0.006	0.001	0.017**	0.004**	0.031	0.008	0.001	0.001	0.010	0.002	0.008	−0.001	0.011	−0.001
α	−0.006	0.096*	0.179*	0.179**	0.085	0.296	−0.015	0.070	−0.218	−0.131	0.110	0.074	−0.024	0.046
SUE	0.014**	0.009***	0.006	0.007	0.028	0.016	0.006	0.004	0.011	0.010	0.008	0.009**	0.015***	0.010***
log(Market Cap)	−0.005	−0.002	−0.015	−0.009	−0.045	−0.023	−0.010	0.001	−0.016	0.011	−0.006	−0.002	0.008	0.008
IHS(Book/Market)	0.030	−0.010	−0.017	−0.033	−0.040	−0.008	0.073**	0.018	−0.007	−0.067	0.028	0.008	0.003	0.010
log(Share Turnover)	−0.013	0.008	−0.001	0.040**	−0.023	0.033	−0.012	0.032**	−0.044	−0.012	−0.019	0.012	0.023	0.018
Observations	647,078	647,078	125,136	125,136	30,367	30,367	150,999	150,999	98,390	98,390	156,317	156,317	85,869	85,869
Adjusted R^2	0.001	0.0005	0.002	0.001	0.006	0.005	0.001	0.001	0.003	0.003	0.001	0.0003	0.001	0.0004

Note: *p<0.1; **p<0.05; ***p<0.01

Table A9

10-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. Standard errors are clustered by time. The *, **, and *** indicate significance at the 10%, 5%, and 1% levels. 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 label (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 *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Ten-day ahead return regressions

	Dependent variable:													
	$Retrf_{1,10}$	$CAR_{1,10}$	$Retrf_{1,10}$	$CAR_{1,10}$	$Retrf_{1,10}$	$CAR_{1,10}$	$Retrf_{1,10}$	$CAR_{1,10}$	$Retrf_{1,10}$	$CAR_{1,10}$	$Retrf_{1,10}$	$CAR_{1,10}$	$Retrf_{1,10}$	$CAR_{1,10}$
	1996-2018		1996-2000		2001		2002-2006		2007-2009		2010-2014		2015-2018	
Constant	3.396^{***}	1.975^{***}	0.114	1.828^{***}	4.102^{**}	7.289^{***}	2.493^{**}	1.968^{***}	18.527^{***}	6.089^{***}	1.146^{*}	1.140^{***}	-3.316^{***}	-2.005^{***}
Sent	2.793^{***}	0.821^{*}	4.604^{***}	2.748^{***}	-0.528	1.867	2.989^{***}	2.632^{***}	4.210^{*}	0.096	1.280	-0.813	-1.796^{*}	-0.979
$CAR_{0,0}$	-0.040^{***}	-0.038^{***}	-0.013	-0.007	-0.035	-0.015	-0.032^{*}	-0.032^{*}	-0.111^{***}	-0.102^{***}	0.005	-0.010	-0.009	-0.020
$CAR_{-1,-1}$	-0.051^{***}	-0.049^{***}	-0.027^{**}	-0.017	-0.030	-0.025	-0.079^{***}	-0.066^{***}	-0.086^{**}	-0.099^{**}	-0.0001	-0.002	-0.047^{**}	-0.045^{**}
$CAR_{-2,-2}$	-0.065^{***}	-0.059^{***}	-0.043^{***}	-0.027^{*}	-0.006	0.040	-0.079^{***}	-0.068^{**}	-0.128^{***}	-0.132^{***}	-0.003	-0.001	-0.008	-0.030
$CAR_{-30,-3}$	-0.005^{*}	-0.007^{***}	-0.005	0.001	-0.020^{**}	-0.013	-0.028^{***}	-0.021^{***}	0.010	-0.006	-0.004	-0.005	-0.012^{**}	-0.020^{***}
$CAR^2_{0,0}$	0.002	0.003^{***}	-0.001	-0.001	-0.003	-0.002	0.005^{***}	0.006^{***}	0.002	0.004^{**}	-0.0003	0.001	0.003^{**}	0.002^{*}
VIX	0.020	0.002	0.084^{***}	0.008	0.339^{***}	0.042^{***}	0.018	0.004	0.024	0.006	0.027	-0.005^{**}	0.118^{***}	0.007
SUE	0.039^{**}	0.021^{***}	-0.035^{*}	-0.028	0.134^{***}	0.008	-0.025	-0.012	-0.038	0.069^{***}	0.059^{***}	0.026^{**}	0.073^{***}	0.056^{***}
Short Interest (%)	-0.027^{***}	-0.010^{*}	-0.008	-0.015	-0.081^{***}	-0.052^{**}	-0.020	0.017	-0.090^{***}	-0.025	0.018^{*}	-0.005	0.023	0.017
IO (%)	-0.002^{**}	-0.002^{***}	0.001	0.0001	0.001	-0.018^{***}	0.007^{***}	0.0002	-0.048^{***}	-0.024^{***}	0.0003	-0.0005	0.004^{***}	0.003^{***}
log(Market Cap)	-0.218^{***}	-0.121^{***}	0.188^{*}	0.038	0.127	-0.231	-0.266^{*}	-0.113	-0.936^{***}	-0.091	0.322^{***}	-0.273^{***}	-0.078	-0.005
IHS(Book/Market)	0.218^{***}	-0.001	0.235^{*}	0.258^{**}	0.453^{**}	0.729^{***}	0.433^{***}	-0.010	0.321	-0.452^{***}	0.122^{*}	0.032	-0.027	-0.053
log(Illiquidity)	-0.084	-0.046^{**}	0.276^{***}	0.136^{*}	0.715^{***}	0.085	-0.146	-0.031	-0.292	0.086	0.376^{***}	-0.234^{***}	-0.148^{**}	-0.072^{**}
α	-0.360^{*}	-0.052	1.470^{***}	1.676^{***}	-0.350	1.206^{**}	-0.318	-0.345	-1.871^{***}	-2.029^{***}	1.198^{***}	0.622^{***}	-1.056^{**}	-0.449
Observations	618,369	618,369	111,817	111,817	26,383	26,383	144,278	144,278	97,376	97,376	154,433	154,433	84,082	84,082
Adjusted R^2	0.002	0.002	0.004	0.001	0.042	0.007	0.006	0.006	0.010	0.010	0.002	0.001	0.012	0.003

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

Table A10

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 $\mathrm{Retrf}_{0,0}$ and $\mathrm{CAR}_{0,0}$ regressions omit the $\mathrm{CAR}_{0,0}$ control. The row label (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 *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Return predictability

		1996-2018	1996-2000	2001	2002-2006	2007-2009	2010-2014	2015-2018
$\mathrm{Retrf}_{0,0}$	Sent	9.184***	9.842***	12.611***	9.694***	12.709***	5.117***	9.022***
$\mathrm{Retrf}_{0,0}$	Sent (4pm-9:30am)	6.18***	6.01***	8.783***	7.47***	7.076***	3.888***	5.87***
$\mathrm{Retrf}_{1,1}$	Sent	1.192***	2.129***	0.566	1.16***	1.174	0.598**	0.48
$\mathrm{Retrf}_{1,10}$	Sent	2.793***	4.604***	-0.528	2.989***	4.21*	1.28	-1.796*
$\mathrm{CAR}_{0,0}$	Sent	8.086***	9.209***	10.562***	9.084***	9.715***	4.404***	8.251***
$\mathrm{CAR}_{0,0}$	Sent (4pm-9:30am)	5.949***	5.718***	7.594***	7.445***	6.96***	3.946***	5.495***
$\mathrm{CAR}_{1,1}$	Sent	0.914***	1.584***	1.314	0.899***	1.156**	0.227	0.719***
$\mathrm{CAR}_{1,10}$	Sent	0.821*	2.748***	1.867	2.632***	0.096	-0.813	-0.979

Table A11

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 label (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 *, **, and *** indicate significance at the 10%, 5%, and 1% levels. Each ownership series in these regressions has been trimmed to exclude in each month the bottom 2.5% of observations.

Mutual fund ownership effects on sentiment predictability (trimmed ownership)

Return regressions

		Mutual Fund Ownership (%)		
		Passive/Market	Active/Market	Passive/Fund Total
$\text{Retrf}_{0,0}$	Sent	9.306***	9.212***	9.216***
	Sent×Ownership	-0.071	0.204***	-0.053***
$\text{Retrf}_{0,0}$	Sent (4pm-9:30am)	6.272***	6.194***	6.277***
	Sent (4pm-9:30am)×Ownership	-0.061	0.213***	-0.059***
$\text{Retrf}_{1,1}$	Sent	1.17***	1.186***	1.178***
	Sent×Ownership	-0.08	0.017	-0.013
$\text{Retrf}_{1,10}$	Sent	2.77***	2.861***	2.776***
	Sent×Ownership	-0.498***	0.216**	-0.137***

CAR regressions

		Mutual Fund Ownership (%)		
		Passive/Market	Active/Market	Passive/Fund Total
$\text{CAR}_{0,0}$	Sent	8.169***	8.081***	8.088***
	Sent×Ownership	-0.048	0.188***	-0.045***
$\text{CAR}_{0,0}$	Sent (4pm-9:30am)	6.002***	5.935***	6.004***
	Sent (4pm-9:30am)×Ownership	-0.007	0.189***	-0.036**
$\text{CAR}_{1,1}$	Sent	0.925***	0.926***	0.932***
	Sent×Ownership	-0.047	0.032	-0.018*
$\text{CAR}_{1,10}$	Sent	0.975**	0.932**	0.894**
	Sent×Ownership	-0.346***	0.15**	-0.115***

Table A12
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. The *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

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 A13
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. The *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

SUE **and** $SAFE$ **forecastability by** $SENT$ **excluding 4Q2017 and 1Q2018**

	1996-2017 Q3	1996-2000	2001	2002-2006	2007-2009	2010-2014	2015-2017 Q3
SUE	4.078***	3.971***	9.67***	4.323***	3.182**	3.144***	1.678
SAFE	0.552***	0.369	1.399***	0.743***	0.967**	0.379*	0.528**

Table A14

Forecasting regressions for SUE and SAFE. 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. The *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

SUE and SAFE forecasting regressions from 1996 to 2018

	Dependent variable:	
	SUE	SAFE
Constant	0.385	-0.169^{***}
Sent	3.733^{***}	0.557^{***}
Lag(SUE)	0.263^{***}	
Lag(SAFE)		0.213^{***}
Forecast Dispersion	-0.601^{***}	0.238^{***}
Forecast Revisions	57.751^{***}	7.491^{***}
$\text{CAR}_{-2,-2}$	0.012^{***}	0.002^{***}
$\text{CAR}_{-30,-3}$	0.005^{***}	0.002^{***}
Short Interest (%)	-0.010^{***}	-0.003^{***}
IO (%)	-0.001	0.0003^{***}
log(Market Cap)	-0.032	-0.018^{***}
IHS(Book/Market)	0.034	-0.051^{***}
log(Illiquidity)	-0.024	-0.029^{***}
α	1.394^{***}	0.034^{**}
Observations	31,581	29,733
Adjusted R^2	0.137	0.122
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A15
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 label (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 *, **, and *** indicate significance at the 10%, 5%, and 1% levels. These specifications drop all event days that fall on earnings announcement days, or on subsequent business days.

Return predictability (dropped earnings days)

		1996-2018	1996-2000	2001	2002-2006	2007-2009	2010-2014	2015-2018
$\text{Retrf}_{0,0}$	Sent	7.684***	8.972***	11.802***	7.967***	10.834***	3.832***	6.137***
$\text{Retrf}_{0,0}$	Sent (4pm-9:30am)	4.832***	5.382***	8.283***	5.951***	5.045***	2.543***	3.574***
$\text{Retrf}_{1,1}$	Sent	1.131***	2.047***	0.301	1.075***	1.021	0.691**	0.345
$\text{Retrf}_{1,10}$	Sent	3.012***	4.731***	-0.202	2.931***	4.075	1.524*	-1.624
$\text{CAR}_{0,0}$	Sent	6.599***	8.323***	9.809***	7.4***	7.752***	3.207***	5.332***
$\text{CAR}_{0,0}$	Sent (4pm-9:30am)	4.637***	5.133***	7.089***	5.966***	4.898***	2.716***	3.088***
$\text{CAR}_{1,1}$	Sent	0.87***	1.444***	0.854	0.875***	1.115**	0.29	0.619**
$\text{CAR}_{1,10}$	Sent	0.85*	2.709**	2.576	2.581***	-0.28	-0.798	-1.102

Table A16
These regressions include as controls: constant, $CAR_{0,0}$, $CAR_{-1,-1}$, $CAR_{-2,-2}$, $CAR_{-30,-3}$, SUE, $SI(\%)$, $IO(\%)$, $\log(Market\ Cap)$, $IHS(Book/Market)$, $log(Illiquidity)$, and lagged α. The row label (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 *, **, and *** indicate significance at the 10%, 5%, and 1% levels. These specifications *do not include* the VIX and the squared lagged CARs as explanatory variables.

Return predictability (no volatility controls)

		1996-2018	1996-2000	2001	2002-2006	2007-2009	2010-2014	2015-2018
$\text{Retrf}_{0,0}$	Sent	9.593***	9.956***	14.579***	10.2***	13.775***	5.484***	9.177***
$\text{Retrf}_{0,0}$	Sent (4pm-9:30am)	6.552***	6.116***	10.493***	7.96***	7.9***	4.328***	5.931***
$\text{Retrf}_{1,1}$	Sent	1.002***	2.038***	0.314	1.118***	0.359	0.526*	0.42
$\text{Retrf}_{1,10}$	Sent	2.225***	4.104***	-5.802	2.291**	2.673	1.009	-2.373**
$\text{CAR}_{0,0}$	Sent	7.993***	9.083***	11.76***	9.099***	9.558***	4.452***	8.215***
$\text{CAR}_{0,0}$	Sent (4pm-9:30am)	5.835***	5.584***	8.499***	7.454***	6.701***	3.972***	5.468***
$\text{CAR}_{1,1}$	Sent	0.861***	1.58***	1.32	0.879***	0.926*	0.233	0.718***
$\text{CAR}_{1,10}$	Sent	0.627	2.771***	1.286	2.187**	-0.62	-0.768	-1.031

Table A17

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 label (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 *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

VIX effects on sentiment predictability

Return regressions

		VIX
$\text{Retrf}_{0,0}$	Sent	0.477
	Sent×VIX	0.425***
$\text{Retrf}_{0,0}$	Sent (4pm-9:30am)	2.534*
	Sent (4pm-9:30am)×VIX	0.178**
$\text{Retrf}_{1,1}$	Sent	2.395
	Sent×VIX	-0.059
$\text{Retrf}_{1,10}$	Sent	9.571**
	Sent×VIX	-0.331

CAR regressions

		VIX
$\text{CAR}_{0,0}$	Sent	3.26***
	Sent×VIX	0.235***
$\text{CAR}_{0,0}$	Sent (4pm-9:30am)	3.953***
	Sent (4pm-9:30am)×VIX	0.098**
$\text{CAR}_{1,1}$	Sent	1.053*
	Sent×VIX	-0.007
$\text{CAR}_{1,10}$	Sent	6.501***
	Sent×VIX	-0.277***

Table A18

This table shows the estimated β_0 from (A5). For the $\{1, 1\}$ regressions the dependent variable is the next day's sentiment $Sent^i_{t,1,1}$, and for the $\{1, 10\}$ regressions the dependent variable is the average sentiment measured over the next 10 days $Sent^i_{t,1,10}$. In both cases, the independent variable is the time t sentiment $Sent^i_t$ (or $Sent^i_{t,0,0}$). *** indicates significance at the 1% level or better. Note that for a given i and j, (A5) is the same for $\text{Retrf}_{i,j}$ and $\text{CAR}_{i,j}$.

News autocorrelation coefficient β_0 from (A5)

Panel A: News autocorrelation channel conditional on intermediary capacity								
	Capacity							
	CR (daily)		CR (monthly)		CR (quarterly)		Lev (quarterly)	
	$\hat{\beta}_0$	s.e.	$\hat{\beta}_0$	s.e.	$\hat{\beta}_0$	s.e.	$\hat{\beta}_0$	s.e.
$\text{Retrf}_{1,1}$	0.2503***	0.0029	0.2462***	0.0028	0.2462***	0.0028	0.2457***	0.0028
$\text{Retrf}_{1,10}$	0.1809***	0.002	0.1776***	0.0019	0.1776***	0.0019	0.1772***	0.0019
$\text{CAR}_{1,1}$	0.2503***	0.0029	0.2462***	0.0028	0.2462***	0.0028	0.2457***	0.0028
$\text{CAR}_{1,10}$	0.1809***	0.002	0.1776***	0.0019	0.1776***	0.0019	0.1772***	0.0019

Panel B: News autocorrelation channel conditional on mutual fund ownership						
	Ownership					
	Passive/Market		Active/Market		Passive/Fund Total	
	$\hat{\beta}_0$	s.e.	$\hat{\beta}_0$	s.e.	$\hat{\beta}_0$	s.e.
$\text{Retrf}_{1,1}$	0.2459***	0.0028	0.247***	0.0028	0.2462***	0.0028
$\text{Retrf}_{1,10}$	0.1772***	0.0019	0.1786***	0.0019	0.1772***	0.0019
$\text{CAR}_{1,1}$	0.2459***	0.0028	0.247***	0.0028	0.2462***	0.0028
$\text{CAR}_{1,10}$	0.1772***	0.0019	0.1786***	0.0019	0.1772***	0.0019

Model Appendix: Time Variation in the News-Returns Relationship

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1 One-period model

Assume a one period model, where an agent (indexed by i) solves the following mean-variance portfolio problem with benchmarking penalty

$$\max_{w} w^{\top}(\mu_i - P) - \frac{\gamma_i}{2} w^{\top}\Sigma w - \frac{1}{2}(w-x)^{\top}\Lambda_i(w-x) \tag{1}$$

for $w, x, \mu_i, P \in \mathbb{R}^N$. P is the vector of security prices, w is the agent's portfolio holdings, μ_i is agent i's expectations about end-of-period security values, and Σ is the covariance matrix of end-of-period security values conditional on the investor's information set. The vector x captures the benchmark target, and $\Lambda_i \in \mathbb{R}^{N\times N}$ is a symmetric matrix which represents the deviation penalty. $\gamma_i \geq 0$ is the investor's risk aversion.

The first-order condition for the problem is

$$\mu_i - P - \gamma_i \Sigma w - \Lambda_i(w-x) = 0.$$

Rearranging we find

$$w_i = (\gamma_i\Sigma + \Lambda_i)^{-1}(\mu_i - P + \Lambda_i x). \tag{2}$$

The price elasticity of demand is

$$\frac{\partial w_i}{\partial P} = -(\gamma_i\Sigma + \Lambda_i)^{-1}, \tag{3}$$

so higher benchmarking penalty *or* higher risk aversion play a similar role of decreasing price elasticity. Note (3) is also the elasticity of demand with respect to an investor's beliefs about future returns μ_i.

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Market clearing requires

$$\sum_i \phi_i w_i = S,$$

where ϕ_i is the fraction of the population represented by the i-th investor with $\sum_i \phi_i = 1$, and $S \in \mathbb{R}^N$ is the supply of shares. Using (2) we get

$$\sum_i \phi_i \left(\gamma_i \Sigma + \Lambda_i\right)^{-1} \left(\mu_i - P + \Lambda_i x\right) = S. \tag{4}$$

After rearranging

$$\sum_i \phi_i \left(\gamma_i \Sigma + \Lambda_i\right)^{-1} \left(\mu_i + \Lambda_i x\right) - S = \sum_i \phi_i (\gamma_i \Sigma + \Lambda_i)^{-1} P.$$

Assume that Σ is a diagonal matrix with all entries equal to σ^2. And assume that the benchmarking penalty $\Lambda_i = \lambda_i I$ for $\lambda_i \in \mathbb{R}$ and I an $N \times N$ identity matrix. The market clearing condition for stock $j \in \{1, \ldots, N\}$ is therefore

$$\sum_i \frac{\phi_i}{\gamma_i \sigma^2 + \lambda_i} \left(\mu_{ij} + \lambda_i x_j\right) - S_j = P_j \sum_i \frac{\phi_i}{\gamma_i \sigma^2 + \lambda_i}.$$

The risk premium in the price is not central to the present analysis, so we set $S_j = x_j = 0, \forall j$. With this we get the following equation for the equilibrium price of security j

$$\sum_i \frac{\phi_i}{\gamma_i \sigma^2 + \lambda_i} \mu_{ij} = P_j \sum_i \frac{\phi_i}{\gamma_i \sigma^2 + \lambda_i},$$

from which we get

$$P_j = \left(\sum_i \frac{\phi_i}{\gamma_i \sigma^2 + \lambda_i}\right)^{-1} \sum_i \frac{\phi_i}{\gamma_i \sigma^2 + \lambda_i} \mu_{ij}. \tag{5}$$

Since the supply of shares and the benchmark target x_j are zero, there is no risk discount in the price and P_j is simply the weighted average investor belief about future payoff of stock j.

We now specialize the equilibrium to three types of investors. A fraction ϕ_1 represents non-institutional investors. These investors have $\gamma_1 = 1$ (without loss of generality) and face no benchmarking constraints on portfolio holdings so $\lambda_1 = 0$. A fraction ϕ_2 of investors are financial intermediaries. They are less risk-averse than non-institutional investors, so $\gamma_2 = \gamma < 1$ and face no benchmarking restrictions, so $\lambda_2 = 0$. Shin (2009) shows that a VaR constraint leads to an equivalent optimization problem to (1) where γ represents the shadow cost of the VaR constraint. We can therefore interpret γ for financial intermediaries as a measure of the degree to which they are constrained in their risk-taking activities. Finally, passive institutional investors, or indexers, have zero risk-aversion but face a benchmarking restriction $\lambda_3 > 1$, because the i-th indexer is required by mandate to not deviate too far away from its benchmark index x (assumed to be zero). The degree to which the i-th investor is constrained is given by $\gamma_i \sigma^2 + \lambda_i$, so assuming $\sigma^2 \approx 1$, we

Investor	Weight	Risk Aversion	Benchmarking	Constrained
Non-institutional	ϕ_1	$\gamma_1 = 1$	$\lambda_1 = 0$	Medium
Intermediaries	ϕ_2	$\gamma_2 < 1$	$\lambda_2 = 0$	Least
Passive	ϕ_3	$\gamma_3 = 0$	$\lambda_3 > 1$	Most

can say that intermediaries are less constrained than non-institutional investors, and non-institutional investors are less constrained than indexers. The key features of the three types of investors can be summarized as follows:

We now specify how each investor group updates beliefs based on news. Assume that I_j represents good news about security j, and that $\mu_{ij} = f_i(I_j, \dots)$ with $\partial\mu_{ij}/\partial I_j > 0$, where the $\dots$ indicate that beliefs can depend on other factors besides news. We assume that non-institutional investors and intermediaries update their beliefs in proportion to the information content τ of news, so

$$\frac{\partial \mu_{ij}}{\partial I_j} = f(\tau) \qquad \text{for } i \in \{1, 2\},$$

where $f(\tau) \in (0,1)$ and is increasing in τ. Furthermore, we assume that $\sigma^2 = \sigma^2(\tau) \in (0,1)$ for $i = 1, 2$ and that $\sigma^2(\tau)$ is decreasing in the information content τ of news.[1] Indexers don't update beliefs in response to news, so $\partial\mu_{3j}/\partial I_j = 0$. As in (1), this reflects institutional constraints on the behavior of indexers.

Using the price from (5) we find that the sensitivity of P_j to news is

$$\frac{\partial P_j}{\partial I_j} = \frac{\frac{\phi_1}{\sigma^2(\tau)} + \frac{\phi_2}{\gamma_2\sigma^2(\tau)}}{\frac{\phi_1}{\sigma^2(\tau)} + \frac{\phi_2}{\gamma_2\sigma^2(\tau)} + \frac{\phi_3}{\lambda_3}} f(\tau).$$

Note that the denominator is positive, and that $\phi_1 = 1 - \phi_2 - \phi_3$. Making this substitution and multiplying by σ^2 we find:

$$\begin{aligned}\frac{\partial P_j}{\partial I_j} &= \frac{1 - \phi_2 - \phi_3 + \frac{\phi_2}{\gamma_2}}{1 - \phi_2 - \phi_3 + \frac{\phi_2}{\gamma_2} + \frac{\phi_3}{\lambda_3}\sigma^2(\tau)} f(\tau), \\ &= \frac{1 + \frac{1-\gamma_2}{\gamma_2}\phi_2 - \phi_3}{1 + \frac{1-\gamma_2}{\gamma_2}\phi_2 + \frac{\sigma^2(\tau)-\lambda_3}{\lambda_3}\phi_3} f(\tau).\end{aligned} \tag{6}$$

The following properties hold in equilibrium:

Proposition 1. *Price sensitivity to news increases with more intermediaries and decreases with more passive investors.*

Proposition 2. *Price sensitivity to news increases when intermediaries are less constrained, i.e., have lower γ.*

[1] This would happen under normality if news I_j consisted of the dividend plus noise, and τ was the precision of the noise term – though this argument ignores the equilibrium effect of the impact of precision on the informativeness of prices. But I think it would still go through even in equilibrium.

Proposition 3. *Price sensitivity to news increases as the information content of news grows.*

To check Proposition 3, observe that higher τ increases $f(\tau)$ and decreases $\sigma^2(\tau)$ and both effects tend to increase $\partial P_j/\partial I_j$.

To check Proposition 2, note that in the top expression in (6) both the numerator and denominator increase by the same amount when γ falls; since both are positive and the numerator is smaller than the denominator, this increases the price sensitivity, i.e., for $x, y > 0$, $\frac{d}{dx}(\frac{x}{x+y}) = \frac{1}{x+y} - \frac{x}{(x+y)^2} = \frac{1}{x+y}(1 - \frac{x}{x+y}) > 0$.

In what follows, we drop $f(\tau)$ from (6) since it's positive and does not affect the sign of the derivatives. To check Proposition 1, note that:

$$\frac{\partial}{\partial \phi_2}\left(\frac{\partial P_j}{\partial I_j}\right) = \frac{\frac{1-\gamma_2}{\gamma_2}}{1 + \frac{1-\gamma}{\gamma}\phi_2 + \frac{\sigma^2-\lambda}{\lambda}\phi_3} - \frac{1 + \frac{1-\gamma_2}{\gamma_2}\phi_2 - \phi_3}{(1 + \frac{1-\gamma_2}{\gamma_2}\phi_2 + \frac{\sigma^2(\tau)-\lambda_3}{\lambda_3}\phi_3)^2}\frac{1-\gamma_2}{\gamma_2}.$$

Since the denominator is positive, the sign of this is the same as the sign of

$$\left(1 + \frac{1-\gamma_2}{\gamma_2}\phi_2 + \frac{\sigma^2(\tau) - \lambda_3}{\lambda_3}\phi_3\right) - \left(1 + \frac{1-\gamma_2}{\gamma_2}\phi_2 - \phi_3\right) = \sigma^2(\tau)\phi_3 > 0.$$

To check that more indexers decrease the price sensitivity to news, note that

$$\frac{\partial}{\partial \phi_3}\left(\frac{\partial P_j}{\partial I_j}\right) = -\frac{1}{1 + \frac{1-\gamma_2}{\gamma_2}\phi_2 + \frac{\sigma^2(\tau)-\lambda_3}{\lambda_3}\phi_3} - \frac{1 + \frac{1-\gamma_2}{\gamma_2}\phi_2 - \phi_3}{(1 + \frac{1-\gamma_2}{\gamma_2}\phi_2 + \frac{\sigma^2(\tau)-\lambda_3}{\lambda_3}\phi_3)^2}\frac{\sigma^2(\tau) - \lambda_3}{\lambda_3}.$$

Since the denominator is positive, the sign of this is the same as the sign of

$$-\left(1 + \frac{1-\gamma_2}{\gamma_2}\phi_2 + \frac{\sigma^2(\tau) - \lambda_3}{\lambda_3}\phi_3\right) - \left(1 + \frac{1-\gamma_2}{\gamma_2}\phi_2 - \phi_3\right)\frac{\sigma^2(\tau) - \lambda_3}{\lambda_3}.$$

Since $\lambda_3 > 1$ and $\sigma^2(\tau) < 1$ the sign of the second term above is positive and the entire expression is therefore less than

$$-\left(1 + \frac{1-\gamma_2}{\gamma_2}\phi_2 + \frac{\sigma^2(\tau) - \lambda_3}{\lambda_3}\phi_3\right) + \left(1 + \frac{1-\gamma_2}{\gamma_2}\phi_2 - \phi_3\right) = -\sigma^2(\tau)\phi_3 < 0.$$

2 Two-period model

We extend the model to two periods, which allows us to make predictions on price *under-reaction* to news, conditional on investor composition, intermediary constraints, and news informativeness. The key feature of the two-period model is based on Hong and Stein (1999, HS): we assume that non-institutional investors and intermediaries behave like *newswatchers* in HS: they "formulate their asset demands based on the static-optimization notion that they buy and hold until the liquidating dividend" and "they do not condition on current or past prices." HS refer to this as a "Walrasian equilibrium with private valuations," as opposed to a rational expectations equilibrium. HS motivate this behavior as a simple form of bounded rationality (see their discussion on page 2149). This assumption can be thought of as a reduced form version Sims' (2011) rational inattention. Since we are focused on price responses to public news over a short time interval, we are not concerned about overreaction, and so do not introduce HS's momentum traders.

We assume that a fraction $\theta \in [0,1]$ of the non-institutional and intermediary sector pays attention to stock j in period 0, and the remaining fraction $1-\theta$ pays attention to the stock in period 1. As in HS, time 0 investors remain in the market in period 1. Investors who pay attention to stock j receive the same public signal I_j. We interpret θ as the technological capacity constraint faced by investors. As technology improves, investors are able to follow more stocks, and with respect to stock j, a greater fraction of investors is able to follow the stock in period 0. Stock j pays a liquidating dividend in period 2. Our newswatchers optimize objective function (1) using their information I_j with respect to the liquidating dividend. As in HS, they do not condition on prices. The $1-\theta$ fraction of investors who do not follow stock j in period 0 simply stay out of the market for j until period 1 – they do not have capacity to devote to following stock j in period 0. The indexers behave as before. We assume $\mu_{1j} = \mu_{2j} = \mu$ and $\mu_{3j} = 0$ for simplicity.

Given our assumptions, the period 1 price is the same as the price in the one-period model, and is given by (5), i.e.,

$$P_{1j} = \frac{\frac{\phi_1}{\sigma^2}\mu + \frac{\phi_2}{\gamma_2\sigma^2}\mu}{\frac{\phi_1}{\sigma^2} + \frac{\phi_2}{\gamma_2\sigma^2} + \frac{\phi_3}{\lambda_3}} = \frac{\phi_1\mu + \frac{\phi_2}{\gamma_2}\mu}{\phi_1 + \frac{\phi_2}{\gamma_2} + \frac{\phi_3}{\lambda_3}\sigma^2}.$$

The period 1 price reflects *all* information. Given the HS assumptions, the period 0 equilibrium is identical to the period 1 equilibrium, except the fraction of non-institutional and intermediary investors is given by $\theta\phi_1$ and $\theta\phi_2$. The period 0 price is therefore

$$P_{0j} = \frac{\phi_1\mu + \frac{\phi_2}{\gamma_2}\mu}{\phi_1 + \frac{\phi_2}{\gamma_2} + \frac{\phi_3}{\lambda_3}\frac{\sigma^2}{\theta}}. \tag{7}$$

The HS newswatcher assumption leads to a very tractable equilibrium, and, as in their paper, there is price underreaction. To see this note that

$$P_{0j} = \alpha(\theta)P_{1j} \qquad \text{and} \qquad P_{1j} - P_{0j} = (1-\alpha(\theta))P_{1j} \tag{8}$$

where

$$\alpha(\theta) = \frac{\phi_1 + \frac{\phi_2}{\gamma_2} + \frac{\phi_3}{\lambda_3}\sigma^2}{\phi_1 + \frac{\phi_2}{\gamma_2} + \frac{\phi_3}{\lambda_3}\frac{\sigma^2}{\theta}} \qquad \text{and} \qquad \alpha(\theta) \in [0,1].$$

Note that $\alpha(\theta)$ is increasing in θ. Therefore, when news I_j arrives, the period 0 price reaction will be smaller than the full (period 1) price reaction, and the price change from period 0 to period 1, $P_{1j} - P_{0j}$, will be nonzero and will go in the same direction as the period 0 price response:

$$\frac{\partial}{\partial I_j}(P_{1j} - P_{0j}) > 0.$$

In light of (8) the following proposition is immediate:

Proposition 4. *Propositions 1, 2, and 3 all apply to the period 0 price response to news and to the period 1 return* $P_{1j} - P_{0j}$ *in response to news.*

Finally, if technology improves, i.e., as θ increases, the model makes an unambiguous prediction:

Proposition 5. *As* θ *increases, the period 0 price response to news* $\partial P_{0j}/\partial I_j$ *increases, and the period 1 price change in response to news* $\partial(P_{1j} - P_{0j})/\partial I_j$ *decreases.*

This follows from (8) and the fact that $\alpha(\theta)$ is increasing in θ.

Of course, allowing the period 1 investors to participate in period 0 trading while conditioning on the period 0 price of j, or allowing for arbitrageurs who can profit from understanding the dynamics of the model, would make our results less stark. But the main intuition of price underreaction and its dependence on technological constraints would remain.

2.1 Period 0 and 1 holdings by intermediaries

From (2), the demands of the three investor types for stock j are

$$\begin{aligned} w_{1j} &= \frac{1}{\sigma^2}(\mu_j - P_j) \\ w_{2j} &= \frac{1}{\gamma_2\sigma^2}(\mu_j - P_j) \\ w_{3j} &= -\frac{1}{\lambda_3}P_j, \end{aligned}$$

where we assume that $\mu_{1j} = \mu_{2j} = \mu_j > 0$ and $\mu_{3j} = 0$. Market clearing thus requires that

$$\theta\phi_1 w_{1j} + \theta\phi_2 w_{2j} + \phi_3 w_{3j} = S_j > 0.$$

Plugging in the above demands, P_j must satisfy

$$\theta\frac{\phi_1}{\sigma^2}(\mu_j - P_j) + \theta\frac{\phi_2}{\gamma_2\sigma^2}(\mu_j - P_j) - \frac{\phi_3}{\lambda_3}P_j = S_j.$$

Rearraging we find that

$$\begin{aligned} P_j &= \left(\theta\frac{\phi_1}{\sigma^2} + \theta\frac{\phi_2}{\gamma_2\sigma^2}\right)\left(\theta\frac{\phi_1}{\sigma^2} + \theta\frac{\phi_2}{\gamma_2\sigma^2} + \frac{\phi_3}{\lambda_3}\right)^{-1}\mu_j - \left(\theta\frac{\phi_1}{\sigma^2} + \theta\frac{\phi_2}{\gamma_2\sigma^2} + \frac{\phi_3}{\lambda_3}\right)^{-1}S_j \\ &= \frac{\theta\phi_1\gamma_2\lambda_3 + \theta\phi_2\lambda_3}{\theta\phi_1\gamma_2\lambda_3 + \theta\phi_2\lambda_3 + \phi_3\gamma_2\sigma^2}\mu_j - \frac{\gamma_2\sigma^2\lambda_3}{\theta\phi_1\gamma_2\lambda_3 + \theta\phi_2\lambda_3 + \phi_3\gamma_2\sigma^2}S_j. \end{aligned}$$

The period 0 demand of the intermediary sector $X_2(\theta) = \theta\phi_2 w_2$ is therefore given by

$$\begin{aligned} X_{2j}(\theta) &= \theta\phi_2\frac{1}{\gamma_2\sigma^2}(\mu_j - P_j) \\ &= \theta\phi_2\frac{1}{\gamma_2\sigma^2}\frac{\phi_3\gamma_2\sigma^2}{\theta\phi_1\gamma_2\lambda_3 + \theta\phi_2\lambda_3 + \phi_3\gamma_2\sigma^2}\mu_j + \frac{\theta\phi_2\lambda_3}{\theta\phi_1\gamma_2\lambda_3 + \theta\phi_2\lambda_3 + \phi_3\gamma_2\sigma^2}S_j \\ &= \frac{\phi_2\phi_3}{\phi_1\gamma_2\lambda_3 + \phi_2\lambda_3 + \phi_3\gamma_2\sigma^2/\theta}\mu_j + \frac{\phi_2\lambda_3}{\phi_1\gamma_2\lambda_3 + \phi_2\lambda_3 + \phi_3\gamma_2\sigma^2/\theta}S_j. \end{aligned}$$

Given that all quantities in $X_{2j}(\theta)$ are positive, it is easy to see that $\partial X_{2j}(\theta)/\partial\theta > 0$, and therefore $X_{2j}(1) - X_{2j}(\theta) > 0$ for $\theta < 1$. So the intermediary sector adds to its holdings of stock j in period 1. Furthermore, since $\partial\mu_j/\partial I_j > 0$, we will have that $\partial(X_{2j}(1) - X_{2j}(\theta))/\partial I_j > 0$, meaning that with good news, intermediaries increase their period 1 buying by even more.

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