Time Variation in the News-Returns Relationship*

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Abstract

The speed of reaction 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, these interaction variables also increase price responses to lagged news (underreaction). A simple model with limited attention and three investor types – institutional, non-institutional, passive – predicts the varying response to news we observe. A long-short trading strategy based on news sentiment earns high returns, and conditioning the strategy on the interaction variables substantially increases returns. The interactions we document are robust to the choice of news source.

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

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.

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

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

Time variation in annual *Sent* coefficients

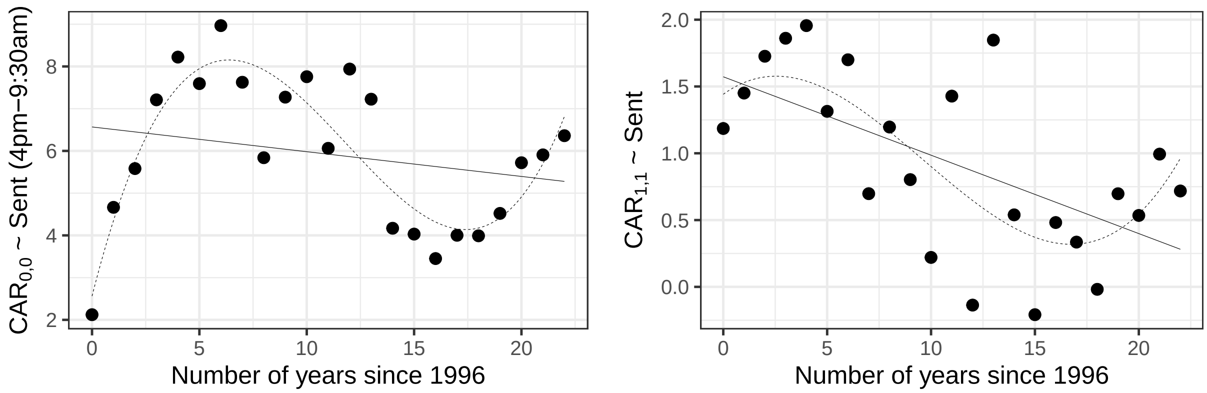

Fig. 1. This figure shows annual *Sent* coefficients from regressions of abnormal returns relative to the Fama-French (2015) model augmented with momentum on either contemporaneous news (left) or news lagged by one day (right). The coefficients are fitted with a trendline and a third-degree polynomial in time to show cyclical variation. The contemporaneous regressions use pre-9:30AM news to calculate day t sentiment.

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 to the Fama-French (2015) model augmented with momentum. 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. We supplement these regression results with trading simulations. We find that trading on news sentiment is profitable and that conditioning the trading strategy on the interaction variables increases profitability net of transaction costs.

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

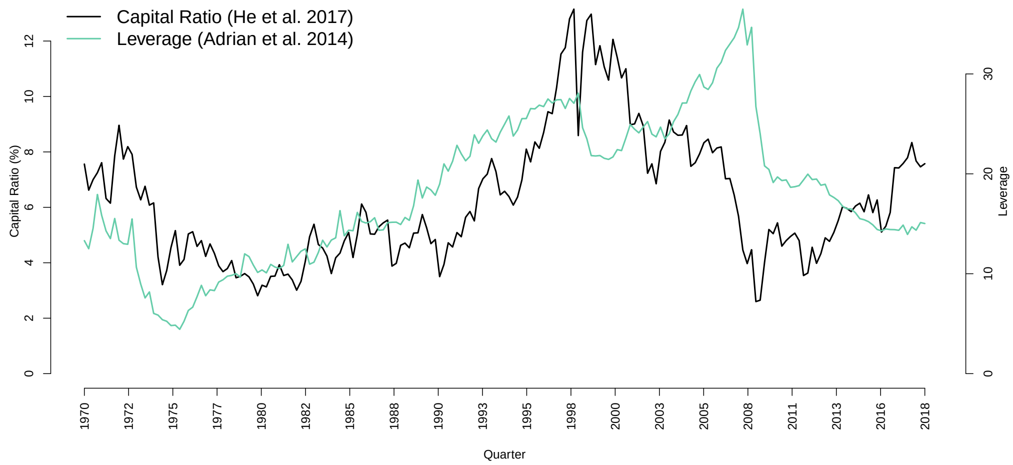

Fig. 2. This chart shows the quarterly intermediary capital ratio and leverage. These series are defined in Section 5.1.

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 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.[3] 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

[3]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.

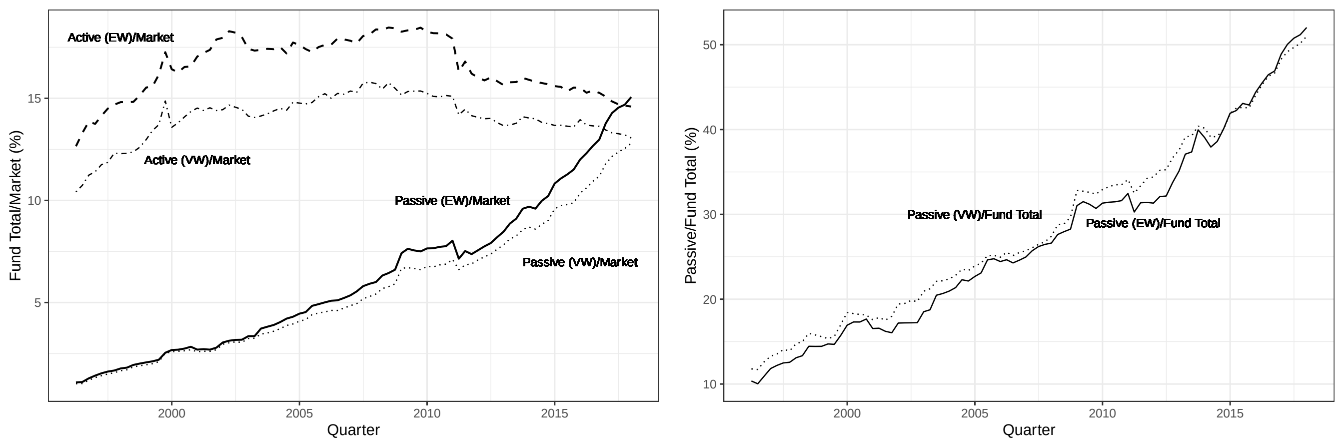

Fig. 3. The left chart shows the fraction of S&P 500 firms' market capitalization that is owned by either active or passive mutual funds. The right chart shows the ratio of passive mutual fund assets invested in S&P 500 firms to total mutual fund assets invested in those firms. EW (VW) refers to equal-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

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 trading simulations show that the economic magnitude of stock underreaction to news is very large. In the zero-transaction cost case, grossing up our long-short strategy based on the intermediary capital ratio yields a 27% annualized excess return relative to the Fama-French (2015) five factor model augmented with momentum. Introducing realistic transaction costs and restricting the turnover of the strategy leads to 8.8% annualized excess returns. The other interaction variables (ownership and news informativeness) also help performance, and the no-interaction results are the weakest though they are still economically large and statistically significant.

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 discuss channels through which institutional trading could affect the news-returns relationship. 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. An alternative explanation, based on strategic order-splitting, posits that institutions, aware of the price impact of their trades, rationally delay some of their trading to balance immediacy versus price impact. In robustness checks, we also examine the potential impact of short sale constraints and serial correlation in news flow. Though we find a role for each of these channels, they cannot fully account for our findings.

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 of 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.[4] 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 results with ours in Section 6.

TSM use articles from the Dow Jones news service and the Wall Street Journal for their analysis, while we use the Thomson Reuters news archive. The similarity of our results suggests that the effects we document transcend a single news source and are reflective of news flow more generally. Section 6 explores this idea more carefully by using text measures derived from three alternative news sources: the Wall Street Journal, Dow Jones (which includes the Wall Street Journal), and the Financial Times. We find that the samples (firm-day observations) covered by Thomson Reuters and Dow Jones are quite similar to each other but differ from the more limited coverage in the Wall Street Journal and Financial Times. After controlling for sample selection, our main findings are statistically indistinguishable when using Thomson Reuters or one of the three other news sources. Thus our results are representative of news flow in general, as opposed to news flow specifically coming from Thomson Reuters.

The rest of the paper proceeds as follows. Section 2 describes the data and the

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

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 and illustrates their magnitude through a backtested trading strategy. Section 6 compares results using alternative news sources. Section 7 describes possible mechanisms leading to underreaction and robustness checks undertaken in appendices. Section 8 concludes. The Internet Appendix contain further technical details and supporting results.[5]

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 a major business news provider 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

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

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 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.[6] 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 A1.1 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).[7] This leaves us with 1.36 million articles. The left panel of Figure 4 shows the distribution of articles throughout the day. The majority of articles about S&P 500 firms are released from 7am to 5pm. The right panel of Figure 4 shows the average number of daily articles by month of the year. News volume is very seasonal with peaks in February, April, July

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

[7]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.

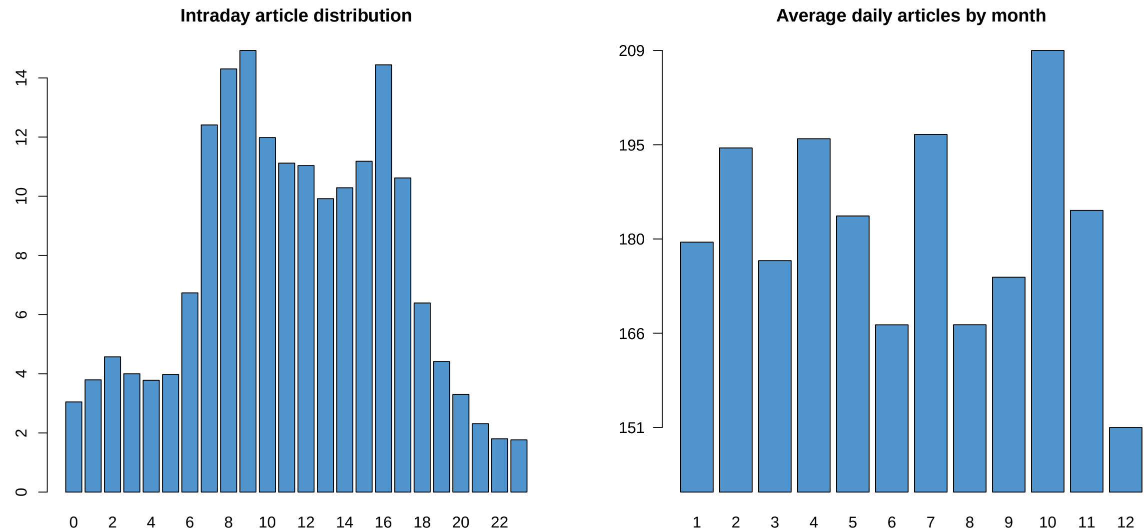

Fig. 4. The left panel shows the average number of articles in each hour of the day. The right panel shows the average number of daily articles within each month.

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 A2.1 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 ($Sent_t^i$) 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.[8]

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.[9] This entropy measure is 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

[8] 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.

[9] 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 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).

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) has peaks around 2002 and 2014. The average number of words per articles (after stopwords have been excluded, panel C) 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 D) 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 E) is strongly countercyclical, exhibiting peaks during times of market stress. Panel F of Figure 5 shows that average daily entropy exhibits substantial time variation.[10]

In Section 6.2, we also use news data from Dow Jones, the Wall Street Journal, and the Financial Times. Section A1.2 of the Internet Appendix discusses the mapping from CRSP company identifiers (PERMNOs) of S&P 500 firms to articles from these three alternative news sources. For articles from the Financial Times, we compute article-level sentiment using the method described above and then aggregate sentiment to the firm-day level. The Dow Jones and Wall Street Journal news data are from RavenPack News Analytics. For these two news sources, we use the Composite Sentiment Score (CSS) from RavenPack News Analytics as the sentiment measure because the CSS variable resembles

[10] 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.

our sentiment calculation above.[11] We maintain the same 4pm cutoff rules as for the Thomson Reuters archive. We only keep day t articles about firms that are in S&P 500 on day t.

The three alternative news sources have different coverage (in terms of firm-day observations) from Thomson Reuters. Hence, to rule out the effect of sample selection, we create a restricted sample with respect to each of the three alternative news sources. The restricted sample with respect to the Dow Jones archive consists of stock-day observations where both Thomson Reuters and Dow Jones have non-missing sentiment. We define the restricted samples with respect to the Wall Street Journal and with respect to the Financial Times in a similar way. We refer to our original sample from Thomson Reuters as the unrestricted sample. Table A6 in the Internet Appendix summarizes the number of firm-day observations for S&P 500 firms from each of the news sources, as well as the number of firm-day observations that fall into each of the restricted samples.

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

[11] The Composite Sentiment Score (CSS) is a number between 0 and 100. The direction of the score is determined by the tone of the article's words and phrases.

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 filing, though this information is not yet available to market participants.[14] To control

[12] More details are given in Section A2.2 in the Internet Appendix.

[13] Institutions with over \$100 million in assets, including mutual funds, hedge funds, insurance companies, 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.

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

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

[15] In Sec. A6.6 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.

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] 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 features may affect price reactions to news. 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]

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

[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. In Table A18, we replicate TSM's exact specification and show the results are similar to ours.

[20]We discuss the volatility controls further in Section A6.7, but note that the inclusion of these controls has little effect on the $Sent$ coefficients in our regressions.

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. The full-sample 1.9 basis points of return predictability by sentiment represents an economically important effect, which we discuss in detail in Section 5.4.

3.2 Contemporaneous responses

The left panel of Figure 1 shows the sentiment coefficient in annual regressions 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 Section A3 of the Internet 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 $\Lambda_2 = diag(\lambda_2), \lambda_2 = 0$. 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 (17) 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 (17). We take $\lambda_3 > 1$ and $0 < \sigma < 1$ to support our interpretation of the passive investors as the most constrained investors in (17), which we believe properly reflects institutional constraints faced by indexers.

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

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 uncertainty 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 depends 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 7.1.

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 problem 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 informativeness (entropy). Our predictions imply the following hypotheses for the signs of the interaction coefficients:

Return	Intermediary Capacity	Passive Ownership	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. Sections 5.1–5.3 empirically test these predictions. Section 5.4 discusses the economic magnitude of our findings and its dependence on these three interaction variables.

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

$$CR_t = \frac{\sum_i Market\ Equity_{i,t}}{\sum_i (Market\ Equity_{i,t} + Book\ Debt_{i,t})} \tag{12}$$

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:

$$Y_{t,u,v}^i = s_0 \times Sent_t^i + s_1 \times Capacity_t + s_2 \times Sent_t^i \times Capacity_t + \boldsymbol{\beta}'\boldsymbol{X}_t^i + \epsilon_{t,u,v}^i, \qquad (13)$$

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

[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.

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.

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 A4.2 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 intermediary capital 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.

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. We explore the economic magnitude of this interaction further in the trading simulations in Section 5.4.

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.

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

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

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

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 $CAR_{0,0}$ 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

[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.

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.

We also calculate the impulse response of excess and cumulative abnormal returns to a sentiment shock in the context of regression (14), 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.

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. Section A6.1 and Figure A9 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 (13) and (14) where intermediary capacity and ownership ratios are replaced with daily, monthly, quarterly, or annual average entropy:

$$Y^i_{t,u,v} = s_0 \times Sent^i_t + s_1 \times Entropy_t + s_2 \times Sent^i_t \times Entropy_t + \boldsymbol{\beta}'\boldsymbol{X}^i_t + \epsilon^i_{t,u,v}. \tag{15}$$

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 (15) 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 significant. So a one standard deviation increase in quarterly entropy increases the effect of news on one-day ahead returns by

[27]We demean all entropy measures in (15) using their full-sample means.

$7.916 \times 0.048 = 0.380$, 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.

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.

We also calculate the impulse response of excess and abnormal returns to a sentiment shock in the context of regression (15), 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.

5.4 Magnitude of the effect

To assess the economic magnitude of stock price underreaction to news, we construct a trading strategy that goes long and short, respectively, the top and bottom 20% of firms each day based on their daily 4pm-4pm sentiment $Sent_t^i$ (defined in Section 2.1). In the base version of the strategy, the weight $w_{base}(i,t)$ for stock i on day t is proportional to that stock's daily sentiment:

$$w_{base}(i,t) = \begin{cases} |Sent_t^i| / \sum_j |Sent_t^j| & \text{for } i,j \in \text{longs (high sentiment)}, \\ -|Sent_t^i| / \sum_j |Sent_t^j| & \text{for } i,j \in \text{shorts (low sentiment)}. \end{cases} \tag{16}$$

The long weights adds up to 1 and the short weights add up to -1.

The base weights lead to high turnover for the trading strategy because of the day-to-day variability in the composition of the top and bottom 20% of stocks by sentiment. To induce persistence in the portfolio holdings we introduce a smoothing parameter called *keep* and follow a strategy similar to Ke, Kelly, and Xiu (2021):

$$\begin{aligned} &w_{use}(i,t) = keep \times w_{base}(i,t) + (1 - keep) \times w_{use}(i,t-1), \\ &w_{use}(i,0) = w_{base}(i,0). \end{aligned} \tag{17}$$

Lower values of *keep* lead to lower turnover.

We argued theoretically in Section 4 and then showed empirically in this section that the predictability of news for future returns is higher during times of high intermediary capital, for stocks with high active ownership, and during times of high entropy. We want to capture these interaction terms in our trading simulations. For intermediary capital, we use the monthly capitalization ratio CR_t from (12). Periods of high active ownership are captured using $Active/Market_t$, defined as the within-month mean of the within-day means of the firm-day level $Active/Market_{i,t}$. Our $Entropy_t$ variable is a rolling average of the last three monthly entropies.

We incorporate these into our trading strategies by increasing gross position sizes during times of high predictability. The conditioning scales $w_{use}(t)$ in (17) by

$$max\left(0, 1 + scale \times \frac{X(m) - \bar{X}}{\sigma_X}\right) \tag{18}$$

where $X(m)$ is the value of the conditioning variable in month m, the month immediately prior to day t, and $scale \in \{0.165, 0.33, 0.66\}$. The mean ($\bar{X}$) and standard deviation (σ_X) of the conditioning variable are computed using an expanding window of length up to 25 years from the start of the sample to month m. The intermediary capital ratio series starts on 1/31/1970, so even the initial observations for CR_t use 25 years of data. The $Active/Market$ series starts on 1/1/1996. The $Entropy$ series with a rolling mean of 3 months starts on 6/30/1998. If there are less than 12 observations of a macro series as of month m, then the scaling weight is set to 1. Going forward, w_{use} refers to the portfolio weights scaled by the term in (18) or scaled by 1 if there is not enough data.

The portfolio return on day $t+1$ is given by

$$\tilde{r}^p_{t+1} = w_{use}(t)^\top r_{t+1}, \tag{19}$$

where $w_{use}(t)$ is the vector of scaled portfolio weights on day t and r_{t+1} is the vector of stock returns from day t to $t+1$. Because $\tilde{r}^p_{t+1}$ assumes zero transaction costs, we refer to it as the frictionless portfolio return.

To calculate portfolio turnover, we follow Ke, Kelly, and Xiu (2021) and define strategy turnover on day t as

$$to(t) \equiv \frac{1}{2}\sum_{i=1}^{n} |w_{use}(i,t) - w_{adj}(i,t-1)|,$$

where

$$w_{adj}(i,t-1) = \frac{w_{use}(i,t-1)(1+r_{i,t})}{1+\sum_{i=1}^{n} w_{use}(i,t-1)r_{i,t}},$$

where $r_{i,t}$ is the return on stock i from day $t-1$ to t. $w_{adj}(i,t-1)$ reflects what $w_{use}(i,t-1)$ would become due to differences in stock returns from $t-1$ to t.[28] Entirely turning over the portfolio from one day to the next (if none of the top and bottom 20% of names

[28]The difference between $w_{use}(i,t)$ and $w_{adj}(i,t)$ is very minor in practice.

overlap) results in a turnover of 2 (e.g., sell \$1 of longs, buy \$1 of new longs, cover \$1 of shorts, sell \$1 of new shorts).

We assume that selling and then buying a stock happens at the prevailing bid-offer in the market.[29] We assume a transaction cost of 3 basis points (bps) per unit of turnover (this is the full bid-offer spread for U.S. stock exchanges estimated by Hagströmer 2021). For transaction cost tc, the portfolio return is given by

$$r_t^p = \tilde{r}_t^p - to(t) \times tc, \tag{20}$$

where $\tilde{r}_t^p$ is the frictionless portfolio return in (19).

Results

We run 48 versions of the trading strategy which are parameterized by:

- $keep \in \{0.33, 1\}$,
- $tc \in \{0, 3 \text{ bps}\}$,
- Interaction variable: none, CR, $Active/Market$, $Entropy$,
- $scale \in \{0.165, 0.33, 0.66\}$.

Table 7 shows the daily alpha (in basis points) relative to the Fama-French (2015) five factor model augmented with momentum for each strategy variant when $scale = 0.33$ (e.g., 4 means 252×4 bps $\approx 10\%$ annual alpha).

The first column of the table shows the results for $keep = 1, tc = 0$, which is the base case, frictionless version of the strategy. Without using any conditioning variables, the strategy generates 7.7 basis points of daily alpha, which translates to an almost 19.5% annualized excess return. As the next two rows show, scaling up the gross size of the

[29] This constrains the maximum size of the strategy. We comment further on this issue below.

strategy during times of high intermediary capital increases the daily alpha to 10.7 basis points (27% per year) and scaling up during times of high active ownership increases the daily alpha to 9.6 basis points. The final row shows that conditioning on entropy does not improve the baseline, frictionless alpha (in fact daily alpha falls slightly to 7.4 basis points). All four alphas (no-interaction, CR, active share, and entropy) are highly statistically significant as their p-values are all zero to three digits.

The second column shows the frictionless results for the $keep = 0.33$ strategy. The alphas get cut roughly in half, but the economic magnitude is still high. For example, for the $keep = 0.33$ and CR interaction strategy, the daily alpha of 5.4 basis points translates to an annualized excess return of 13.6%, an economically large effect. Again all four p-values are zero.

The impact of transaction costs is important for high turnover strategies, such as these. For the CR_t interaction results, the portfolio with $keep = 1$ has an average daily turnover of 2.02 over the entire sample, while the $keep = 0.33$ portfolio has an average daily turnover of 0.62. The turnover numbers for the no-interaction portfolios, as well as for the portfolios using the other conditioning variables, are similar.

The third column introduces transaction costs of 3 bps for each round-trip trade of the $keep = 1$ strategy (selling at bid and buying at ask according to equation 20). The daily alphas fall to about 40% of the frictionless ones but the economic magnitude remains large and all alphas are significant at the 5% level or better. The CR interaction yields a daily alpha of 4.7 basis points (11.8% annual), the $Active/Market$ is second best (3.8 bps), and the *Entropy* interaction now outperforms the no-interaction strategy by 0.6 basis points per day (around 1.5% per year outperformance).

Finally, the fourth column shows the performance of strategies with $keep = 0.33$ and $tc = 3$ bps. All alphas are significant at the 1% level or better, with the ranking from highest to lowest being CR, active share, and entropy conditioning variables and then the no-interaction strategy. The CR interaction alpha is 3.5 bps per day or 8.8% per year, which is highly economically significant, even in the presence of restricted turnover and the imposition of transaction costs.

Tables A7 and A8 of the Internet Appendix show that the above results are robust for other choices of *scale* in (18). The $scale = 0.165$ results (Table A7) are slightly weaker than the Table 7 ones, and the $scale = 0.66$ results (Table A8) are stronger (the annualized return of the baseline CR strategy is 34.7% per year). Strategy performance and turnover are not sensitive to different values of *scale* in (18). The alphas of *all* 48 tested strategies are economically large and statistically significant.

Interpretation

Our trading strategy results are consistent with the prior literature, though our focus on conditioning information is novel. 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. 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 25% range (their Table 3 for value-weighted returns).[30]

We note that liquidity providers, including high-frequency hedge funds and other market makers, can skew their bidding for order flow in the direction of our news-based signals, and thus effectively trade the news underreaction effect without having to pay the bid-offer spread. This can greatly increase the scalability of news-based strategies, as well as their profitability relative to our transaction-cost benchmarks. Furthermore, we did not fully explore the space of possible trading strategy, but simply used a set of simple trading rules.[31] For these reasons, we believe our transaction cost adjusted results

[30] We do not use value-weighted returns because of our focus on S&P 500 firms.

[31] We could use a hybrid signal from all four of our news sources (see Section 6), increase emphasis on outlier events relative to the weights in (16), or focus more on novel (high entropy) articles (as opposed to only looking at high entropy time periods). We leave these strategy variants for future work.

are conservative relative to what can be achieved by high-frequency traders who augment their usual liquidity-provision strategies with our news-based signals, or relative to a more refined set of strategies.

We emphasize that the economic mechanisms discussed in the paper would be interesting even in the absence of any associated profitable trading strategies. That markets systematically underreact to news and that the size of the underreaction depends crucially on intermediary capital, the active ownership share in stocks, and entropy are important economic findings in their own right. The fact that they lead to profitable trading strategies after adjusting for real-world turnover and transaction costs is icing on the cake.

6 Alternative news sources

In Section 6.1, we compare our results with prior work on the news-returns relationship which uses data from the Financial Times. In Section 6.2, we check whether our main results, which use the Thomson Reuters news archive, hold when using other news sources: Dow Jones,[32] the Wall Street Journal, and the Financial Times. After controlling for sample selection (in terms of which firms receive news coverage), the main findings from the Thomson Reuters archive are statistically indistinguishable from those which use the three other corpora, which suggests that our underreaction and interaction results are broadly true, and are not specific to a single news source.

6.1 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 A14

[32]Dow Jones includes the Wall Street Journal, Barron's, MarketWatch, and Dow Jones Financial Wires.

(where we separately estimate the response to high and low sentiment news, see Internet Appendix Section A6.2), 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.[33]

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

[33] These numbers differ from those in Table A6 because the table counts firm-day observations and some days have multiple articles about the same firm.

to be January 1996–September 2013, which is the overlapping period between our full sample and the FS sample.

The top panel of Table 8 corresponds to the subsample with bad news ($CAR_{0,0} < 0$), and the bottom panel to the subsample with goods news ($CAR_{0,0} \geq 0$).[34] 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 8 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 8 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, as Frank and Sanati note, "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. We discuss this compositional difference in the two

[34] The news source and index composition affect our Table 8 and Table 8 in Frank and Sanati (2018) through the definition of a stock-day observation — a day on which a company in the index is covered in an article from the news source. Neither table uses a text-based sentiment measure or any other textual measure; the top and bottom panels split observations based on contemporaneous abnormal returns.

news archives at length in Section 6.2.

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 results in Table A14 do not show this asymmetry. We believe this is because sorting on news-day returns and on the text-based 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 A14, identifies a different set of events than does sorting on returns.

6.2 Result comparison across different news sources

We next examine whether our results hold for three alternative news sources: Dow Jones (DJ), the Wall Street Journal (WSJ), and the Financial Times (FT).[35] Specifically, for each of the four main specifications – the baseline regression in (2), the intermediary capital regression in (13), the mutual fund ownership regression in (14), and the entropy regression in (15) – we test whether the results are statistically indistinguishable using sentiment from the Thomson Reuters (TR) archive versus sentiment from one of the three alternative news sources.[36]

When comparing the Thomson Reuters news archive to alternative news sources, there can be two sources of differences: the set of firm-day observations that each news source covers may differ (composition), and the coverage of a specific firm-day event may also differ. In our first set of results, we keep the composition of the firm-day events identical, and analyze only differences arising from diverging coverage of the same events by different news sources. We next keep coverage constant by focusing only on the Thomson Reuters

[35]We focus on these news sources because, like Thomson Reuters, they are major providers of business news. We do not have access to an archive of news from Bloomberg, another major source.

[36]In the entropy specification in (15), we use our original entropy measure obtained from the Thomson Reuters archive.

archive, but analyze the composition effect by varying the sets of firm-day observations to match those of the alternative news sources.

We first restrict the sample to only include firm-day observations where both Thomson Reuters and the alternative news source have non-missing sentiment. This is the restricted sample described in Section 2.1. For example, when we compare Thomson Reuters sentiment with Dow Jones sentiment, we run regressions only using firm-day observations with both non-missing Thomson Reuters sentiment and with non-missing Dow Jones sentiment, and we refer to this as the restricted firm-day sample with respect to Dow Jones. We define the restricted sample with respect to the Wall Street Journal and the restricted sample with respect to the Financial Times in the analogous way.

The empirical tests are as follows. For a given regression specification using the sentiment measure from news source k, where $k \in$ {TR, DJ, WSJ, FT}, let β^k denote the coefficient of interest and $\hat{\beta}^k$ denote the empirical estimate using the restricted sample. For the baseline regression in equation (2), the coefficient of interest is the loading s on sentiment. For the intermediary capital regression in (13), the coefficient of interest is s_2, the interaction between intermediary capital and sentiment. For the mutual fund ownership regression in (14), the coefficient of interest is s_2, the interaction between mutual fund ownership and sentiment. Finally, for the entropy regression in (15), the coefficient of interest is s_2, the interaction between entropy and sentiment.

For each of these coefficients, we test the null hypothesis that

$$H_0 : \beta^k = \beta^{k'}, \tag{21}$$

where $k = \text{TR}$ and $k' \in \{\text{DJ}, \text{WSJ}, \text{FT}\}$. We test equality using the empirical covariance matrix of the estimates $\{\hat{\beta}^k, \hat{\beta}^{k'}\}$.[37] The finding from an alternative news source is

[37] We obtain the empirical covariance matrix by setting up the regressions for news sources k and k' as a system of seemingly unrelated equations and estimating them jointly.

qualitatively different from our finding using Thomson Reuters when the difference in β estimates is statistically significant *and* the coefficients have opposite signs. If the difference is statistically significant but the coefficients have the same sign, then the responses measured through the two news sources differ in magnitude but not in their directional effects. The direction of the response to sentiment and to various interactions with sentiment are our main focus. If the signs of the coefficients differ but we cannot reject equality of the coefficients, then the difference in signs is not statistically significant, and the conclusions from the two news sources are statistically indistinguishable.

Table 9 presents the results of these tests. Each cell in Table 9 shows the test for a particular regression specification. Stars without an ✗ indicate statistically significant differences in coefficient magnitudes but no difference in sign, and thus do not indicate qualitatively different conclusions from the two news sources. A "–" indicates that the signs of the estimated coefficients differ but that the coefficients from from the two news sources are statistically indistinguishable. An ✗ indicates that the coefficient estimates using sentiment from Thomson Reuters and the alternative news source have different signs *and* are statistically different, with stars indicating the level of significance. The entries marked ✗ are thus the only cases that support a qualitative difference between two news sources.

Column 1 in Table 9 indicates the dependent variable and Column 2 shows the sample of firm-day observations used for the regression analyses, with DJ indicating the restricted sample with respect to Dow Jones, WSJ for Wall Street Journal, and FT for Financial Times. Column 3 shows the impact of sentiment and columns 4-14 indicate impacts of the key interaction variables. Specifically, column 3 corresponds to the full sample regression in equation (2), columns 4-7 correspond to the intermediary capital regression in equation (13), columns 8-10 correspond to the mutual fund ownership regression in equation (14), and columns 11-14 correspond to the entropy regression in equation (15). For example, the cell in row 2 and column 4 shows the test result for the intermediary capital regression in equation (13), which uses the restricted sample with respect to Wall Street Journal, the contemporaneous raw excess return ($Retrf_{0,0}$) as the dependent variable, and the daily intermediary capital ratio (CR) as the key interaction variable.[38]

Table 9 shows that our key results hold for all three alternative news sources after controlling for the news selection effect, i.e., focusing only on the firm-day observations where Thomson Reuters and the alternative news source both have non-missing sentiment. We first observe in column (3) that the contemporaneous impact of news sentiment on returns always has the same sign across all four news sources for both excess and abnormal returns, though the magnitude of the impact may differ. Across the 108 forecasting tests (excess or abnormal returns, one- or ten-day ahead, three alternative news sources, nine different forecasting coefficients), we are able to reject that the models are qualitatively similar (an ✗ with stars) only four times: using Dow Jones sentiment to predict $CAR_{1,10}$; the interaction of WSJ sentiment with quarterly intermediary leverage to predict $CAR_{1,1}$; the interaction of WSJ sentiment with daily and annual entropy to predict $Retrf_{1,10}$. Such remarkable agreement shows that, when focusing on the same set of firm-day events, the news underreaction dynamics we document are highly consistent across different news outlets.

6.2.1 Differential coverage

We next analyze the impact of selective coverage of firm-day events by different news sources. We repeat the analysis of Table 9 but compare the results obtained using the unrestricted Thomson Reuters sample – i.e., the one we use in the entirety of this paper outside of Section 6.2 – versus those obtained using the Thomson Reuters sample, but restricted to overlapping firm-day observations with the DJ, WSJ, and FT news archives. We call the latter the restricted Thomson Reuters sample. Because the re-

[38] We use the 4pm-4pm sentiment as the independent variable in these regressions. In unreported results, we also regress the contemporaneous return $Retrf_{0,0}$ on the 4pm-9:30am sentiment (using the different news samples in this section) and the results are similar.

stricted Thomson Reuters sample conditions on firm-day observations overlapping with other news sources, we are able to understand the impact of selective coverage (by other news sources) on our results.

Table A25 in the Internet Appendix shows the results. When using excess returns (the top panel of the table), we cannot reject qualitative similarity between results obtained using the unrestricted and restricted Thomson Reuters archives even once. This suggests that our results are robust even across different firm-day observations. When looking at the abnormal return results in the bottom panel of Table A25, we can reject once for the DJ sample restriction (for the daily entropy interaction for $CAR_{0,0}$) and twice for the WSJ sample restriction (for the quarterly leverage and Passive/Market interactions for $CAR_{1,10}$). When comparing results obtained using the unrestricted Thomson Reuters archive to those obtained using the part of the Thomson Reuters archive with overlapping firm-day observations to the FT, we find seven rejections in the abnormal returns (bottom) panel. These results suggest the Thomson Reuters has very similar coverage to the DJ news service, quite similar coverage to the WSJ, but relatively different coverage compared to the FT.

To better understand how the Thomson Reuters news coverage compares to that in the Dow Jones, Wall Street Journal, and the Financial Times, we analyze the characteristics of firms covered by these news sources. Figure A6 in the Internet Appendix shows that the Wall Street Journal and Financial Times cover companies that are, on average, larger than those covered by Dow Jones and Thomson Reuters.[39] They also carry fewer articles, and about companies whose returns are better explained by the Fama-French (2015) five factor model augmented with momentum. FT- and WSJ-covered firms have higher market betas, lower SMB loadings, higher value loadings, lower profitability loadings, and lower loadings on conservative-minus-aggressive investment factor (i.e., they behave more like firms that invest aggressively). Across all these dimensions, the FT-covered firms are more

[39]Internet Appendix Section A5.1 explains the methodology used to construct Figures A6 and A7.

extreme than the WSJ firms. Figure A7 shows that the Wall Street Journal and Financial Times devote a much larger fraction of their news coverage to financial firms than do Dow Jones and Reuters, and less of their news coverage to utilities and to healthcare firms. Again, the FT is more extreme in this regard (a greater fraction of its news coverage goes to financial firms) than the WSJ.

To summarize, there are two distinctions between the Thomson Reuters data set and alternative news collections. First, the firm-day observations across different news corpora differ. Adjusting for these differences allows us to conclude that our return-news effects and the impacts of our three interaction variables are remarkably consistent across the Thomson Reuters, Dow Jones, Wall Street Journal, and Financial Times corpora. Then zeroing in on the composition differences, we find that the Reuters and DJ news sources have very similar news coverage, as do the WSJ and the FT. The news coverage of the FT differs the most from that of Thomson Reuters. The very different firms covered by Thomson Reuters and the Financial Times likely explain why our findings in Table 8 differ from those of Table 8 in Frank and Sanati (2018).

7 Possible mechanisms and robustness checks

This section discusses possible mechanisms leading to underreaction, and it describes robustness checks based on alternative explanations.

7.1 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.[40]

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.[41] 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, 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.

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).[42] In all cases this involves splitting up a large trade into smaller components and

[40]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."

[41]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.

[42]There is ample empirical and anecdotal evidence of strategic trading by institutional investors con-

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.[43]

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

cerned 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.

[43]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.

stration 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.

7.2 Robustness checks and other channels

In Sections 5 and 6 we presented evidence consistent with our hypotheses that variation in intermediary capital, passive ownership, and news informativeness robustly 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 (Miller 1977; Asquith, Pathak, and Ritter 2005; Nagel 2005) and serial correlation in news flow (Wang, Zhang, and Zhu 2018; Huang, Tan, and Wermers 2020). We analyze these two channels and find that they cannot explain our main findings. To conserve space, these results are presented in the Internet Appendix: Section A6.2 shows that short-sale constraints alone cannot fully explain stock price underreaction, and Section A6.3 rules out serial correlation in news flow as the channel for underreaction.

We perform an extensive set of additional robustness checks, which are also detailed in the Internet Appendix. Section A6.4 shows the results of regressions in (2) for one- and ten-day ahead returns hold over different subperiods of the data. Section A6.5 verifies that the ownership results in Table 5 are not driven by outliers. In Section A6.6 we check whether earnings announcements impact our results. Section A6.7 checks whether the effect of sentiment on future returns can be explained by either idiosyncratic or systematic volatility. Finally, Section A6.8 checks whether the effects of intermediary capital, ownership, and entropy on the news-returns relationship simply reflects economic uncertainty, as captured by the VIX. In all cases, we conclude that our main results are not explained away by these additional considerations.

8 Conclusion

An underreaction to news by the stock market is surprising. 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.

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. A model with three types of investors — institutional, non-institutional, and passive — who have limited attention to news helps explain many of our findings. Furthemore, we show that our results hold up under multiple choices of news source.

The magnitudes of the effects we document are economically as well as statistically significant. We illustrate this via the performance of a trading strategy that goes long positive sentiment stocks and shorts negative sentiment stocks. The strategy earns high abnormal returns, and these returns remain notable after accounting for transaction costs. More importantly, conditioning the strategy on the levels of our interaction variables substantially increases returns.

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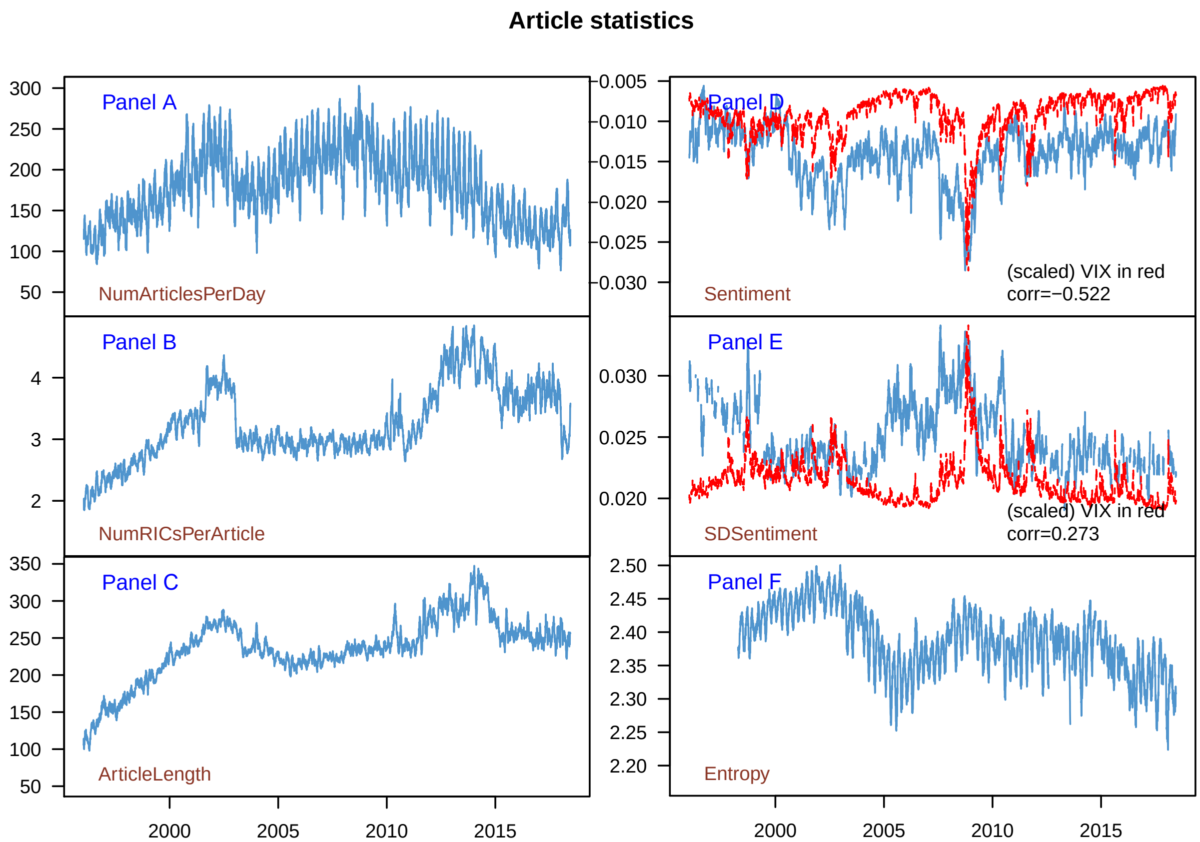


Fig. 5. This figure shows the number articles per day, the number of RICs per article, the average article length (in number of words), daily average of article sentiment, the daily standard deviation of article sentiment, and the average daily entropy (defined in Section 5.3). Data are daily. The VIX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

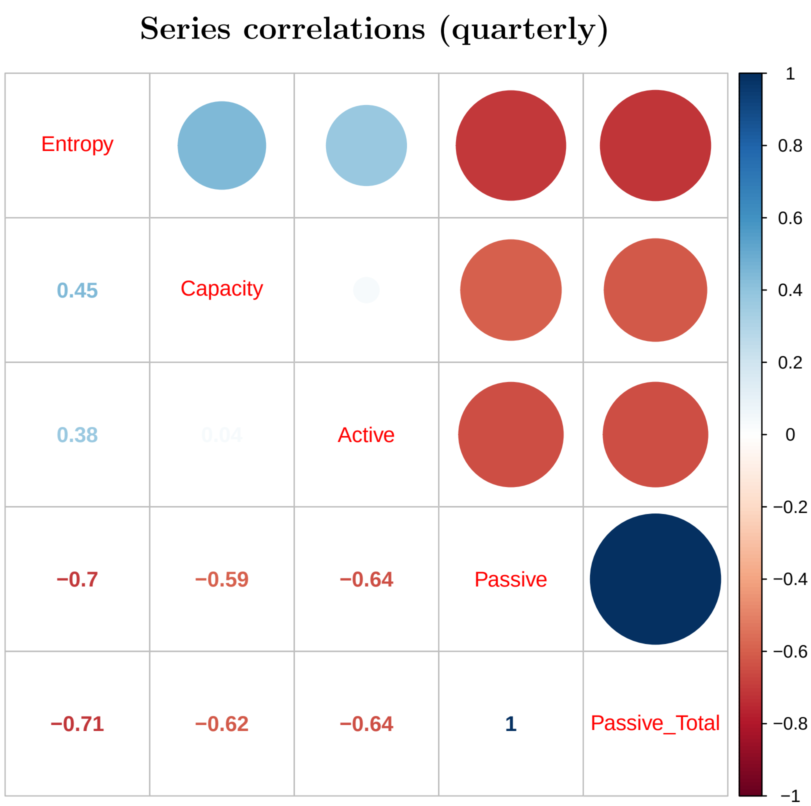
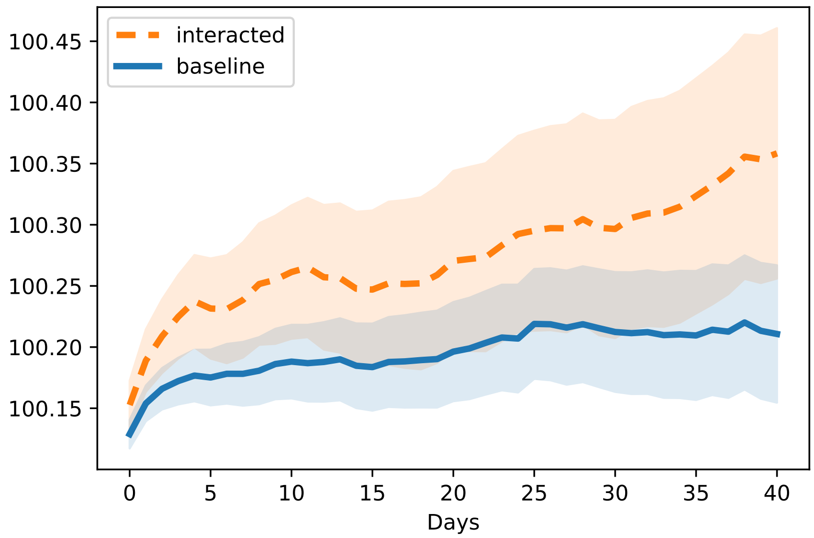


Fig. 6. Correlations between quarterly entropy, intermediary capacity, and ownership measures. The entropy and ownership variables are within quarter averages. The intermediary capacity variable is a quarterly average of monthly observations from He et al. (2017). Active and Passive refer to the the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

Impulse responses to {sentiment × monthly intermediary capacity} shocks

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



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

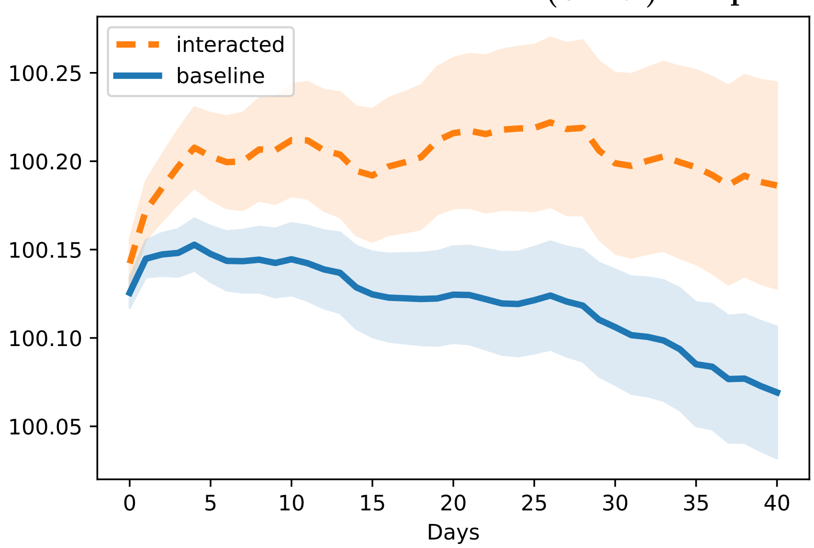


Fig. 7. Impulse response functions estimated using the local projection method of Jorda (2005). The figure shows the baseline response (labeled *baseline*) of future excess returns and cumulative abnormal returns (CARs) to a one standard deviation sentiment shock, as well as the response conditional 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 excess return (abnormal return) that includes days $t+i, \ldots, t+j$ where t is the event date. Returns are measured in percent. 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
$\mathrm{Retrf}_{1,1}$	703,994	0.036	2.696	−94.254	−1.037	1.082	102.358
$\mathrm{CAR}_{1,1}$	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
$\overline{\mathrm{Sent}}_D$	706,545	−0.011	0.004	−0.123	−0.014	−0.009	0.005
$\mathrm{Sent} - \overline{\mathrm{Sent}}_D$	706,545	−0.000	0.021	−0.272	−0.010	0.012	0.239
$\left(\mathrm{Sent} - \overline{\mathrm{Sent}}_D\right)^+$	706,545	0.008	0.010	0	0	0.01	0
$\left(\mathrm{Sent} - \overline{\mathrm{Sent}}_D\right)^-$	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
$\beta_{\mathrm{Mktrf}} \times \mathrm{Mktrf}_{1,1}$	704,199	0.0003	0.014	−0.205	−0.005	0.006	0.224
$\beta_{\mathrm{SMB}} \times \mathrm{SMB}_{1,1}$	704,199	−0.00000	0.003	−0.087	−0.001	0.001	0.097
$\beta_{\mathrm{HML}} \times \mathrm{HML}_{1,1}$	704,199	0.00002	0.005	−0.163	−0.001	0.001	0.234
$\beta_{\mathrm{RMW}} \times \mathrm{RMW}_{1,1}$	704,199	−0.00000	0.004	−0.114	−0.001	0.001	0.095
$\beta_{\mathrm{CMA}} \times \mathrm{CMA}_{1,1}$	704,199	0.00002	0.004	−0.097	−0.001	0.001	0.133
$\beta_{\mathrm{UMD}} \times \mathrm{UMD}_{1,1}$	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)
$\mathrm{Retrf}_{0,0}$	Sent	9.271***	9.186***	9.182***	9.227***
	Sent×Capacity	0.363***	0.443***	0.504***	0.227***
$\mathrm{Retrf}_{0,0}$	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**
$\mathrm{Retrf}_{1,1}$	Sent	1.012***	1.197***	1.196***	1.132***
	Sent×Capacity	0.135	0.202	0.185	0.052
$\mathrm{Retrf}_{1,10}$	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)
$\mathrm{CAR}_{0,0}$	Sent	8.215***	8.096***	8.099***	8.119***
	Sent×Capacity	0.447***	0.498***	0.537***	0.159***
$\mathrm{CAR}_{0,0}$	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***
$\mathrm{CAR}_{1,1}$	Sent	0.833***	0.919***	0.92***	0.912***
	Sent×Capacity	0.13**	0.194***	0.186***	0.021
$\mathrm{CAR}_{1,10}$	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, $CAR^2_{0,0}$ 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.

Entropy effects on sentiment predictability

Return regressions

		Entropy			
		Daily	Monthly	Quarterly	Annual
$\text{Retrf}_{0,0}$	Sent	9.51***	9.623***	9.688***	9.696***
	Sent×Entropy	12.267***	37.742***	45.873***	49.938***
$\text{Retrf}_{0,0}$	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***
$\text{Retrf}_{1,1}$	Sent	1.015***	1.066***	1.044***	1.034***
	Sent×Entropy	7.386*	8.052	9.441	8.471
$\text{Retrf}_{1,10}$	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
$\text{CAR}_{0,0}$	Sent	8.349***	8.404***	8.453***	8.464***
	Sent×Entropy	8.299***	32.217***	38.1***	42.353***
$\text{CAR}_{0,0}$	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***
$\text{CAR}_{1,1}$	Sent	0.87***	0.882***	0.893***	0.893***
	Sent×Entropy	3.199	4.979	7.916**	7.542*
$\text{CAR}_{1,10}$	Sent	0.414	0.467	0.473	0.485
	Sent×Entropy	13.222**	20.05**	16.103	14.839

Table 7
Each row shows daily alphas, in basis points (bps), from the trading strategy explained in Section 5.4. The alphas are relative to the Fama and French (2015) five factor model with momentum. The columns correspond to different values of the *keep* variable in (17). The columns without the TC label assume zero transaction costs; the ones with a TC label assume transaction costs equal 3 bps per unit of turnover (round-trip transaction). The rows correspond to different conditioning variables (none, intermediary capitalization, active ownership, and entropy, respectively) that impact the gross size of the long-short strategy via (18), with the *scale* variable set to 0.33. The numbers in parentheses represent p-values with standard errors calculated using Newey-West with lags equal to the floor of $4(N/100)^{2/9}$ where N is the number of observations in the sample (see Hoechle 2007).

News trading strategy six-factor alphas (bps per day) with $scale = 0.33$

Condition	Keep=1	Keep=0.33	Keep=1 TC	Keep=0.33 TC
None	7.678	3.287	2.399	1.666
	(0.000)	(0.000)	(0.037)	(0.011)
CR	10.725	5.376	4.675	3.519
	(0.000)	(0.000)	(0.002)	(0.000)
Pct Active	9.612	4.402	3.775	2.610
	(0.000)	(0.000)	(0.012)	(0.003)
Entropy	7.407	3.201	2.987	1.843
	(0.000)	(0.000)	(0.018)	(0.012)

Table 8
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)

Table 9

We test the null hypothesis H_0 from (21) that regression results are indistinguishable using sentiment from Thomson Reuters versus sentiment from one of the three alternative news sources, when both are restricted to the overlapping set of firm-day observations. A "–" indicates that the β^k coefficient estimates using sentiment from Thomson Reuters and that from the alternative news source have different signs but are not statistically different; stars without an ✗ indicate the coefficients are statistically different but their signs are the same. Statistically significant qualitative differences – requiring different signs *and* statistically different coefficients – are indicated by an ✗. The *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Comparing results using sentiment from Thomson Reuters versus alternative news sources

		Full	Intermediary				Mutual Fund Ownership			Entropy			
			CR (Daily)	CR (Monthly)	CR (Quarterly)	Lev (Quarterly)	Passive/Market	Active/Market	Passive/Fund Total	Daily	Monthly	Quarterly	Annual
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
$Retrf_{0,0}$	DJ	***	✗***	✗***	✗***								*
	WSJ	***	–	–	–	✗***	–			–	**	**	**
	FT				–	**				–			
$Retrf_{1,1}$	DJ		–	–	–		–		–				
	WSJ		–	–	–		–						
	FT				–	–					–		–
$Retrf_{1,10}$	DJ							**					–
	WSJ									✗*		–	✗*
	FT				–								
$CAR_{0,0}$	DJ	***	✗***	**	**								
	WSJ	***	✗**	✗**	✗**	–				–	**	**	
	FT	**				***					–	–	–
$CAR_{1,1}$	DJ	*		–	–		–			–			
	WSJ			–	–	✗**	–						
	FT				–		–			–		–	–
$CAR_{1,10}$	DJ	✗**								–			
	WSJ	–				–	–			–		–	–
	FT	–											