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Time Variation in the News–Returns Relationship

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Abstract

The speed of stock price reaction 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, noninstitutional, and passive) predicts the observed variation in news responses. A long–short trading strategy based on news sentiment earns high returns, which increase when conditioning on the interaction variables. The interactions we document are robust to the choice of news source.

I. Introduction

Tetlock, Saar-Tsechansky, and Macskassy (TSM) (2008) 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 in the contemporaneous and future response of prices to news; and we find that this time variation is associated with changes in intermediary risk-bearing capacity, passive fund ownership, and the information content of news.

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TABLE 1

Return Regressions

Table 1 shows return regressions in the full sample, using specifications (1) and (2). $RETRF_{i,j}$ ($CAR_{i,j}$) 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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable							
	$RETRF_{0,0}$	$CAR_{0,0}$	$RETRF_{0,0}$	$CAR_{0,0}$	$RETRF_{1,1}$	$CAR_{1,1}$	$RETRF_{1,10}$	$CAR_{1,10}$
	1	2	3	4	5	6	7	8
SENT	9.184***	8.086***			1.192***	0.914***	2.793***	0.821*
SENT (4:00PM–9:30AM)			6.180***	5.949***				
$CAR_{0,0}$					0.001	0.001	−0.040***	−0.038***
$CAR_{-1,-1}$	0.001	−0.001	0.001	−0.001	−0.004	−0.008	−0.051***	−0.049***
$CAR_{-2,-2}$	−0.010	−0.015**	−0.008	−0.013*	−0.009*	−0.006	−0.065***	−0.059***
$CAR_{-30,-3}$	−0.001	−0.000	0.001	0.001	−0.001	−0.001	−0.005*	−0.007***
$CAR^2_{0,0}$	0.003	0.002	0.003	0.002	0.000	0.000	0.002	0.003***
VIX	−0.021***	−0.000	−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 (%)	−0.000	−0.007***	−0.005	−0.010***	−0.006*	−0.004*	−0.027***	−0.010*
IO (%)	0.000	−0.000	0.000	−0.000	−0.000	−0.000	−0.002**	−0.002***
log(MARKETCAP)	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	0.000	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***
No. of obs.	618,633	618,633	455,083	455,083	618,367	618,367	618,369	618,369
Adj. R^2	0.011	0.007	0.008	0.005	0.001	0.000	0.002	0.002

We begin by confirming that TSM's results on stock price underreaction to news hold in our data. TSM find that a 1-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 to 2018.[1] In our sample, a 1-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.

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. Graph A shows the impact of contemporaneous news sentiment on returns for each year. Graph B shows the impact of news sentiment on next-day returns. Returns are

[1] Our news data are 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.

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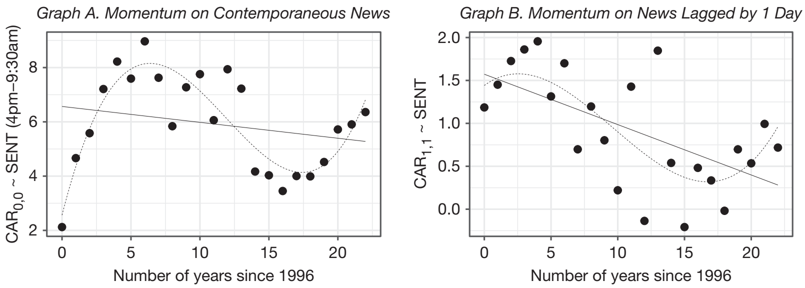
FIGURE 1

Time Variation in Annual SENT Coefficients

Figure 1 shows annual SENT coefficients from regressions of abnormal returns relative to the Fama–French (2015) model augmented with momentum on either contemporaneous news (Graph A) or news lagged by 1 day (Graph B). 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.



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 II and III. Each graph 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 Figure 1. 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.

Time Variation in Annual SENT Coefficients

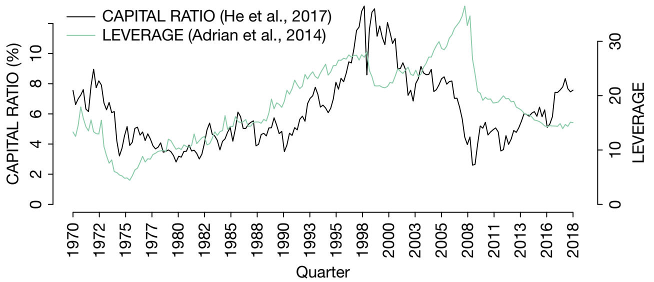
If the time variation in the underreaction to news were simply driven by growing information processing capacity, we would expect to see a consistent decline in magnitude of the next-day reaction in Graph B of Figure 1. We would also expect to see an *increase* in the contemporaneous reaction of prices 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 2 graphs 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 noninstitutional 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

FIGURE 2

Intermediary Capital Ratio and Leverage

Figure 2 shows the quarterly intermediary capital ratio and leverage. These series are defined in Section V.A.



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 *greater* underreaction over the subsequent 1 to 40 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.

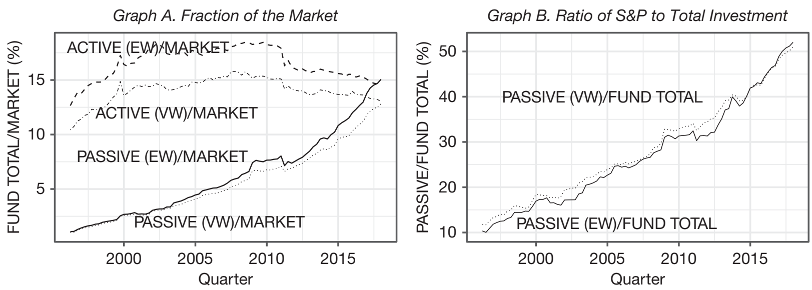
Along with changes in the risk-bearing capacity of the intermediation sector, the last 2 decades have witnessed a move toward passive investing, and away from actively managed mutual funds. Passive investors should be less responsive to news. Figure 3 shows that the fraction of all S&P 500 stocks that 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 experience *less* 1- to 40-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.

[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.

FIGURE 3

Active Versus Passive Fund Ownership

Graph A of Figure 3 shows the fraction of S&P 500 firms' market capitalization that is owned by either active or passive mutual funds. Graph B 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.



The market's response to news should also depend on the informativeness of news, and some periods may be richer in news than others. Our third interacting variable is *entropy*, a measure of news informativeness which we explain in Section II.A. Graph F 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 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 longshort strategy based on the intermediary capital ratio yields a 27% annualized excess return relative to the Fama–French (2015) 5-factor model augmented with momentum. Introducing realistic transaction costs and restricting the turnover of the strategy leads to 8.9% 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. In the Supplementary Material, we 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

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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 article 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 (2004) and Das and Chen (2007), who propose measures of information and sentiment in text from Internet message boards. We revisit Tetlock et al. (2008), which built on Tetlock (2007) in predicting returns from news sentiment. Engelberg, Reed, and Ringgenberg (2012), Garcia (2013), Sinha (2016), Heston and Sinha (2017), Larsen and Thorsrud (2022), Froot et al. (2018), Calomiris and Mamaysky (2019), Garcia, Hu, and Rohrer (2023), Ke, Kelly, and Xiu (2021), 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 et al. (2014) and He et al. (2017), and passive investing, as in Appel et al. (2016) and the many articles discussed in Wermers (2021). 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 VI.

TSM use articles from the Dow Jones (DJ) news service and the *Wall Street Journal* (WSJ) for their analysis, while we primarily use the Thomson Reuters (TR) 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 VI explores this idea more carefully by using text measures derived from three alternative news sources: the WSJ, DJ (which includes the WSJ), and the *Financial Times* (FT). We find that the samples (firm-day observations) covered by TR and DJ are quite similar to each other but differ from the more limited coverage in the WSJ and FT. After controlling for sample selection, our main findings are statistically indistinguishable when using TR 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 TR.

The rest of the article proceeds as follows: Section II describes the data and the methodology used to construct our sentiment and news informativeness measures. Section III presents the regression results documenting the time variation depicted in Figure 1. Section IV uses a simple model to formulate hypotheses on how intermediary capital, passive ownership, and news informativeness should affect the price response to news. Section V tests the predictions of

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

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Section IV and illustrates their magnitude through a backtested trading strategy. Section VI compares results using alternative news sources. Section VII concludes the study. The Supplementary Material contains further technical details and supporting results, including a discussion in Section A6 of how strategic order-splitting by large institutions may be related to our results.

II. Data

Our primary 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.

A. 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 i) refinements of the coverage of a specific event (e.g., an initial, short article gets written when some corporate event occurs, and this article gets expanded and refined over time), or ii) 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 6-hour windows, and then select the first article with a TR "urgency code" ≥ 2 in each of the PNACs that appear in that window.[5] This rule tries to avoid duplication of articles from type i) chains and while retaining relevant articles from type ii) chains.

Next, we select TR 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.A of the Supplementary Material.

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.

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

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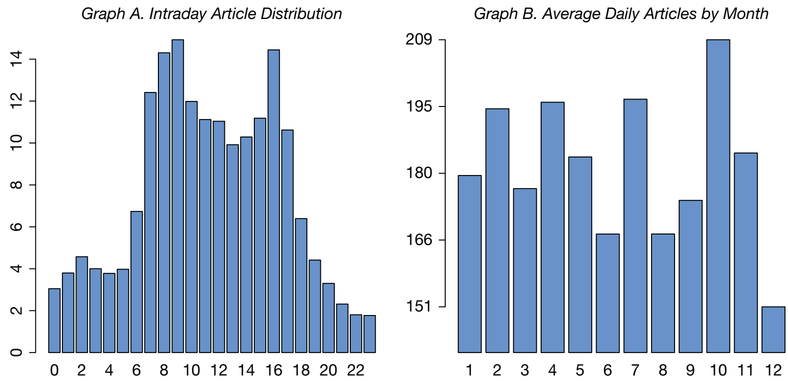
FIGURE 4
Article Distribution

Graph A of Figure 4 shows the average number of articles in each hour of the day. Graph B shows the average number of daily articles within each month.



We also drop any article with fewer than 25 words or that mentions more than 7 RICs (companies).[6] This leaves us with 1.36 million articles. Graph A of Figure 4 shows the distribution of articles throughout the day. The majority of articles about S&P 500 firms are released from 7:00AM to 5:00PM. Graph B shows the average number of daily articles by month of the year. News volume is very seasonal with peaks in February, April, July, and October, which partly reflect the earnings release cycle.

We next convert articles to lower case, remove stopwords, stem and tokenize the text, and perform sentiment negation using the Das and Chen (2007) method. This process is described in more detail in Section A2.A of the Supplementary Material. The sentiment of article j is calculated as

$$\mathrm{SENT}^j = \frac{n_j^{pos} - n_j^{neg}}{n_j},$$

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 4:00PM–4:00PM sentiment for firm i on business day t is the equal-weighted average sentiment of articles for firm i that appear between 4:00PM on day $t-1$ and 4:00PM on day t. For some of our specifications we also compute the 4:00PM–9:30AM sentiment. Here, we drop articles on day t that occur strictly after 9:30AM New York time. For

[6]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 7 RICs in the middle 8 years of the sample. Furthermore, as the histogram in Figure A3 in the Supplementary Material shows, there appears to be a sharp drop-off in article frequency when we go from 7 to 8 RICs.

Monday sentiment, in addition to including the 4:00PM–midnight articles from Sunday, we include articles from 4:00PM–midnight on the prior Friday.[7]

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 4 words (or, more generally, tokens). We measure the cross-entropy (or *entropy*, for short) of an article as

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

where $\widehat{p}_i$ is the empirical frequency of a 4-gram in the article, and $\widehat{q}_i$ is the estimated conditional probability of the 4-gram in the training corpus.[8] This entropy measure is large when 4-grams appearing in the new text are rare in the training corpus (i.e., when the new text is unusual relative to the training corpus).

Table 2 presents headlines of some sample articles from our corpus, sorted by entropy. For example, in June of 2005, the lowest entropy article (that satisfied our selection criteria) had an entropy of 0.08 and the headline "AMEX Nabors Industries Ltd (us;NBR) MOC Buy Imbalance: 193,000 shrs. ⟨NBR.A⟩." In that month, the highest entropy article had an entropy of 3.20 and the headline "FACTBOX--European aluminium smelters face energy threat." The relationship between the headlines of the sample articles and their entropy scores suggests that entropy is a useful proxy for the information content of news.

Figure 5 shows the time-series behavior of some summary statistics about the text archive. The average number of daily articles (Graph 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 (Graph B) has peaks around 2002 and 2014. The average number of words per articles (after stopwords have been excluded, Graph 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 (Graph 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

[7]Our 4:00PM day $t-1$ to 4:00PM 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.

[8]More precisely, $\widehat{q}_i$ is the estimated conditional probability of the fourth word in the 4-gram given the first 3 words defined as $(\widehat{c}(w_1 w_2 w_3 w_4)+1)/(\widehat{c}(w_1 w_2 w_3)+10)$, where $\widehat{c}$ counts the occurrence of a given phrase, e.g., $w_1 w_2 w_3 w_4$, 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 3 months from the month in which an article appears. The justification for this and further details are in Glasserman and Mamaysky (2019).

TABLE 2

Examples of Article Headlines Sorted by Entropy

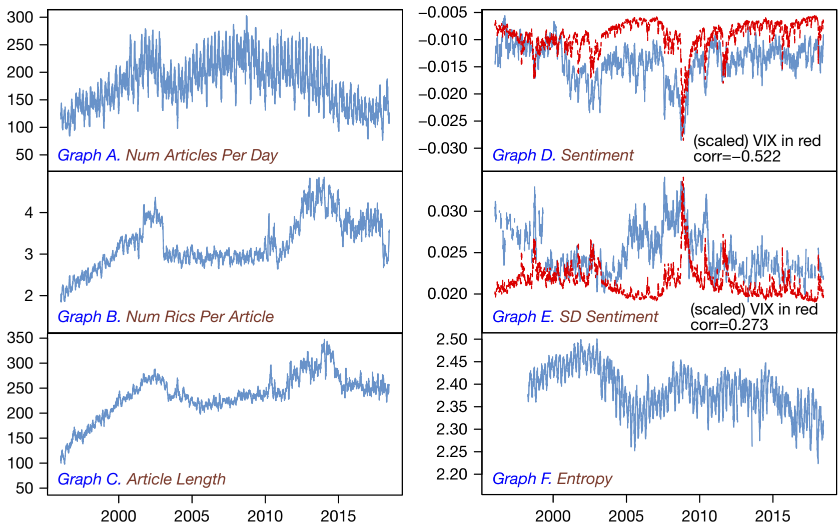
Table 2 presents the headlines of the 8 highest and lowest entropy articles in 2 months of our sample. Within each month, we look for articles with greater than or equal to 25 words and fewer than or equal to 7 RICs. Also, we exclude any articles with the string "shh margin" in the headline. The "total" column shows the number of words in the article, after stopwords have been removed.

Month	Headline	Entropy	Total
June 2005	AMEX Nabors Industries Ltd (us;NBR) MOC Buy Imbalance: 193,000 shrs. <NBR.A>	0.08	49
June 2005	AMEX Nabors Industries Ltd (us;NBR) No Imbalance <NBR.A>	0.12	46
June 2005	TEXT-Target <TGT.N> dividend	0.34	25
June 2005	TEXT-CVS Corp. <CVS.N> May sales	0.38	26
June 2005	UPDATE 1-Billionaire investor Kerkorian extends stake in	2.83	191
June 2005	RESEARCH ALERT-UBS cuts Tribune to ""neutral""	2.85	40
June 2005	FACTBOX-Citigroup, Merrill neck-and-neck in broker rankings	2.94	116
June 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

FIGURE 5

Article Statistics

Figure 5 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 V.C). Data are daily. The VIX (scaled to match the series in question) is shown in red.



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, Graph 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 over our sample.[9]

In Section VI.B, we also use news data from DJ,[10] the WSJ, and the FT. These three alternative news sources only cover part of our original sample period (from 1996 to 2018). Both the DJ data and WSJ data cover the 2000–2018 period, while the FT data cover the 2005–2018 period. Section A1.B of the Supplementary Material 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 FT, we compute article-level sentiment using the method described previously and then aggregate sentiment to the firm-day level. The DJ and WSJ 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 our sentiment calculation previously.[11] We maintain the same 4:00PM cutoff rules as for the TR 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 TR. 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 DJ archive consists of stock-day observations where both TR and DJ have non-missing sentiment. We define the restricted samples with respect to the WSJ and with respect to the FT in a similar way. We refer to our original sample from TR as the unrestricted sample. Table A6 in the Supplementary Material 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.

B. Financial Data

We run all of our specifications with either raw excess returns (RETRF) or with cumulative abnormal returns (CARs) relative to our 6-factor model, which uses the 5 factors from Fama and French (2015) augmented with momentum. We estimate the 6-factor model using daily data in the 12-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 (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html).

[9] Average entropy is calculated using the set of articles described in Section II.A. 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 Supplementary Material, which causes a sharp drop in our aggregate entropy series in this time period if these articles are not excluded.

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

[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.

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 et al. (2017) and Adrian et al. (2014) from Asaf Manela's and Tyler Muir's websites (https://sites.google.com/site/tylersmuir/), respectively. We calculate passive and active mutual fund ownership for a given stock following Appel et al. (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 for effects of post-earnings announcement drift,[15] we obtain earnings announcement dates from IBES for each firm-quarter, then compute standardized unexpected earnings (SUE), following Bernard and Thomas (1989) and TSM, as

$$\mathrm{SUE}_q = \frac{\mathrm{UE}_q - \mu_q}{\sigma_q}, \quad \mathrm{UE}_q = E_q - E_{q-4}, \tag{1}$$

[12]More details are given in Section A2.B of the Supplementary Material.

[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.

[15]In Section A7.F of the Supplementary Material, we show removing earnings announcements from our sample does not change the results.

TABLE 3

Summary Statistics for Returns Regressions

Table 3 shows 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.

Statistic	No. of Obs.	Mean	Std. Dev.	Min	Pctl(25)	Pctl(75)	Max
$\text{RETRF}_{1,1}$	703,994	0.036	2.696	−94.254	−1.037	1.082	102.358
$\text{CAR}_{1,1}$	703,981	0.004	2.239	−100.028	−0.849	0.819	96.015
SENT	706,545	−0.011	0.021	−0.283	−0.021	0.000	0.231
SENT (4:00PM–9:30AM)	519,011	−0.012	0.021	−0.250	−0.022	0.000	0.147
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	0.000	10.864	19.892	74.202
PASSIVE/MARKET (%)	704,448	5.492	3.614	0.000	2.694	7.608	28.889
PASSIVE/FUND_TOTAL (%)	704,388	26.215	14.466	0.001	15.300	34.676	99.984
VIX	706,338	20.639	8.584	9.140	14.530	24.180	80.860
SUE (5% win)	650,310	−0.051	1.465	−4.596	−0.538	0.576	3.392
SHORT_INTEREST (%)	669,804	2.846	3.522	0.000	1.021	3.176	77.916
INSTITUTIONAL_OWNERSHIP (%, 1% win)	700,560	67.545	18.906	0.936	57.997	80.317	108.205
log(MARKET_CAP)	660,337	23.795	1.299	19.079	22.862	24.731	27.481
IHS(BOOK/MARKET) (1% win)	704,320	0.450	0.296	−0.065	0.245	0.596	1.578
log(SHARE_TURNOVER)	705,979	−4.983	0.731	−7.803	−5.499	−4.527	−1.061
log(ILLIQUIDITY)	705,957	−23.034	1.430	−27.683	−24.001	−22.105	−13.853
α	704,320	0.014	0.122	−1.132	−0.048	0.069	1.268
$\beta_{\text{MKTRF}} \times \text{MKTRF}_{1,1}$	704,199	0.000	0.014	−0.205	−0.005	0.006	0.224
$\beta_{\text{SMB}} \times \text{SMB}_{1,1}$	704,199	−0.000	0.003	−0.087	−0.001	0.001	0.097
$\beta_{\text{HML}} \times \text{HML}_{1,1}$	704,199	0.000	0.005	−0.163	−0.001	0.001	0.234
$\beta_{\text{RMW}} \times \text{RMW}_{1,1}$	704,199	−0.000	0.004	−0.114	−0.001	0.001	0.095
$\beta_{\text{CMA}} \times \text{CMA}_{1,1}$	704,199	0.000	0.004	−0.097	−0.001	0.001	0.133
$\beta_{\text{UMD}} \times \text{UMD}_{1,1}$	704,199	−0.000	0.005	−0.138	−0.001	0.001	0.222

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] Table 3 presents summary statistics for all the variables. All return variables are in percentage points.

III. 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.

A. Lagged Responses

Graph B 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

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

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

where $Y^i_{t,u,v}$ is the abnormal return variable, SENT^i_t is lagged sentiment, and $\boldsymbol{X}^i_t$ is a vector of lagged control variables including a constant. Stock i enters our analysis on day t if that stock was a member of the S&P 500 index on day t, and if a news article about that stock appeared in our news sample from 4:00PM on business day $t-1$ to 4:00PM 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 6-factor model described in Section II.B) 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 10 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: $\mathrm{CAR}^2_{0,0}$ and the level of the VIX on the event day.[20]

To interpret the magnitude of the results in Figure 1 and compare with TSM, we present the full-sample results for 1- and 10-day ahead returns in columns 5–8 of Table 1. Over the full sample, the SENT coefficient for 1-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 1-standard-deviation positive sentiment shock. In their Table 2, TSM show that a 1-standard-deviation increase in their negative news measure decreases 1-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 V.D.

[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: $\mathrm{CAR}_{0,0}$, $\mathrm{CAR}_{-1,-1}$, $\mathrm{CAR}_{-2,-2}$, and $\mathrm{CAR}_{-30,-3}$, where $\mathrm{CAR}_{u,v}$ on day t is the cumulative abnormal return over trading days $[t+u, t+v]$. For $i \in \{0,-1,-2\}$, $\mathrm{CAR}_{i,i}$ is calculated using coefficient estimates from the 6-factor model over the trading days $[t-251+i, t-21+i]$. $\mathrm{CAR}_{-30,-3}$, $\mathrm{CAR}_{1,1}$, and $\mathrm{CAR}_{1,10}$ use the $i=0$ trading day window coefficient estimates. In all cases, the alpha is set to 0 when calculating CARs.

[19]TSM use stock turnover rather than the Amihud (2002) illiquidity measure. In Table A18 in the Supplementary Material, we replicate TSM's exact specification and show the results are similar to ours.

[20]We discuss the volatility controls further in Section A7.G of the Supplementary Material, but note that the inclusion of these controls has little effect on the SENT coefficients in our regressions.

B. Contemporaneous Responses

Graph A 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

$$Y_t^i = s \times \text{SENT}_t^i + \beta' \boldsymbol{X}_t^i + \varepsilon_t^i. \tag{3}$$

$\boldsymbol{X}_t^i$ is the same set of controls as in (2) with the exception of $\text{CAR}_{0,0}$, 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 $\text{FFCAR}_{+0,+0}$ 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 4:00PM 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 4:00PM to 6:30PM and then from 8:00AM to 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."

Graph A 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 4 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.

IV. Hypothesis Development

Motivated by Figure 1, we now develop hypotheses to explain the time-variation in the news–returns relationship. We do this by describing the implications of a two-period model with three types of investors and multiple risky securities. The details of the model are available in Section A3 of the Supplementary Material.

The model's three types of agents are passive investors, intermediaries, and noninstitutional investors. Passive investors are risk-neutral but, like an index fund, their portfolio is constrained by a benchmark. Intermediaries are also risk-neutral, but they are subject to a capital constraint that introduces effective risk aversion. Noninstitutional investors are the most risk averse. Each type of investor sets its utility-maximizing demands for stocks, and market prices are then determined by the requirement that they clear the market. The fractions of passive investors and intermediaries are proxies for the degree of passive investment and the availability of intermediary capital in the market.[21]

[21]Frank and Sanati (2018) propose a model with liquidity traders, retail investors, and arbitrageurs. Our models differ in several important respects, including the following: our passive investors provide

The three types of investors may have different beliefs, in the form of conditional means, about the payouts (terminal dividends) of the risky securities. In particular, noninstitutional investors and intermediaries update their forecasts positively (negatively) in response to positive (negative) news about dividends, whereas passive investors ignore this information. These differences have implications for the contemporaneous price response to information: we show that the price sensitivity to news increases with more intermediaries and decreases with more passive investors; it increases when intermediaries are less constrained; and it increases as the information content of news grows.

To study the underreaction to lagged news, we examine the response of the price in period 2 to information in period 1. For this, we introduce two additional model features. We introduce a parameter that measures the technological capacity constraint faced by investors. The constraint limits the fraction of investors who can follow each stock; as technology improves, more investors are able to follow every stock.

We further assume that that the investors who do follow a stock (intermediaries and noninstitutional investors) 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. The model then leads to the following predictions. We start with a naive prediction that considers only the change in technology.

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.

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.

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an important proxy for the extent of passive investment in the market; we allow for variation in the informativeness of news, both empirically and theoretically; a technological constraint limits the ability of all our agents to respond news; retail investors in Frank and Sanati (2018) respond to good news but not bad news.

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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 driven by time variation in the informativeness of news. We will use the entropy measure discussed in Section II.A 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 II. 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.

V. Testing Drivers of the News–Returns Relationship

In Section IV, 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 V.A–V.C empirically test these predictions. Section V.D discusses the economic magnitude of our findings and its dependence on these three interaction variables.

A. Intermediary Capital

We have argued in Section IV that less capital constrained intermediaries should increase stock price responses to contemporaneous and lagged news. Two measures of this risk-bearing capacity have been proposed in the literature. Adrian et al. (2014) look at the book leverage of all broker-dealers:

$$\text{LEVERAGE}_t^{\text{BD}} = \frac{\text{TOTAL\_FINANCIAL\_ASSETS}_t^{\text{BD}}}{\text{TOTAL\_FINANCIAL\_ASSETS}_t^{\text{BD}} - \text{TOTAL\_LIABILITIES}_t^{\text{BD}}},$$

which is broker-dealer assets divided by the book equity of the sector. When it is high, $\text{LEVERAGE}_t^{\text{BD}}$ 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, $\text{LEVERAGE}_t^{\text{BD}}$ 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 et al. (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

$$\text{(4)} \qquad \text{CR}_t = \frac{\sum_i \text{MARKET\_EQUITY}_{i,t}}{\sum_i \left(\text{MARKET\_EQUITY}_{i,t} + \text{BOOK\_DEBT}_{i,t}\right)},$$

where the sum is taken over all New York Fed primary dealers as of time t, and $\text{MARKETEQUITY}_{i,t}$ is the market capitalization of the ith 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 $\text{LEVERAGE}_t^{\text{BD}}$ for completeness.

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

$$\text{(5)} \quad Y_{t,u,v}^i = s_0 \times \text{SENT}_t^i + s_1 \times \text{CAPACITY}_t + s_2 \times \text{SENT}_t^i \times \text{CAPACITY}_t + \beta' \boldsymbol{X}_t^i + \varepsilon_{t,u,v}^i,$$

where CAPACITY_t is the most recently available level of either $\text{LEVERAGE}_t^{\text{BD}}$ 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

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

TABLE 4

Intermediary Capacity Effects on Sentiment Predictability

The regressions in Table 4 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 (4:00PM–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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

		Intermediary CAPACITY			
		CR (Daily)	CR (Monthly)	CR (Quarterly)	Lev (Quarterly)
		1	2	3	4
Panel A. Return Regressions					
$RETRF_{0,0}$	SENT	9.271***	9.186***	9.182***	9.227***
	SENT × CAPACITY	0.363***	0.443***	0.504***	0.227***
$RETRF_{0,0}$	SENT (4:00PM–9:30AM)	6.197***	6.136***	6.137***	6.232***
	SENT (4:00PM–9:30AM) × CAPACITY	0.371***	0.432***	0.448***	0.137**
$RETRF_{1,1}$	SENT	1.012***	1.197***	1.196***	1.132***
	SENT × CAPACITY	0.135	0.202	0.185	0.052
$RETRF_{1,10}$	SENT	1.877***	2.796***	2.779***	2.305***
	SENT × CAPACITY	0.474	0.778**	0.657*	0.622***
Panel B. CAR Regressions					
$CAR_{0,0}$	SENT	8.215***	8.096***	8.099***	8.119***
	SENT × CAPACITY	0.447***	0.498***	0.537***	0.159***
$CAR_{0,0}$	SENT (4:00PM–9:30AM)	6.168***	5.978***	5.979***	6.001***
	SENT (4:00PM–9:30AM) × CAPACITY	0.332***	0.302***	0.318***	0.129***
$CAR_{1,1}$	SENT	0.833***	0.919***	0.920***	0.912***
	SENT × CAPACITY	0.130**	0.194***	0.186***	0.021
$CAR_{1,10}$	SENT	0.523	0.841*	0.844*	0.795*
	SENT × CAPACITY	0.640***	0.840***	0.769***	0.184**

intermediary sector, as well as that of its institutional clients. Table 4 presents the results of this specification. The first 3 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 2 columns of Panel B of Table 4, we see that higher CR_t levels are associated with much larger reactions of prices to contemporaneous news (we focus here on the 4:00PM–9:30AM news measure). A 10% increase in CR_t (roughly the range of the series) is associated with a 50% increase in the contemporaneous price–news reaction (0.302×10 for the monthly specification against $s_0 = 5.978$). Crucially, this 10% increase is also associated with a large increase in the $CAR_{1,1}$ and $CAR_{1,10}$ sensitivities to lagged news. For example, moving from a 3% monthly CR_t level (the sample minimum) to 13% (the sample maximum), the $CAR_{1,10}$ sensitivity to time t sentiment increases by $10\% \times 0.84 = 8.4\%$. This is the same order of magnitude as the contemporaneous stock price reaction to news. A 10% increase in CR_t also leads to a $0.194 \times 10\% = 1.94\%$ increase in $CAR_{1,1}$. Indeed, this amount of variation is enough to capture the entire sample range of both annual $CAR_{1,1}$ sentiment coefficients in Figure 1.

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

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

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 1-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 1-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 6 shows the results of this analysis. Section A4.B of the Supplementary Material details the methodology.

Graph A of Figure 6 plots the impulse response of excess returns. The solid line in the graph is the baseline case where intermediary capacity is equal to its long-term mean (Case 1). On the news day (day 0), a 1-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 1 month.

The dashed line in the graphs of Figure 6 corresponds to Case 2, where intermediary capacity is 1-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.

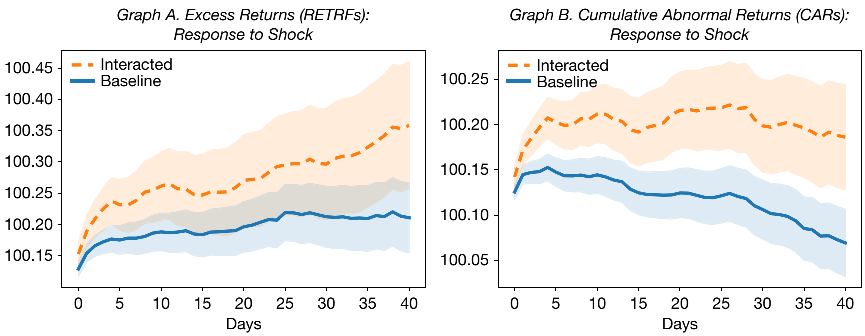
Graph B of Figure 6 shows the same analysis, but for cumulative abnormal returns. The difference between the baseline response (solid line) and the response conditional on high intermediary capacity (dashed line) is similar to the case of excess returns. Interestingly, at horizons longer than the 10-day 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 1-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

FIGURE 6

Impulse Responses to {Sentiment × Monthly Intermediary Capacity} Shocks

Impulse response functions estimated using the local projection method of Jorda (2005). Figure 6 shows the baseline response (labeled *baseline*) of future excess returns and cumulative abnormal returns (CARs) to a 1-standard-deviation sentiment shock, as well as the response conditional on a 1-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. Graph A shows cumulative excess returns, and Graph B shows CARs. The cumulative responses show the arithmetic sums of 1-day returns; the geometric cumulative returns are almost identical. Standard errors are based off time-clustered panel regressions of 1-day ahead future returns on lagged sentiment, and assume independence of 1-day returns across time, and between the baseline and the conditinal responses. The shaded regions represent 2 standard error bands around the impulse response.



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 IV (a pronounced news underreaction when an informationally constrained intermediary sector becomes less financially constrained).

From the end of day 0 to the end of trading day 40, we see a 20-basis-point increase in excess return for a stock experiencing a 1-standard-deviation positive sentiment shock, conditional on intermediary capacity being 1-standard-deviation above its long-run mean. In response to a 2-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 V.D.

B. Mutual Fund Ownership

We turn next to testing the effect of passive ownership in Prediction 3 of Section IV. 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 IV.

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.

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

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- ACTIVE/MARKET: The fraction of shares outstanding held by actively managed mutual funds.
- PASSIVE/FUND_TOTAL: The fraction of shares outstanding held by passively managed mutual funds divided by the fraction of shares held by all mutual funds.

Table 5 presents the results of estimating the following modification of equation (2):

(6)
$$Y^i_{t,u,v} = s_0 \times \text{SENT}^i_t + s_1 \times \text{OWNERSHIP}^i_t + s_2 \times \text{SENT}^i_t \times \text{OWNERSHIP}^i_t + \beta' \boldsymbol{X}^i_t + \varepsilon^i_{t,u,v},$$

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. Panel A of Table 5 shows results for the excess returns, and Panel B shows the results for CARs.

The middle column of Table 5 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 4:00PM–9:30AM sentiment. However, higher active ownership of a stock marginally increases the degree of the underreaction to news 1-day ahead,[26] and meaningfully increases the degree of underreaction to news 10 days ahead with a coefficient of 0.176 (significant at the 1% level).

The third column of Table 5 shows that a higher PASSIVE/FUND_TOTAL ratio decreases the contemporaneous stock price response to news with a SENT × 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 1-day responses and a coefficient of −0.1 (significant at the 1% level) for 10-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 $\text{CAR}_{0,0}$ response to contemporaneous news falls by 10%, its $\text{CAR}_{1,1}$ response to lagged news is cut by 30% (the 0.909 coefficient is decreased by 0.015×20), and its $\text{CAR}_{1,10}$ response to lagged news switches signs from strongly positive to strongly negative. The results for PASSIVE/MARKET are qualitatively similar to those for PASSIVE/FUND_TOTAL. These results are consistent with Prediction 3 from Section IV 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 (6), where the interacting variable is PASSIVE/FUND_TOTAL. The results are qualitatively similar to those of Section V.A where the interacting variable is intermediary capacity. Conditional

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

[26]The sentiment-ownership interaction for 1-day ahead CARs and ACTIVE/MARKET is 0.034, as can be seen from Panel B of Table 5. The p-value of this coefficient is 0.14.

TABLE 5

Mutual Fund Ownership Effects on Sentiment Predictability

The regressions in Table 5 include as controls: CONSTANT, $CAR_{0,0}$, $CAR_{-1,-1}$, $CAR_{-2,-2}$, $CAR_{-30,-3}$, SUE, SI (%), IO (%), log(MARKET_CAP), IHS(BOOK/MARKET), log(ILLIQUIDITY), lagged α, $CAR_{0,0}^2$, and VIX. The $RETRF_{0,0}$ and $CAR_{0,0}$ regressions omit the $CAR_{0,0}$ control. The row label (4:00PM–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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

		Mutual Fund OWNERSHIP (%)		
		PASSIVE/ MARKET	ACTIVE/ MARKET	PASSIVE/ FUND_TOTAL
		1	2	3
Panel A. Return Regressions				
$RETRF_{0,0}$	SENT	9.197***	9.120***	9.175***
	SENT × OWNERSHIP	−0.035	0.205***	−0.047***
$RETRF_{0,0}$	SENT (4:00PM–9:30AM)	6.204***	6.169***	6.207***
	SENT (4:00PM–9:30AM) × OWNERSHIP	−0.039	0.193***	−0.050***
$RETRF_{1,1}$	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	−0.410**	0.252***	−0.117***
Panel B. CAR Regressions				
$CAR_{0,0}$	SENT	8.093***	8.028***	8.078***
	SENT × OWNERSHIP	−0.022	0.181***	−0.042***
$CAR_{0,0}$	SENT (4:00PM–9:30AM)	5.956***	5.936***	5.966***
	SENT (4:00PM–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***	−0.100***

on a 1-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 Supplementary Material.

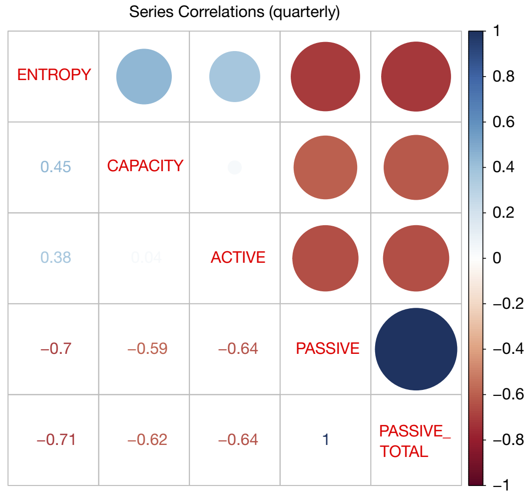
C. The Informativeness of News

As we argued in Prediction 4 of Section IV, 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. Graph F 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 Supplementary Material, 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 A7.A and Figure A9 of the Supplementary Material give details of this analysis.

Figure 7 shows the correlation between quarterly average entropy, quarterly average ownership ratios from Section V.B, and quarterly intermediary capacity.

FIGURE 7
Series Correlations (Quarterly)

Figure 7 shows the 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 ACTIVE/MARKET and PASSIVE/MARKET variables. Passive_total refers to PASSIVE/FUND_TOTAL.



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 (5) and (6) where intermediary capacity and ownership ratios are replaced with daily, monthly, quarterly, or annual average entropy:

$$Y^i_{t,u,v} = s_0 \times \mathrm{SENT}^i_t + s_1 \times \mathrm{ENTROPY}_t + s_2 \times \mathrm{SENT}^i_t \times \mathrm{ENTROPY}_t + \beta' \boldsymbol{X}^i_t + \varepsilon^i_{t,u,v}. \tag{7}$$

Daily $\mathrm{ENTROPY}_t$ is calculated as the average of all article-level entropies in day t. Monthly $\mathrm{ENTROPY}_t$ 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. Panel A shows results for excess returns as the dependent variable, and Panel B 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 4:00PM–9:30AM news, the s_0 coefficient in (7) is 6.22 and the interaction coefficient with entropy is 23.183; both

[27]We demean all entropy measures in (7) using their full-sample means.

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TABLE 6

Entropy Effects on Sentiment Predictability

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 (4:00PM–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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

		ENTROPY			
		Daily	Monthly	Quarterly	Annual
		1	2	3	4
Panel A. Return Regressions					
$RETRF_{0,0}$	SENT	9.510***	9.623***	9.688***	9.696***
	SENT × ENTROPY	12.267***	37.742***	45.873***	49.938***
$RETRF_{0,0}$	SENT (4:00PM–9:30AM)	6.392***	6.490***	6.526***	6.530***
	SENT (4:00PM–9:30AM) × ENTROPY	5.645	25.973***	28.795***	31.679***
$RETRF_{1,1}$	SENT	1.015***	1.066***	1.044***	1.034***
	SENT × ENTROPY	7.386*	8.052	9.441	8.471
$RETRF_{1,10}$	SENT	1.878***	1.821***	1.648**	1.517**
	SENT × ENTROPY	13.835	30.828*	15.164	−1.924
Panel B. CAR Regressions					
$CAR_{0,0}$	SENT	8.349***	8.404***	8.453***	8.464***
	SENT × ENTROPY	8.299***	32.217***	38.100***	42.353***
$CAR_{0,0}$	SENT (4:00PM–9:30AM)	6.166***	6.195***	6.220***	6.229***
	SENT (4:00PM–9:30AM) × ENTROPY	1.740	20.348***	23.183***	26.066***
$CAR_{1,1}$	SENT	0.870***	0.882***	0.893***	0.893***
	SENT × ENTROPY	3.199	4.979	7.916**	7.542*
$CAR_{1,10}$	SENT	0.414	0.467	0.473	0.485
	SENT × ENTROPY	13.222**	20.050**	16.103	14.839

are highly significant. Given the standard deviation of quarterly entropy from Table 3 of 0.048, a 1-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 1-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 1-standard-deviation increase in quarterly entropy increases the effect of news on 1-day ahead returns by $7.916 \times 0.048 = 0.380$, which is a very large effect relative to s_0. The impact for 1-day ahead returns with annual entropy is similarly large. For 10-day ahead returns, the interaction term for quarterly and annual entropy is positive and larger than the interaction term for 1-day ahead returns, but is not significant. However, the interaction terms for daily and monthly entropy for 10-day ahead returns are large, positive, and significant (e.g., the sentiment-monthly entropy interaction term for 10-day ahead returns is 20.05 and significant at the 5% level). The results are consistent with Prediction 4 from Section IV 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 (7), where the interacting variable is monthly entropy. The results are qualitatively similar to those of Sections V.A and V.B where the interacting variables are intermediary capacity and PASSIVE/FUND_TOTAL. Conditional on a 1-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

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results are shown in Figure A5 in the Supplementary Material. The magnitude of the return response to a news shock, conditional on a 1-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.

D. Magnitude of the Effect

To assess the economic magnitude of stock price underreaction to news, we construct a trading strategy based on news sentiment and our interaction variables (the capital ratio, passive ownership, and entropy). We outline the strategy here and provide complete details in the Section A4.A of the Supplementary Material.

The strategy goes long and short, respectively, the top and bottom 20% of firms each day based on their daily 4:00PM–4:00PM sentiment SENT_t^i (defined in Section II.A). 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. To reduce turnover, we follow a strategy similar to Ke et al. (2021) and introduce a smoothing parameter called KEEP that induces persistence in the portfolio holdings to produce weights:

$$w_{use}(i,t) = \text{KEEP} \times w_{base}(i,t) + (1 - \text{KEEP}) \times w_{use}(i,t-1),$$

initialized with $w_{use}(i,0) = w_{base}(i,0)$. Lower values of KEEP lead to lower turnover.

We argued theoretically in Section IV 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 (4). Periods of high active ownership are captured using $\text{ACTIVE}/\text{MARKET}_t$, defined as the within-month mean of the within-day means of the firm-day level $\text{ACTIVE}/\text{MARKET}_{i,t}$. Our ENTROPY_t variable is a rolling average of the last three monthly entropies.

We incorporate these variables into our trading strategy by increasing gross position sizes during times of high predictability. We use a parameter SCALE between 0 and 1 to determine how much each interaction variable scales our portfolio weights. The conditioning scales w_{use} on day t by

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

where $X(m)$ is the value of the conditioning variable in month m, the month immediately prior to day t. 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. Larger values of SCALE result in greater variation in the portfolio weights through the interaction variables. The details of the KEEP and SCALE parameters are explained in Section A4.A of the Supplementary Material.

We assume a transaction cost rate tc of 3 basis points (bps) per unit of turnover (i.e., the full bid–offer spread for U.S. stock exchanges estimated by Hagströmer (2021)). The total transaction cost each day is then TC times the total turnover,

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TABLE 7

News Trading Strategy 6-Factor Alphas (bps per day) with SCALE = 0.33

Each row in Table 7 shows daily alphas, in basis points (bps), from the trading strategy explained in Section V.D. The alphas are relative to the Fama and French's (2015) 5-factor model with momentum. The columns correspond to different values of the KEEP variable in Supplementary Material equation (A10). 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 Supplementary Material equation (A11), 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)).

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)
ACTIVE/MARKET	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)

which we measure as in Ke et al. (2021). We subtract the total transaction cost each day from the frictionless return.

We run 48 versions of the trading strategy which are parameterized by $\text{KEEP} \in \{0.33, 1\}$, $\text{TC} \in \{0, 3\,\text{bps}\}$, $\text{SCALE} \in \{0.165, 0.33, 0.66\}$, and interaction variable in {none, CR, ACTIVE/MARKET, ENTROPY}. Table 7 presents the daily alpha (in basis points) relative to the Fama–French (2015) 5-factor model augmented with momentum for each strategy variant when $\text{SCALE} = 0.33$ (e.g., a daily alpha of 4 means $252 \times 4\,\text{bps} \approx 10\%$ annual alpha).

The first column of Table 7 shows the results for $\text{KEEP} = 1, \text{TC} = 0$, 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. More importantly, as we look across the columns we see that, in every case, conditioning the strategy on the capital ratio or the percent of active ownership generates higher alpha. Interacting the strategy with entropy also leads to higher alphas in the last 2 columns, where we account for transaction costs. The fourth column shows that even with the introduction of transaction costs and after restricting portfolio turnover, the strategy generates an annualized alpha between 4.2% and 8.9%, depending on the conditioning variable.

These results are discussed in greater detail in Section A4.A of the Supplementary Material, and Tables A7 and A8 in the Supplementary Material show that they are robust to other choices of SCALE.

Our trading strategy performance is 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 et al. (2021) report frictionless long/short returns in the 25% range (their Table 3 for value-weighted returns). 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.

We emphasize that the economic mechanisms discussed in the article 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. Our trading strategy analysis serves primarily to show that the magnitudes of these effects are meaningful.

VI. Alternative News Sources

In Section VI.A, we compare our results with prior work on the news–returns relationship which uses data from the FT. In Section VI.B, we check whether our main results, which use the TR news archive, hold when using other news sources: DJ, the WSJ, and the FT. After controlling for sample selection (in terms of which firms receive news coverage), the main findings from the TR 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.

A. Stock Market Reactions to Shocks

In work related to ours, Frank and Sanati (FS) (2018) 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 (where we separately estimate the response to high and low sentiment news, see Section A7.B of the Supplementary Material), 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 Oct. 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 FT articles about S&P 500 firms from 1982 to 2013.[28]

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 $\text{CAR}_{0,0}$, 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 Oct. 2014 in this analysis. And we restrict the sample period to be Jan. 1996–Sept. 2013, which is the overlapping period between our full sample and the FS sample.

The top portion of Table 8 corresponds to the subsample with bad news ($\text{CAR}_{0,0} < 0$), and the bottom portion to the subsample with goods news ($\text{CAR}_{0,0} \geq 0$).[29] 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 $\text{CAR}_{0,0}$ for this comparison). The top portion 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 1 to 40 days. This indicates overreaction to bad news. On the other hand, the bottom portion 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 our Table 8 and those in Table 8 of FS are likely due to our different news samples. FT articles are much less frequent than Reuters articles and, as Frank and Sanati note, "the FT 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 news archives at length in Section VI.B.

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

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

[29]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; both portions of the table split observations based on contemporaneous abnormal returns.

TABLE 8

Replication of Table 8 in Frank and Sanati (2018)

In 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 Oct. 2014, and the sample period is restricted to Jan. 1996–Sept. 2013. The top portion corresponds to the sample with $CAR_{0,0} < 0$, and the bottom portion includes observations with $CAR_{0,0} \geq 0$. All returns are shown in basis points. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Sort: Cap. Ratio (Growth Rate)	Shock	No. of Obs.	CAR [0,0]	[1,1]	[1,10]	[1,21]	[1,40]	[2,10]	[2,21]	[2,40]
Q1	–	41,377	−152.810***	2.329**	20.504***	44.221***	67.815***	19.106***	41.892***	65.486***
			(−146.468)	(2.067)	(5.817)	(9.294)	(10.139)	(5.639)	(9.018)	(9.898)
Q2	–	42,672	−145.921***	3.252***	18.980***	41.372***	70.790***	15.982***	38.120***	67.517***
			(−153.572)	(3.104)	(6.320)	(10.045)	(12.853)	(5.678)	(9.523)	(12.412)
Q3	–	35,192	−113.604***	1.351	15.244***	28.487***	51.851***	13.953***	27.135***	50.500***
			(−138.705)	(1.540)	(5.878)	(7.485)	(10.095)	(5.724)	(7.304)	(9.963)
Q4	–	42,456	−121.610***	1.585*	15.324***	24.457***	47.578***	13.954***	22.869***	45.973***
			(−149.775)	(1.884)	(6.274)	(6.749)	(9.599)	(6.027)	(6.496)	(9.411)
Q5	–	41,892	−156.399***	2.680**	19.725***	39.153***	97.770***	17.828***	36.613***	95.206***
			(−149.232)	(2.222)	(5.661)	(7.974)	(14.910)	(5.319)	(7.666)	(14.727)
Q5 – Q1	–		−3.589**	0.351	−0.779	−5.069	29.955***	−1.278	−5.279	29.720***
			(−2.427)	(0.213)	(−0.157)	(−0.741)	(3.198)	(−0.268)	(−0.792)	(3.213)
Q1	+	40,723	160.001***	−1.395	6.945**	25.070***	44.710***	8.790***	26.465***	46.106***
			(146.653)	(−1.236)	(2.088)	(5.467)	(6.812)	(2.809)	(5.927)	(7.116)
Q2	+	42,502	153.246***	1.483	4.800	23.965***	42.906***	3.901	22.482***	41.426***
			(149.904)	(1.424)	(1.644)	(5.937)	(7.912)	(1.412)	(5.736)	(7.755)
Q3	+	34,734	121.407***	1.313	12.020***	26.650***	42.150***	10.527***	25.338***	40.837***
			(149.725)	(1.545)	(4.591)	(7.013)	(8.096)	(4.303)	(6.882)	(7.969)
Q4	+	41,897	126.732***	0.771	8.894***	24.563***	48.341***	8.223***	23.809***	47.583***
			(166.352)	(0.973)	(3.707)	(6.994)	(9.871)	(3.614)	(6.952)	(9.841)
Q5	+	41,196	169.116***	3.174***	5.447	34.528***	70.908***	2.371	31.368***	67.671***
			(147.331)	(2.640)	(1.631)	(7.258)	(11.115)	(0.760)	(6.776)	(10.761)
Q5 – Q1	+		9.115***	4.569***	−1.499	9.458	26.198***	−6.419	4.902	21.565**
			(5.756)	(2.770)	(−0.318)	(1.431)	(2.862)	(−1.453)	(0.762)	(2.388)

different sorts. In Table 1, regressions of contemporaneous returns on news and all our control variables the R^2s 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.

B. Result Comparison Across Different News Sources

We next examine whether our results hold for three alternative news sources: DJ, the WSJ, and the FT.[30]

We first rerun the baseline regressions in specification (2) using data from these three news sources. Table 9 presents the estimates of the SENT coefficient s. Column 1 uses our original TR data and columns 2–4 use the three alternative news sources. The sentiment variables are standardized so the coefficients can be interpreted as the effects of a 1-standard-deviation increase in news sentiment. Table 9

[30]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.

TABLE 9

Baseline Regressions Using Data from Different News Sources

Table 9 shows baseline regressions in specifications (2) and (3) using data from four different news sources (Thomson Reuters (TR), Dow Jones (DJ), *Wall Street Journal* (WSJ), and *Financial Times* (FT)). $\text{RETRF}_{i,j}$ ($\text{CAR}_{i,j}$) 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. Coefficients have been standardized to reflect a 1-standard-deviation increase in the explanatory variable. These regressions include as controls: CONSTANT, $\text{CAR}_{0,0}$, $\text{CAR}_{-1,-1}$, $\text{CAR}_{-2,-2}$, $\text{CAR}_{-30,-3}$, SUE, SI (%), IO (%), log(MARKET_CAP), IHS(BOOK/MARKET), log(ILLIQUIDITY), lagged α, $\text{CAR}_{0,0}^2$, and VIX. The $\text{RETRF}_{0,0}$ and $\text{CAR}_{0,0}$ regressions omit the $\text{CAR}_{0,0}$ control. Standard errors are clustered by time. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	TR	DJ	WSJ	FT
	1	2	3	4
$\text{RETRF}_{0,0}$	0.194***	0.345***	0.067***	0.265***
$\text{RETRF}_{1,1}$	0.025***	0.025***	0.013	0.013
$\text{RETRF}_{1,10}$	0.059***	0.043**	0.020	0.101***
$\text{CAR}_{0,0}$	0.171***	0.249***	0.065***	0.177***
$\text{CAR}_{1,1}$	0.019***	0.021***	0.013**	−0.000
$\text{CAR}_{1,10}$	0.017*	0.038***	0.005	−0.001

presents that for TR, DJ, and WSJ, news sentiment is positively related to contemporaneous, 1-day ahead, and 10-day ahead cumulative abnormal returns. The effect is statistically significant for all the specifications except the predictive regression for 10-day cumulative abnormal return using WSJ sentiment. In terms of magnitude, our original TR sentiment has a smaller effect than DJ sentiment and a larger effect than WSJ sentiment. For example, a 1-standard-deviation increase in DJ sentiment leads to a 2.1 basis point increase in 1-day ahead cumulative abnormal return, while the effect is 1.9 basis point using TR sentiment and 1.3 basis point using WSJ sentiment. Using the FT data, we find that sentiment is positively related to contemporaneous abnormal returns, while the relationship between FT sentiment and 1- and 10-day ahead returns is statistically indistinguishable from 0.[31]

The overall takeaway from Table 9 is that the news–returns relationship in (2) is consistent across different news sources. We next run the intermediary capital, ownership, and entropy interaction regressions (equations (5)–(7)) separately for the four news sources. As this analysis contains a large amount of information, we show these results in Tables A25–A27 in the Supplementary Material. To provide a concise summary, for each of our main specifications (the baseline regression in (2), the intermediary capital regression in (5), the mutual fund ownership regression in (6), and the entropy regression in (7)), we test whether the results are statistically indistinguishable when using sentiment from the TR archive versus using sentiment from one of the three alternative news sources.[32]

When comparing the TR 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

[31] Recall from Section II.A that the FT data covers the 2005–2018 period, which is much shorter than our original TR sample period (from 1996–2018). The shorter sample period could drive the difference in the baseline results. In Section VI.C, we provide further evidence that the difference in news coverage may drive the difference in the results across the four news sources.

[32] In all cases, the entropy specification in (7) uses our original entropy measure obtained from the Thomson Reuters archive.

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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 TR 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 TR and the alternative news source have non-missing sentiment. This is the restricted sample described in Section II.A. For example, when we compare TR sentiment with DJ sentiment, we run regressions only using firm-day observations with both non-missing TR sentiment and with non-missing DJ sentiment, and we refer to this as the restricted firm-day sample with respect to DJ. We define the restricted sample with respect to the WSJ and the restricted sample with respect to the FT in the analogous way.

The empirical tests are as follows: For a given regression specification using the sentiment measure from news source k, where $k \in \{\text{TR, DJ, WSJ, FT}\}$, let β^k denote the coefficient of interest and $\widehat{\beta}^k$ 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 (5), the coefficient of interest is s_2, the interaction between intermediary capital and sentiment. For the mutual fund ownership regression in (6), the coefficient of interest is s_2, the interaction between mutual fund ownership and sentiment. Finally, for the entropy regression in (7), the coefficient of interest is s_2, the interaction between entropy and sentiment.

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

$$H_0 : \beta^k = \beta^{k'}, \tag{8}$$

where $k = \text{TR}$ and $k' \in \{\text{DJ, WSJ, FT}\}$. We test equality using the empirical covariance matrix of the estimates $\left\{\widehat{\beta}^k \widehat{\beta}^{k'}\right\}$.[33] The finding from an alternative news source is qualitatively different from our finding using TR 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 10 presents the results of these tests. Each cell in Table 10 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

[33]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.

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coefficients from from the two news sources are statistically indistinguishable. An ✗ indicates that the coefficient estimates using sentiment from TR 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 of Table 10 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 DJ, 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 (5), columns 8–10 correspond to the mutual fund ownership regression in equation (6), and columns 11–14 correspond to the entropy regression in equation (7). For example, the cell in row 2 and column 4 shows the test result for the intermediary capital regression in equation (5), which uses the restricted sample with respect to WSJ, the contemporaneous raw excess return ($\text{RETRF}_{0,0}$) as the dependent variable, and the daily intermediary capital ratio (CR) as the key interaction variable.[34]

Table 10 presents 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 TR 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, 1- or 10-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 DJ sentiment to predict $\text{CAR}_{1,10}$; the interaction of WSJ sentiment with quarterly intermediary leverage to predict $\text{CAR}_{1,1}$; the interaction of WSJ sentiment with daily and annual entropy to predict $\text{RETRF}_{1,10}$. 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.

C. Differential Coverage

We next analyze the impact of selective coverage of firm-day events by different news sources. We repeat the analysis of Table 10 but compare the results obtained using the unrestricted TR sample (i.e., the one we use in the entirety of this article outside of Section VI.B) versus those obtained using the TR sample, but restricted to overlapping firm-day observations with the DJ, WSJ, and FT news archives. We call the latter the restricted TR sample. Because the restricted TR sample conditions on firm-day observations overlapping with other news sources,

[34]We use the 4:00PM–4:00PM sentiment as the independent variable in these regressions. In unreported results, we also regress the contemporaneous return $\text{RETRF}_{0,0}$ on the 4:00PM–9:30AM sentiment (using the different news samples in this section) and the results are similar.

TABLE 10

Comparing Results Using Sentiment from Thomson Reuters Versus Alternative News Sources

In Table 10, we test the null hypothesis H_0 from (8) 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 ✗. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

			Intermediary CAPACITY				Mutual Fund OWNERSHIP			ENTROPY			
		Full	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	–											

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we are able to understand the impact of selective coverage (by other news sources) on our results.

Table A28 in the Supplementary Material 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 TR 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 A28, we can reject once for the DJ sample restriction (for the daily entropy interaction for $\text{CAR}_{0,0}$) and twice for the WSJ sample restriction (for the quarterly leverage and PASSIVE/MARKET interactions for $\text{CAR}_{1,10}$). When comparing results obtained using the unrestricted TR archive to those obtained using the part of the TR archive with overlapping firm-day observations to the FT, we find seven rejections in the abnormal returns (bottom) panel. These results suggest the TR 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 TR news coverage compares to that in the DJ, WSJ, and the FT, we analyze the characteristics of firms covered by these news sources. Figure A6 in the Supplementary Material shows that the WSJ and FT cover companies that are, on average, larger than those covered by DJ and TR.[35] They also carry fewer articles, and about companies whose returns are better explained by the Fama–French (2015) 5-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 extreme than the WSJ firms. Figure A7 shows that the WSJ and FT devote a much larger fraction of their news coverage to financial firms than do DJ 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 TR 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 TR, DJ, WSJ, and FT 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 TR. The very different firms covered by TR and the FT likely explain why our findings in Table 8 differ from those of Table 8 in Frank and Sanati (2018).

VII. 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

[35]Section A5.A of the Supplementary Material explains the methodology used to construct Figures A6 and A7 in the Supplementary Material.

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, noninstitutional, and passive) who have limited attention to news helps explain many of our findings. Furthermore, 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.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109023001369.

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