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Joint news, attention spillover, and market returns predictability

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Abstract

We analyze over 2.6 million news articles and propose a novel measure of joint news coverage of firms. The measure strongly and negatively predicts market returns, with a monthly R^2 of 3.93% in sample and 6.52% out of sample. The relation is causal, robust to existing predictors, and is especially strong when market uncertainty is high or when market frictions are large. At the firm level, joint news coverage is associated with a 20.3% increase in EDGAR downloads by new IPs from the investor bases of the other covered firms. Our evidence suggests that joint news triggers investor attention spillover across firms, which aggregates and causes marketwide overvaluations and subsequent reversals.

Keywords: Attention spillover, News, Investor base, EDGAR search, Return predictability, Self news.

JEL Classification: G11, G12, G41.

1. Introduction

Extensive literature has been devoted to the prediction of aggregate stock market returns, with most papers focusing on macroeconomic variables.[1] As pointed out by Shiller (2002, 84), "The news media do play an important role both in setting the stage for market moves and in instigating the moves themselves." Consistent with this, an emerging literature finds that aggregate measures of media sentiment influence market returns (Tetlock, 2007; Calomiris and Mamaysky, 2019) and that aggregate media attention to topical themes explains a meaningful portion of market returns and business cycles (Bybee et al., 2021). At the same time, a growing number of studies provide strong evidence that firm level news affect the returns of individual stocks.[2] Given the key role of news on individual stock prices, an important question is whether and how firm-level news can influence market returns.

In this paper, we aim to provide insight into the connections between the firm level and the marketwide effects of news coverage on financial markets. Toward that end, we focus on the effect of news and media coverage in a *cross-firm* setting. We hypothesize that the arrival of news that covers multiple firms (*joint news*) triggers a spillover of investor attention across the covered firms, which then causes high valuations across multiple stocks. During periods when a large number of joint news articles are released, the firm-level spillover effect aggregates and results in marketwide overvaluation and subsequent reversals.[3]

We empirically test the hypothesis by analyzing an extensive database of over 2.6 million news articles covering firms in the S&P 500 index. From this database, we construct a novel measure

[1] See, for example, Ang and Bekaert (2006), Campbell and Yogo (2006), Cochrane (2007), and Goyal and Welch (2008). We refer interested readers to Rapach and Zhou (2013) for a comprehensive overview.

[2] Barber and Odean (2008) show that salient news triggers attention-based buying and high valuations in stock prices. Tetlock, Saar-Tsechansky, and Macskassy (2008) show that the negative words in news stories predict firms' earnings and stock returns. Tetlock (2011) shows that individual investors overreact to stale media information, resulting in a temporary stock price overvaluation. Engelberg, Sasseville, and Williams (2012) find that stock recommendations on the television program *Mad Money* triggers investor attention and is associated with overvaluation. Hillert, Jacobs, and Müller (2014) find that firms extensively covered by the media exhibit strong short-run momentum that reverses in the long run.

[3] The arrival of news about a firm can be either joint news or news that only covers a single firm (*self news*). Self news tends to be idosyncratic and is less likely to trigger an attention spillover across firms. Hence we expect self news coverage to be less important for aggregate stock returns. We examine both types of news in our analysis.

of joint news coverage of firms and investigate how the measure is associated with the returns of the aggregate stock market. We further complement our market-level analysis with firm-level and investor-level results to better understand the underlying economic channels. Based on requests of firms' EDGAR filings by 5.97 million unique Internet Protocol addresses (IPs), we provide direct evidence of attention spillover across firms.

Our conceptual framework builds on Merton (1987), who theorized that investors are only aware of (or familiar with) a limited set of stocks. Hence investors fail to pay attention to news about stocks that they are unaware of or unfamiliar with and avoid investing in such stocks. We hypothesize that the arrival of joint news and its subsequent consumption by investors increases the awareness of other covered stocks (which we refer to as *connected stocks*). This creates a cross-firm attention spillover and results in attention increases across multiple stocks.

As high investor attention induces excessive retail buying and high valuation (Barber and Odean, 2008), we predict that increases in joint news coverage result in a temporary overvaluation of a stock that subsequently reverts. Finally, during periods when a large number of joint news articles are released, attention spillover generates marketwide overvaluation, followed by lower market returns in the future. This results in a negative relation between aggregate joint news coverage of firms and future market returns.

We empirically test our hypothesis by using our news database to construct a monthly cross-firm matrix of abnormal news coverage. The matrix captures changes in the number of news articles mentioning the firms, with the off-diagonal elements corresponding to the extent of joint coverage and the diagonal elements corresponding to the extent of news coverage that only mentions one firm (*self news coverage*), respectively.

Motivated by Banerjee et al. (2013, 2019), who find that the central nodes of an information network are more influential in information transmission, we expect a stronger attention spillover effect for news covering firms that belong to high-centrality nodes of the news coverage matrix. Hence, we define the degree of investor attention spillover to a given firm i, from firms connected to i through joint coverage, $JointNews^i$, as the centrality-weighted sum of abnormal joint news coverage across the connected firms. We then aggregate the firm-level measure and define a value-weighted market-level measure, $JointNews^M$, to capture the extent of marketwide investor attention spillover as driven by joint news coverage. Similarly, we aggregate the firm-level self news coverage measure to a value-weighted market-level measure, $SelfNews^M$. We compare the ability of $JointNews^M$ and $SelfNews^M$ to predict market returns to highlight how the two types of news generate distinctly different responses in investor attention and market prices.

We find that $JointNews^M$ strongly and negatively predicts the one-month-ahead market returns, with a large in-sample R^2 of 3.93%, and a substantial out-of-sample R^2 of 6.52%. The predictability is robust to a large list of alternative predictors, which include the negative news tone (Tetlock, Saar-Tsechansky, and Macskassy, 2008), investor sentiment (Baker and Wurgler, 2006; Huang et al., 2015), and 14 economic predictors (Goyal and Welch, 2008). Compared with other predictors, $JointNews^M$ has the strongest predictive power both in- and out-of-sample and is robust across business cycles. Further, the predictability lasts for at least six months, with a one standard deviation increase in $JointNews^M$ reducing the aggregate stock market returns over the next six months by 0.4% per month.

This suggests that our aggregate joint news coverage measure contains important information about aggregate future market returns that is not captured by the existing predictors. In contrast, $SelfNews^M$ does not have significant power in predicting market returns. The results are consistent with our hypothesis that joint news triggers a spillover of investor attention across firms, which could generate a more substantial impact on market prices than self news that tends to be idiosyncratic.

Next, we turn to the important question whether the significant return predictability of $JointNews^M$ translates into meaningful economic gains for investors in their asset allocation decisions. We show that, for a mean-variance investor, the information in $JointNews^M$ gives rise to annualized certainty equivalent return (CER) gains of 4.95% to 9.31% for reasonable values of coefficients of risk aversion. The annualized Sharpe ratios of portfolios formed based on $JointNews^M$ ranges from 0.80 to 1.05 at the monthly horizon, nearly tripling the market Sharpe ratio of 0.29 for a buy-and-hold strategy. The asset allocation results are also robust after accounting for a 50 basis points transaction cost.

To gain more insight into the micro-foundations of our findings, we turn to firm-level analysis and look for direct links between joint news coverage, investor attention, and stock returns. We first show that joint news coverage of a firm is associated with a significant increase in retail investor attention to the firm as measured by abnormal Google search volume (Da, Engelberg, and Gao, 2011). The result is consistent with our hypothesis that joint news coverage increases investor attention to the covered firms.

Next, we examine the more granular, individual-investor level, information acquisition activities by exploring downloads of 10-K and 10-Q filings in EDGAR by unique Internet Protocol addresses (IPs) (e.g., Lee, Ma, and Wang, 2015; Drake et al., 2020). We proxy for a firm's investor base with a set of IPs that downloaded a firm's filings in the past. We then consider how joint news coverage of a firm-pair expands the firms' investor bases by identifying the number of unique *new* IPs that accessed information about one firm that also overlaps with the existing investor base of the other covered firm.

We find that a one standard deviation increase in joint news coverage of a firm is associated with 20.3% more such new IP activities, and the effect is substantially larger than that of self news coverage. In addition, joint news makes self news more salient to investors—self news-triggered new IP downloads increase by more than 70% for firms in the top tertile of joint news coverage compared to those in the bottom tertile. Consistent with this, we further show that a one standard deviation increase in a firm's joint news coverage is associated with a significantly lower return in the following month, by 13 basis points.

In sum, the firm-level analysis provides direct evidence for our hypothesis that joint news coverage triggers a spillover of investor attention from the connected firms to the focal firm, thereby increasing the overall attention to the firms and resulting in high valuation and low future stock returns. More important, the firm level effects of joint news remain economically meaningful when aggregated and translate into strong market return predictability. In comparison, the effect of self news coverage is weaker at the firm level and remains insignificant when aggregated. The contrast therefore underscores the importance of understanding the channels through which joint news affects investors' information acquisition and aggregate stock returns.

One concern for our interpretation is that joint news coverage is endogenous, so the relation between joint news coverage and market returns may be driven by omitted variables that affect both joint news coverage and market returns. For example, joint news coverage may reflect economic linkages across firms. However, it is unclear how such linkages can drive our findings. First, economic linkages in the absence of market frictions do not generate return predictability. Second, prior studies document return predictability of related firms in the cross-section, but the predictability is positive and researchers have attributed the findings to investor underreaction to the linkages due to inattention.[4] Our finding of a strong negative relation between joint news coverage and future aggregate market returns is more consistent with joint news coverage generating *attention-driven overvaluation* (Barber and Odean, 2008), a mechanism that is distinctly different from *inattention*.

We further address the above concern by identifying exogenous variations in joint news coverage and assessing the extent to which random, nonfundamental, fluctuations in joint news coverage contributes to return predictability. We follow Peress and Schmidt (2020) and exploit episodes of sensational news (Eisensee and Strömberg, 2007) that are unrelated to the financial market as exogenous shocks to $JointNews^M$.

We first establish that, all else equal, sensational news significantly reduces $JointNews^M$, confirming that the episodes distract media attention and lower joint news coverage. We then use the sensational news as an instrument for $JointNews^M$ to predict future market returns. We find that the relation between $JointNews^M$ and market returns remain strong, with a one standard deviation increase in the predicted $JointNews^M$ significantly lowering the following months market return, by 48 basis points. Hence, the two-stage instrumental variable analysis suggests that the effect of joint news coverage on market returns is causal. That is, random, exogenous, fluctuations

[4] See, for example, Moskowitz and Grinblatt (1999), Cohen and Frazzini (2008), Menzly and Ozbas (2010), Lee et al. (2019), Rapach et al. (2019), and Ali and Hirshleifer (2020).

in *JointNews*^{M} drive a substantial portion of the variable's predictive power, above and beyond what fundamental linkages alone could explain.

So far we have established that joint news coverage broadens a firm's investor base and increases investors' attention to the stock. We have explained that the negative relation between *JointNews*^{M} and future market returns is consistent with the behavioral hypothesis that joint news results in an attention spillover, triggering excessive buying and temporary overvaluation, which subsequently reverses (Barber and Odean, 2008). However, the relation could also be consistent with a rational explanation that increased investor attention improves risk sharing and reduces a stock's required rate of return (Merton, 1987).

To assess the extent to which our findings are attributable to the rational or mispricing-based explanations, we examine how the return predictability of *JointNews*^{M} varies with the level of market uncertainty and the degree of market frictions. Under the mispricing-based explanation, the predictability should be stronger when arbitrage is more costly, that is, when market friction is great and when market uncertainty is high. On the other hand, the rational explanation would suggest that the predictability would be strong irrespective of arbitrage costs. We find that *JointNews*^{M} only significantly predicts negative market returns when arbitrage is more costly, suggesting that the behavioral mechanism is more plausible.

Our paper contributes directly to the growing literature that shows media and news play an important role in aggregate stock returns. Previous studies have focused on measures of media and news at the aggregate level. For example, Tetlock (2007) finds that media pessimism exerts downward pressure on the aggregate stock market that subsequently reverses. Garcia (2013) shows that the fraction of positive and negative words in the financial news columns from the *New York Times* predicts market returns during recessions. Froot et al. (2017) document a "reinforcement effect" between returns and media-measured sentiment. Glasserman and Mamaysky (2019) show that the "unusualness" of news with negative sentiment forecasts market stress and Calomiris and Mamaysky (2019) find that news-based word flow measures predict risk and returns in a global setting. Bybee et al. (2021) show that news attention closely tracks a wide range of economic activities and explains 25% of aggregate stock market returns. Our results are robust after accounting for the key variables in the previous studies. More important, our study connects the firm level and aggregate effects of news on stock markets and provides new insight into one of the channels through which news affecst investor behavior and prices.

Our findings also contribute to the literature on investor attention that has mostly focused on its effects on individual stock prices.[5] Two concurrent papers examine investor attention and market returns, taking attention as given. Chen et al. (2020b) find that a common component of 12 investor attention proxies has significant power in predicting market returns, while Da et al. (2021) find that retail and institutional attention have distinctively different predictive powers. Our study is new in that our granular, investor-level, evidence provide a micro-foundation for the way in which investor attention is influenced by news coverage.

The rest of the paper is organized as follows. In Section 2, we explain the conceptual framework and develop the attention spillover hypotheses. In Section 3, we describe the data. In Section 4, we present the empirical results of the return predictability analysis. In Section 5, we explore the micro-foundations and economic mechanisms. We conclude in Section 6.

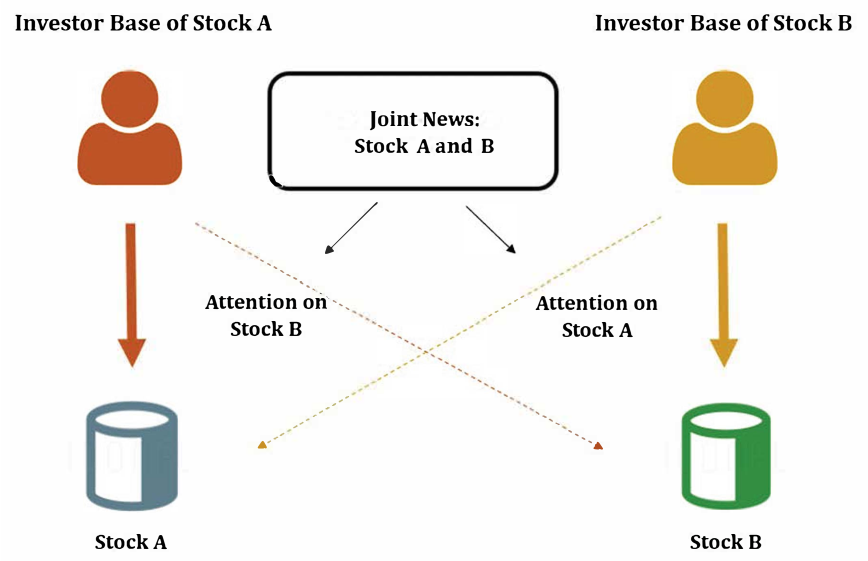
2. Hypothesis Development

In this section, we explain the conceptual framework and develop the attention spillover hypothesis in a cross-firm setting.

As discussed in the introduction, previous studies show that media and news coverage of firms triggers substantial investor reactions. But not all news attracts attention from all investors. The idea of limited investor recognition was suggested by Merton (1987), which theorized that investors

[5]For example, Da, Engelberg, and Gao (2011) show that retail investor attention positively predicts short-term stock returns and a subsequent reversal, while Ben-Rephael, Da, and Israelsen (2017) and Ben-Rephael et al. (2021) find institutional attention facilitates a permanent and efficient reaction to information. Fedyk (2021) shows that prominent news on the Bloomberg terminal attracts more trading and price responses. Bali et al. (2019) and Atilgan et al. (2020) show that attention enhances investors' attraction to lottery stocks. Chen, An, and Yu (2020) find lead-lag effects in returns for stocks displayed together. More recently, Cookson, Engelberg, and Mullins (2021) and Barber et al. (2021) show that fintech brokerages and social interactions influence investor attention and contribute to stock returns. Other papers explore the implications on return comovements (Peng and Xiong, 2006; Drake et al., 2016; Huang, Huang, and Lin, 2019).

are only aware of (or are familiar with) a limited set of stocks. Hence, investors fail to pay attention to news about stocks that they are unaware of or unfamiliar with and avoid investing in such stocks. Motivated by this, we hypothesize that the arrival of a news article that mentions multiple stocks generates a cross-firm attention spillover. That is, investors of one stock, after reading the article, start to pay attention to the other covered stocks, therefore result in higher attention across the other covered stocks.



We illustrate the intuition with a simple example. Consider two stocks, A and B, and focus on the corresponding nonoverlapping sets of their investor bases, I_A and I_B.[6] As in Merton (1987), investors in I_A are only aware of stock A and are only attentive to news about A, and investors in I_B are only aware of stock B and are only attentive to news about B. While news articles that cover only a single stock, A, will only be read by I_A investors, articles that mention both firms (*joint news*) attract attention from both I_A and I_B investors. Therefore, the arrival of joint news and I_A investors' consumption of the news make I_A investors aware of stock B and subsequently start to pay attention to B. We refer to this effect as a spillover of investor attention from stock A to stock B. As a result, both I_A and I_B investors are attentive to stock B. Similarly, investor attention spills over from B to A and stock A now receives the attention from both I_A and I_B investors.

[6]The spillover effect applies only to the nonoverlapping investor base, so we omit the overlapping set in our discussion for brevity.

The intensity of cross-firm attention spillover depends on the importance of a firm in the cross-firm network of news coverage. Building on the influential work of Banerjee et al. (2013, 2019), who find that central nodes of a network are more influential in information transmission, we assign a higher weight to a stock in the attention spillover process if the stock corresponds to a high-centrality node in the cross-firm network of news coverage. That is, the attention spillover from a connected firm to a focal firm is stronger if the connected firm belongs to a higher centrality node.

We summarize hypothesis 1 below:

Hypothesis 1. *The arrival of a news article that covers multiple stocks generates a spillover of investor attention across stocks that are mentioned in the article. The effect is stronger if the spillover originates from higher-centrality nodes of the cross-firm network of news coverage.*

We now discuss the implications of joint news coverage on returns. As shown in Barber and Odean (2008), greater attention triggers more attention-based buying, which results in a temporarily high valuation and subsequent low returns for affected stocks. Hence, we expect that joint news causes high valuation of covered stocks and lower future returns. More important, during periods when a large number of joint news articles are released, the attention spillover effect is widespread, generating systematic high valuation in market prices followed by lower future market returns. Hence we state the following hypothesis:

Hypothesis 2. *During periods when a large number of joint news articles are released, the cross-firm spillover of investor attention aggregates and generates high market prices and results in low future market returns.*

As for self news, due to its idiosyncratic nature and its lack of an attention spillover effect, we expect the self news to have a weak association with market returns.

3. Data and Variables

We measure news coverage across firms by analyzing an extensive database of over 2.6 million U.S. news articles covering firms in the S&P 500 index from January 1996 through December 2014. Using Thomson Reuters's News Analytics and Thomson Reuters news archive, we extract news date, story identifier, the firms mentioned in the news, and the full text of the news. The firm-level stock data are from CRSP, and accounting and financial statement variables are from the merged CRSP-Compustat database. Below we first describe how we construct the joint news coverage measures, followed by descriptions of other variables.

3.1. News coverage measures

We first classify news articles into two categories: 1) joint news that mentions at least two firms, and, 2) self news that only mentions one firm. We then construct a monthly cross-firm news coverage matrix $\mathbf{W}_t$ for each month t:

$$\mathbf{W}_t = \begin{array}{c} \\ stock_1 \\ stock_2 \\ \vdots \\ stock_N \end{array} \begin{array}{c} \begin{array}{cccc} stock_1 & stock_2 & \cdots & stock_N \end{array} \\ \begin{bmatrix} w_{11,t} & w_{12,t} & \cdots & w_{1N,t} \\ w_{21,t} & w_{22,t} & \cdots & w_{2N,t} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1,t} & w_{N2,t} & \cdots & w_{NN,t} \end{bmatrix} \end{array}, \tag{1}$$

where N is the total number of firms in our sample; the off-diagonal element, $w_{ij,t}$ with $i \neq j$, corresponds to the number of news articles that mention firms i and j (*joint coverage*); and the diagonal element, $w_{ii,t}$, is the number of news articles that mention only one firm (*self coverage*).

As hypothesized, more-central firms in the cross-firm network of news coverage tend to have a larger investor base and thus are more likely to generate a greater attention spillover effect onto the other firms through joint news converge. We measure firm i's centrality in the news coverage matrix using the eigenvector centrality of node i.[7] Further, to capture time-variations in news coverage, we detrend the news coverage series and define $\widetilde{w}_{ij,t}$ as the logarithm difference between $w_{ij,t}$ and its past six-month median.

Next, we aggregate the firm pair-level joint news coverage to the firm level to capture the degree of attention spillover to a firm from its connected firms as triggered by joint news. The abnormal joint news coverage for a given firm i, $JointNews^i$, is the sum of abnormal joint news coverage across firm pairs (i, j), $j = 1, \cdots, J$, weighted by the centrality of j. Finally, we aggregate the firm-level measure to the market level and define $JointNews^M$ as the market capitalization–weighted average of $JointNews_i$.

For robustness, we construct an alternative measure, $JointNews^M_{ew}$, as the equal-weighted average of joint news coverage. We similarly construct an aggregated self-news coverage measure, $SelfNews^M$, by value-weighting abnormal self-news coverage across firms and compare the measure's effects with that of $JointNews^M$.

3.2. *Other predictors of market returns*

We consider the incremental contribution of our variables relative to existing predictors of market return. We follow Goyal and Welch (2008) and include the following 14 economic predictors: log dividend price ratio (DP), log dividend yield (DY), log earnings-price ratio (EP), log dividend-payout ratio (DE), stock return variance (SVAR), book-to-market ratio (BM), net equity expansion (NTIS), Treasury bill rate (TBL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR) and inflation rate (INFL).[8]

Next, we construct a negative news tone (News Tone) measure following Tetlock, Saar-Tsechansky, and Macskassy (2008) through textual analysis. Specifically, in each month, we count the negative words in each firm's news articles according to the Loughran and McDonald (2011)

[7] The eigenvector centrality of firm j is the jth element of the principal right eigenvector of the adjacency matrix and is proportional to the sum of the centrality scores of its direct neighbors and therefore accounts for transmission of signals along longer paths and walks. As suggested by Newman (2010), eigenvector centrality describes the informativeness of the links in an information network.

[8] We downloaded the economic predictor data from the website of Amit Goyal.

financial words dictionary and calculate the firm-level negative news tone measure as the fraction of negative words in total words. Then, we define the value-weighted average of the firm-level negative news tones as the market-level new tone measure. We also include the investor sentiment measures proposed by Baker and Wurgler (2006, 2007) (Sent^{BW}) and Huang et al. (2015) (Sent^{PLS}) and the composite investor attention measure by Chen et al. (2020b) (Attn^{PLS}).[9] All the definitions of the variables used in the paper are summarized in Table A1.

3.3. *Summary statistics*

Table 1 reports the summary statistics (Panel A) and the correlation coefficients (Panel B) of the variables used in the paper. Notably, *JointNews*^{M} has an AR(1) coefficient of 0.38 and is much less persistent than most of the other predictors. The monthly excess market return has a mean of 0.41%, a standard deviation of 4.49%, and an AR(1) coefficient of 0.08. These summary statistics are consistent with the literature. Panel B shows that the correlation coefficients between *JointNews*^{M} and other predictors are not high, suggesting that *JointNews*^{M} differs from the other predictors and may contain information for predicting market returns that is incremental to the predictors established in prior literature.

[Insert Table 1 here.]

Given that our joint news measure is related to news, investor attention, and sentiment, we compare the standardized time series of these measures in Figure 1. The figure shows that *JointNews*^{M} (blue solid line) is distinctly different from the composite investor attention Attention^{PLS} of Chen et al. (2020b), the News Tone of Tetlock, Saar-Tsechansky, and Macskassy (2008), and the market sentiment measures, Sent^{BW} and Sent^{PLS}, of Baker and Wurgler (2006) and and Huang et al. (2015). There are also considerable temporal variations in *JointNews*^{M} compared with these other return predictors.

[9] We downloaded the Baker-Wurgler's investor sentiment index from the website of Jeffery Wurgler, the PLS sentiment index from the website of Dashan Huang, and the PLS investor attention index from the website of Guofu Zhou.

[Insert Figure 1 here.]

4. Joint News and Market Return Predictability

In this section, we examine the ability of $JointNews^M$ to predict market returns. We first examine the baseline in-sample forecasting performance and the impact of market uncertainty and frictions on the forecasting performance of $JointNews^M$. Then, we compare the forecasting performance of $JointNews^M$ with alternative predictors established in previous studies. Next, we analyze the out-of-sample forecasting performance and assess the economic value from an asset allocation perspective. We then provide an identification test using instrumental variables. Finally, we conduct some additional robustness checks.

4.1. Market return predictability

To investigate the time-series predictability of market returns, we consider the standard univariate predictive regression model,

$$R_{m,t+1} = \alpha + \beta X_t + \varepsilon_{t+1}, \tag{2}$$

where $R_{m,t+1}$ is the market excess return, that is, the monthly return on the S&P500 index in excess of the risk-free rate,[10] and X_t is one of the return predictors listed in subsection 3.2, specifically, $JointNews^M$, news tone, and investor sentiment proxies, as well as economic predictors (Goyal and Welch, 2008).

[Insert Table 2 here.]

Table 2 reports the in-sample forecasting performance. For comparison, all predictors are standardized to have zero mean and unit variance. Both value- and equal-weighted joint news

[10] In Appendix B, we replicate our key findings replacing the S&P500 index returns with CRSP value-weighted index returns and find the results to be similar.

indices, $JointNews^M$ and $JointNews^M_{ew}$, show strong in-sample return predictability, with the coefficient significant at the 1% level. We illustrate the economic magnitude of the findings using the coefficient estimate of $JointNews^M$. The coefficient of -0.89 suggests that a one standard deviation increase in aggregate joint news coverage predicts a substantially lower market return for the next month, by 89 basis points. The R^2 is 3.93% and is substantially greater than the other predictors, including $SelfNews^M$ and Attn^{PLS}, and the two investor sentiment indices. In contrast, $SelfNews^M$ has no significant forecasting power, suggesting that aggregate self news coverage is not significantly associated with market returns.

We next investigate whether the predictability of joint news coverage varies across business cycles. Following Rapach, Strauss, and Zhou (2010), we compute the R^2 statistics separately for economic expansions (R^2_{up}) and recessions (R^2_{down}),

$$R^2_c = 1 - \frac{\sum_{t=1}^{T} 1_{\{t \in \mathbb{T}_c\}} \cdot \varepsilon_t^2}{\sum_{t=1}^{T} 1_{\{t \in \mathbb{T}_c\}} \cdot (R_{m,t} - \bar{R}^m)^2}, \quad c \in \{up, down\}, \tag{3}$$

where $1_{\{t \in \mathbb{T}_{up}\}}$ ($1_{\{t \in \mathbb{T}_{up}\}}$) is an indicator that takes a value of one when month t is based on an expansion (recession) period set by the National Bureau of Economic Research (NBER), that is, $\mathbb{T}_{up}$ ($\mathbb{T}_{down}$), and zero otherwise; ε_t is the fitted residual, based on the in-sample estimates of the predictive regression model in (2); $\bar{R}^m$ is the full-sample mean of $R_{m,t}$; and T is the number of observations for the full sample. The last two columns of Table 2 show that $JointNews^M$ has an R^2_{up} of 2.25% and an R^2_{down} of 3.31%. These results therefore suggest that, consistent with our hypothesis, the aggregate joint news coverage measure strongly predicts lower future market returns, and this predictability is robust across business cycles.

Uncertainty and market frictions Our finding of a negative relation between $JointNews^M$ and future market returns is consistent with our behavioral hypothesis that joint news results in an attention spillover, triggering excessive buying and a temporary overvaluation and subsequent reversals (Barber and Odean, 2008). However, as explained in the introduction, the relation could also be consistent with a rational alternative explanation that the attention spillover broadens the investor base of a firm and therefore improves risk sharing and reduces the firm's required rate of returns (Merton, 1987).

To gain further insight into which mechanism better explains the predictability of $JointNews^M$, we identify settings under which one mechanism may be more relevant than the other. If the predictability of $JointNews^M$ is driven by mispricing, we expect the predictability would be stronger during times when market friction is great and market uncertainty is high and therefore arbitrage is more costly. On the other hand, the rational explanation would suggest that the predictability would be strong during both high and low uncertainty and friction periods.

To measure market uncertainty, we consider the CBOE volatility index (VIX), the economic uncertainty index (UNC) of Bali, Brown, and Caglayan (2014), the treasury implied volatility (TIV) of Choi, Mueller, and Vedolin (2017), the macro uncertainty index (MU) and the financial uncertainty index (FU) of Jurado, Ludvigson, and Ng (2015), the economic policy uncertainty index (EPU) of Baker, Bloom, and Davis (2016), and the investor disagreement index (DSA) by Huang, Li, and Wang (2021). For market frictions, we collect the equal-weighted short interest ratio (EWSI) of Rapach, Ringgenberg, and Zhou (2016) and compute the value-weighted average of bid-ask spreads (BAS) and price delay measure of Hou and Moskowitz (2005) across S&P500 stocks.[11]

Because all of the proxies will have a common uncertainty or market friction component, following Baker and Wurgler (2006, 2007), we use PCA and simple averaging to iron out the idiosyncratics and extract a common component that is closer to the underlying factor. We estimate the following predictive regression, conditioning on the first principal component or equal-weighted average of market uncertainty or friction measures:

$$R_{m,t+1} = \alpha + \beta JointNews_t^M + \gamma JointNews_t^M \times Z_t + \phi Z_t + \varepsilon_{t+1}, \tag{4}$$

[11]The data we use are obtained from following sources: the VIX is downloaded from the CBOE website; the UNC is downloaded from the website of Turan Bali; the TIV is downloaded from the website of Andrea Vedolin; the MU and FU are downloaded from the website of Sydney Ludvigson; the EPU is downloaded from the website policyuncertainty.com; the DSA is downloaded from the website of Dashan Huang; the EWSI is downloaded from the website of Guofu Zhou.

where Z_t is an indicator that equals one if the market uncertainty or friction measure is in the top 25% quantile and equals zero if the corresponding measure is in the bottom 25% quantile. The variable of interest is γ, which captures the difference between the predictive power in high and low market uncertainty or friction episodes.

[Insert Table 3 here.]

The results are reported in Table 3. The coefficients reported in the "Diff" columns are all negative and significant across all specifications. For example, in high PCA-Uncertainty periods, a one standard deviation increase in $JointNews^M$ is associated with a 1.21% decrease in the subsequent returns, which is 1.38% higher than that in low PCA-Uncertainty periods. Similarly, a one standard deviation increase in $JointNews^M$ predicts a 1.48% decrease in the subsequent returns in high PCA-Friction periods, which is 1.18% higher than that in low PCA-Friction periods. Those results suggest that the negative market return predictability of $JointNews^M$ is more likely to be driven by behavioral mechanisms.

4.2. Comparison with alternative predictors

In this subsection, we examine whether the forecasting power of the $JointNews^M$ is driven by omitted variables related to business cycle fundamentals or changes in news tones or investor sentiment. Specifically, we run the following bivariate predictive regression:

$$R_{m,t+1} = \alpha + \beta X_t + \phi Z_t + \varepsilon_{t+1}, \tag{5}$$

where X_t is $JointNews^M$ or $JointNews^M_{ew}$, and Z_t is one of the alternative predictors listed in subsection 3.2. Our main focus is on the coefficient β.

[Insert Table 4 here.]

Table 4 shows that the coefficients of $JointNews^M$ are negative and remain statistically significant after controlling for the alternative market return predictors, with magnitudes that are similar to the coefficients reported in Table 2. For example, the coefficients of $JointNews^M$ are -0.81 and -0.93, both significant at the 5% confidence level, after controlling for two powerful predictors documented in the literature, namely, aligned investor sentiment and dividend yield, respectively. The results for $JointNews^M_{ew}$ are similar. Together, these results suggest that $JointNews^M$ contains important information in predicting future market returns that cannot be explained by the economic fundamentals and investor sentiment measures established in previous studies.

4.3. Out-of-sample forecasts

The in-sample analysis utilizes all the available data, thereby allowing for more-efficient parameter estimates and more-precise return forecasts. However, Goyal and Welch (2008), among others, argue that the out-of-sample tests are more relevant for assessing the genuine return predictability in real time and avoiding the overfitting issues. In addition, the out-of-sample analyses are much less affected by the finite sample bias, such as the Stambaugh bias (Busetti and Marcucci, 2013). Therefore, it is essential to show the out-of-sample predictive performance of $JointNews^M$.

For out-of-sample forecasts at time t, we only use the information available up to t to forecast stock returns at $t+1$. Following Goyal and Welch (2008), Kelly and Pruitt (2013), and many others, we conduct the out-of-sample analysis by estimating the predictive regression (6), recursively, that is,

$$\hat{R}^m_{t+1} = \hat{\alpha}_t + \hat{\beta}_t X_{1:t;t}, \tag{6}$$

where $X_{1:t;t}$ is the recursively calculated $JointNews^M$, and $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates from regressing $\{R^m_{r+1}\}_{r=1}^{t-1}$ with model (2) recursively. For comparison, we also carry out the out-of-sample regressions for the alternative predictors used in the prior literature.

More specifically, to assess the out-of-sample performance, we apply the Campbell and

Thompson (2008) R^2_{OS} statistic, which measures the proportional reduction in the mean squared forecast error (MSFE) for the predictive regression forecast, relative to the historical average benchmark. Goyal and Welch (2008) show that the historical average is a very stringent out-of-sample benchmark, and typically, individual economic variables fail to outperform the historical average. To compute R^2_{OS}, let r be a fixed number chosen for the initial sample training; this will ensure that the future expected returns can be estimated at time $t = r+1, r+2, ..., T$. Subsequently, we compute the following $s = T - r$ out-of-sample forecasts: $\{\hat{R}^m_{t+1}\}^{T-1}_{t=r}$. Specifically, we use the first five years' data from January 1996 through December 2002 as the initial estimation period, and the forecast evaluation period spans from January 2003 through December 2014.

$$\hat{R}^2_{OS} = 1 - \frac{\sum_{t=r}^{T-1}(R_{m,t+1} - \hat{R}^m_{t+1})^2}{\sum_{t=r}^{T-1}(R_{m,t+1} - \bar{R}^m_{t+1})^2}, \tag{7}$$

where $\bar{R}^m_{t+1}$ denotes the historical average benchmark corresponding to the constant expected return model ($R_{m,t+1} = \alpha + \varepsilon_{t+1}$), that is,

$$R_{m,t+1} = \frac{1}{t}\sum_{s=1}^{t} R^m_s. \tag{8}$$

By construction, the R^2_{OS} statistic lies in the range $(-\infty, 1]$. If $R^2_{OS} > 0$, then it would mean that the forecast $\hat{R}^m_{t+1}$ outperforms the historical average $R_{m,t+1}$ in terms of MSFE.

To evaluate the statistical significance of the R^2_{OS}, we adopt the MSFE-adjusted statistic of Clark and West (2007) (CW-test) and the Diebold and Mariano (1995) statistic modified by McCracken (2007) (DM-test). The CW test tests the null hypothesis that the historical average MSFE is greater than the predictive regression forecast MSFE against the one-sided (right-tail) alternative hypothesis that the historical average MSFE is not greater than the predictive regression forecast MSFE, corresponding to $H_0 : R^2_{OS} \leq 0$ against $H_1 : R^2_{OS} > 0$. Clark and West (2007) show that the test has a standard normal limiting distribution when comparing forecasts from the nested models. The DM test examines the null hypothesis that the MSFE of one forecast is equal to the other forecast. McCracken (2007) shows that the modified DM test statistic follows a nonstandard normal distribution when testing nested models and provides bootstrapped critical values for the nonstandard distribution. We expect the benchmark model's MSFE to be smaller than the predictive regression model's MSFE under the null hypothesis. The MSFE-adjusted statistic accounts for the negative expected difference between the historical average MSFE and the predictive regression MSFE under the null hypothesis to ensure that it can reject the null hypothesis even if the R^2_{OS} statistic is negative.

[Insert Table 5 here.]

The corresponding results are summarized in Table 5, which shows two sets of interesting results. First, in Panel A, it shows that both JointNews measures generate positive and significant R^2_{OS}s and deliver lower MSFEs than that of the historical average. Specifically, $JointNews^M$ delivers an R^2_{OS} of 6.52% and $JointNews^M_{ew}$ delivers an R^2_{OS} of 3.69%. The strong out-of-sample predictability of $JointNews^M$ for market returns is consistent with our in-sample results in Table 2. Compared to $JointNews^M$, all the other predictors show much weaker out-of-sample predictability for excess market returns, as shown in Panels B and C. In general, most of the alternative predictors have negative R^2_{OS}s and their CW- and DM-test statistics are statistically insignificant.

Second, the last two columns of Table 5 show that the predictability of the $JointNews^M$ is significantly strong and stable over both expansion and recession periods, which is consistent with our previous findings in in-sample regressions.

In summary, both in-sample and out-of-sample results confirm that $JointNews^M$ is a powerful and reliable predictor of the excess market returns, and it consistently outperforms the other traditional market return predictors.

4.4. Predictability over longer horizons

So far, we have established that aggregate joint news coverage predicts market returns over the horizon of one month. In this subsection, we turn our focus to longer horizons to investigate the extent to which the associated mispricing can be persistent.[12]

We perform both in- and out-of-sample analysis as in previous sections based on the following predictive regression:

$$R_{m,t+h} = \alpha + \beta JointNews_t^M + \varepsilon_{t+h}, \quad (9)$$

where $R_{m,t+h}$ is the average market excess return for the next h months and h takes a value of 3 or 6.

[Insert Table 6 here.]

Panel A of Table 6 reports the in- and out-of-sample univariate regression results. It shows that $JointNews^M$ can significantly predict the long-run excess market returns up to six months. Along with the results in Tables 4 and 5 for the one-month horizon, it is clear that the forecasting power first increases as the horizon increases, reaches its peak around the three-month horizon, and then declines, both in- and out-of-sample.

Panel B of Table 6 presents the bivariate predictive regression results that include $JointNews^M$ and one of the alternative return predictors. It shows that the predictive power of $JointNews^M$ for three-month horizon excess market return is significant and greater than most of the controlling return predictors, including $Attn^{PLS}$. For the six-month horizon, $JointNews^M$ is weaker but still significant at 5% or 10%. Economically, a one standard deviation increase in $JointNews^M$ reduces the aggregate stock market returns over the next six months by 0.4% per month. The magnitude is comparable to Chen et al. (2020b), who find that a one standard deviation increase in $Attn^{PLS}$ predicts a 0.5% per month reduction in the corresponding market returns.

In summary, $JointNews^M$ significantly predicts future aggregate stock returns, not only at monthly frequency but also at quarterly and semi-annual horizons, both in and out of sample. The result suggests that the clustered arrival of joint news can generate persistent mispricing that

[12]Because of the limits of arbitrage, mispricings from investor attention may not be eliminated by arbitrageurs over a short monthly horizon. There is some in-sample evidence on the predictability of investor attention for a longer horizon beyond one month in the literature. For example, using the Dow 52-week high as an investor attention proxy, Li and Yu (2012) show that the predictive power of investor attention can exist for a multi-month horizon.

is not immediately arbitraged away.

4.5. *Asset allocation analysis*

Given the strong predictive power of *JointNews*^{M}, we next calibrate the economic value investors can obtain if they utilize this information in their asset allocation decisions. We compute the certainty equivalent return (CER) gain and the Sharpe ratio by considering a mean-variance investor who makes asset allocation decisions across equities and risk-free bills using the out-of-sample predictive regression forecasts (see, e.g., Kandel and Stambaugh, 1996; Campbell and Thompson, 2008; Ferreira and Santa-Clara, 2011).

At the end of each month t, the investor optimally allocates

$$w_t = \frac{1}{\gamma}\frac{\widehat{R}_{t+1}}{\widehat{\sigma}^2_{t+1}} \tag{10}$$

of the portfolio to stocks during next month, where γ is the degree of risk aversion, $\widehat{R}_{t+1}$ is the out-of-sample forecast of the excess market return, and $\widehat{\sigma}^2_{t+1}$ is the forecast of its variance. The investor then allocates $1-w_t$ of the portfolio to risk-free bills, and the $t+1$ realized portfolio return is

$$R^p_{t+1} = w_t R_{t+1} + R^f_{t+1}, \tag{11}$$

where R^f_{t+1} is the risk-free return. Following Campbell and Thompson (2008), we estimate $\widehat{\sigma}_{t+1}$ using a five-year rolling window of past returns and restrict w_t to lie between 0 and 1.5 to exclude short sales and to allow for, at most, 50% leverage.

The certainty equivalent return (CER) of the portfolio is

$$CER_p = \widehat{\mu}_p - 0.5\widehat{\sigma}^2_p. \tag{12}$$

The CER gain is the difference between the CER for the investor who uses a predictive regression forecast of market return generated by Equation (6) and the CER for an investor who uses the historical average forecast. We multiply this difference by 12 so that it can be interpreted as the annual portfolio management fee that an investor would be willing to pay to have access to the predictive regression forecast instead of the historical average forecast. To examine the effect of risk aversion, we consider portfolios based on risk aversion coefficients of 1, 3, and 5. In addition, we also consider the case of 50 basis points transaction costs, which is generally considered as a relatively high number.

To analyze the economic value of return predictability at longer horizons, we follow Rapach, Ringgenberg, and Zhou (2016) and let the investor rebalance the portfolio at the same frequency as the forecast horizon. For example, when $h = 3$, the investor uses a quarterly predictive regression or historical average forecast of the excess return over the next three months ($h = 3$) at the end of each quarter and applies Equation (10) to determine the stock weight for the next quarter. The investor follows analogous procedures for semi-annual ($h = 6$) return forecasts and rebalancing.

To assess the statistical significance of the CER gain, we apply the testing procedure in DeMiguel, Garlappi, and Uppal (2009) to examine whether the CER gain is indistinguishable form zero. In addition, we also calculate the monthly Sharpe ratio of the portfolio, which is the mean portfolio return in excess of the risk-free rate divided by the standard deviation of the excess portfolio return. We then test whether the Sharpe ratio of the portfolio strategy based on predictive regression is statistically indifferent from that of the portfolio strategy based on historical average.

[Insert Table 7 here.]

Table 7 shows that the annualized CER gains for $JointNews^M$ across the risk aversions at the monthly horizon are consistently positive and economically large, ranging from 4.95% to 9.31%. More specifically, an investor with a risk aversion of 1, 3, or 5 would be willing to pay an annual portfolio management fee up to 9.31%, 7.71%, and 4.95%, respectively, to have access to the predictive regression forecast based on $JointNews^M$ instead of using the historical average forecast. The net-of-transactions-costs CER gains of the $JointNews^M$ portfolios range from 2.68% to 7.09%

at the monthly horizon, and they are all economically significant. This large economic value also exists at the quarterly and semi-annual horizons.

In addition, the investment portfolio based on aggregate investor attention generates sizable Sharpe ratios. The annualized Sharpe ratios of portfolios formed based on *JointNews*^{M} at monthly horizon range from 0.80 to 1.05, which is nearly triple the market Sharpe ratio of 0.29 for a buy-and-hold strategy. The difference remains significant after deducting the 50 basis points transaction cost. In the long run, the net-of-transactions-costs Sharpe ratios range from 0.87 to 1.05 (0.53 to 0.96) at the quarterly (semi-annual) horizon. In addition, all the CER gains and Shape ratio gains of *JointNews*^{M} in all of the risk-aversion cases are statistically significant.

In summary, there are potentially large investment profits in the asset allocation based on investor attention spillover, suggesting substantial economic values for mean-variance investors. This analysis then emphasizes the important role of investor attention spillover on the aggregate stock market from an asset allocation perspective.

4.6. Omitted variables and instrumental variable analysis

Our result that *JointNews*^{M} negatively predicts future market returns is consistent with the hypothesis that joint news coverage predicts returns via an attention-spillover effect. One concern for this interpretation is that joint news coverage is endogenous, and therefore the relationship between joint news and future returns may be driven by omitted variables that influences joint news coverage.

One example of such omitted variables is economic linkages across firms, which may trigger joint news coverage.[13] However, it is unclear how such linkages can drive the negative relation between joint news coverage and future market returns that we find. First, economic linkages

[13]Although an important function of the news and media sector is to convey the state of the economy and firm fundamentals to investors, other factors such as consumer preferences, human biases, erroneous inference, and unsubstantiated speculation can also influence news coverage. Mullainathan and Shleifer (2005) theorize that media coverage can be influenced by supplier-side preferences and the news providers profit-maximizing choice to cater to the preferences of the consumers. Gentzkow and Shapiro (2006) further show that a model in which firms slant their reports toward the prior beliefs of their customers to build the firm's reputation for quality results in equilibruim biases that make all market participants worse off.

in the absence of market frictions do not generate return predictability. Second, prior studies document return predictability of related firms in the cross-section, but the predictability is positive and researchers have attributed the findings to investor inattention-driven underreaction.[14] Hence it would be difficult for fundamental linkages alone (or investors' inattention to it) to explain the strong negative relation between joint news coverage and future aggregate market returns that we find. Instead, our finding seems to be more in line with the explanation that joint news coverage generates *attention-driven overvaluation* (Barber and Odean, 2008), a mechanism that is distinctly different from *inattention*.

To further address the above concern, we identify exogenous variations in joint news coverage and assess the extent to which the random, nonfundamental, fluctuations in joint news coverage contribute to the market return predictability. To this end, we consider episodes of sensational news that are unrelated to the financial market and use these episodes to generate exogenous shocks to joint news coverage. We then apply instrumental variable analysis to test the relation between joint news and future market returns.

Specifically, we compile a monthly news "distraction" series from the average of the daily news pressure index of Eisensee and Strömberg (2007), which is based on the median number of minutes that U.S. news broadcasts devote to the first three news segments. To obtain variations in the news pressure that are unrelated to the stock market, we exclude days with macro announcements (FOMC meetings, nonfarm payroll, and CPI) and exclude extreme market return days (the top and bottom 20% in annual distribution) as in Peress and Schmidt (2020). We then define a "distraction" indicator (I_{Dist}) as one for observations that belongs to the top 20% for that year. We obtain 19 distraction months for the sample period from January 1996 to December 2014.

[Insert Table 8 here.]

Table 8, Panel A shows the average level of $JointNews^M$ during the distraction months and

[14] See, for example, Moskowitz and Grinblatt (1999), Cohen and Frazzini (2008), Menzly and Ozbas (2010), Lee et al. (2019), and Rapach et al. (2019), and Ali and Hirshleifer (2020).

nondistraction months. For the distraction months, $JointNews^M$ has an average of -0.441, and it is significantly lower than the nondistraction months (0.041). The result shows that sensational news episodes substantially reduce joint coverage of firms, confirming our premises that the episodes distract media attention and lowers joint news coverage.

We then use sensational news as an instrument for $JointNews^M$. Table 8, Panel B presents the two-stage least squares results. In the first stage, we regress $JointNews^M$ on $\mathrm{I}_{\mathrm{Dist}}$ and find that the coefficient on $\mathrm{I}_{\mathrm{Dist}}$ is significantly negative. The inclusion of $\mathrm{I}_{\mathrm{Dist}}$ contributes to an F-statistic of 7.87, suggesting that $\mathrm{I}_{\mathrm{Dist}}$ is not a weak instrument.

In the second stage, we regress market returns on the instrumented $JointNews^M$. The result shows that the instrumented $JointNews^M$ negatively predicts future market returns with a significant coefficient of -3.60. Economically, a one standard deviation increase in the predicted $JointNews^M$ (13.7%) lowers the following month's market return by 48 basis points, a magnitude that is economically meaningful and is 54% of that of $JointNews^M$ in Table 2.

Our results suggest that random exogenous fluctuations in joint news coverage drives a substantial portion of the predictive power of $JointNews^M$. We therefore conclude that the effect of joint news coverage on market returns is causal and the effect is incremental to what fundamental linkages alone could explain.

4.7. Additional robustness checks

In this subsection, we conduct additional robustness checks and consider the two latest sets of news-based measures that have been proposed to predict or explain market returns in the literature.

Calomiris and Mamaysky (2019) develop a methodology to classify the context and content of news articles into five topics (i.e., markets, governments, commodities, corporate governance and structure, and the extension of credit). The paper then proposes the following word flow measures: entropy, number of articles per month (ArtCount), and the sentiment and frequency for each topic (s[Topic] and f[Topic], respectively). [15] Bybee et al. (2021) analyze the full text of

[15] We obtain the word flow measures from the website of Harry Mamaysky.

Wall Street Journal articles and estimate a topic model to summarize news into 180 topic themes. The paper then quantifies news attention allocated to each theme and identifies the following five news attention estimates as the most important: recession, problems, record high, option/VIX, convertible/preferred.[16]

We first examine the extent to which $JointNews^M$ is correlated with these alternative predictors. The correlation coefficient matrix, presented in Table A2, shows that the correlation is small and ranges between -0.34 and 0.17. This suggests that $JointNews^M$, constructed from aggregating firm-level news coverage, captures information that is distinctly different from the information embedded in the other measures.

We then estimate Equation (5) and formally analyze the robustness of the predictability of $JointNews^M$ with Z being the two sets of alternative measures. The results are presented in Table 9, with Panels A and B controlling for the lagged Calomiris and Mamaysky (2019) word flow predictors and the contemporaneous Bybee et al. (2021) topic attention measures, respectively.[17]

[Insert Table 9 here.]

The result shows that, consistent with Calomiris and Mamaysky (2019) and Bybee et al. (2021), the word flow measures and the topic attention measures have significant power in forecasting and explaining the market returns. More importantly, $JointNews^M$ remains highly significant. For example, in Panel A, $JointNews^M$ has a coefficient of -0.962 (t-statistic 3.52), which is as large as the coefficient in Table 2. The in-sample adjusted R^2 increases by 3.57% after including $JointNews^M$, which is also comparable to the in-sample R^2 in Table 2. Similarly, in Panel B, $JointNews^M$ has a significantly negative coefficient of -0.588 (t-statistic 2.32) and is associated with a meaningful incremental R^2 of 1.42% even after controlling for the powerful topic-specific attention measures. These findings indicate that $JointNews^M$, constructed by aggregating firm level

[16]The topic attention measures are downloaded from the website http://www.structureofnews.com.

[17]We follow Bybee et al. (2021), who use contemporaneous topic attention measures to explain economic conditions and asset prices. Hence the coefficient on $JointNews^M$ captures predictability above and beyond the market return fluctuations that can be explained by the contemporaneous topic attention measures.

joint news coverage, contains relevant information about future market returns that is distinctively different from the latest news-based measures.

5. Cross-Sectional Evidence

The above results provide evidence for the strong and robust market return predictability of $JointNews^M$ over time. In this section, we provide direct evidence supporting that joint news coverage of firms triggers cross-firm investor attention spillover and impacts future stock returns. Specifically, we examine the relation between joint news coverage on Google search activities, the EDGAR search activities by unique IP addresses, as well as cross-sectional returns at the firm level. The summary statistics for the firm-level variables are reported in Table A3.

5.1. Joint news and retail investor attention

Following Da, Engelberg, and Gao (2011), we measure a stock's abnormal retail attention as the abnormal search volume (ASV) of the stock, which is the percentage change between Google's daily Search Volume Index (SVI) for a stock and its past one-year mean, skipping the most recent month.[18]

We analyze the relationship between ASV and the joint news and self news measures using the following Fama-MacBeth regression:

$$\begin{aligned} \mathrm{ASV}_{it} = {} & \alpha_t + \beta_t JointNews_{it} + \gamma_t SelfNews_{it} + \phi_t \mathrm{I}_{JointNews} \times SelfNews_{it} \\ & + \theta_t X_{it} + \varepsilon_{it}, \end{aligned} \tag{13}$$

where $\mathrm{I}_{JointNews}$ is the joint news indicator that equals one if the *JointNews* of a firm is above the cross-sectional top tertile, and zero otherwise, and X is a set of control variables that may affect

[18] The SVI is a relative search popularity score, defined on a scale of 0 to 100, based on the number of searches for a term relative to the total number of searches for a specific geographic area and a given period. We focus on searches made on weekdays in the U.S. market. We manually screen all tickers to select those that do not have a generic meaning (e.g., "GPS" for GAP Inc., "M" for Macy's) to ensure that the search results we obtain are truly for the stock and not for other generic items or firm products.

retail investor attention. Following Da, Engelberg, and Gao (2011), we control for log firm size, abnormal turnover, absolute characteristic-adjusted returns (Daniel et al., 1997), log number of analyst coverage, and advertisement expenses/sales ratio.

[Insert Table 10 here.]

The results, reported in Table 10, columns 1 and 2, show that an increase in the joint news coverage of a firm is associated with a highly significant increase in abnormal Google search activities for the firm. A coefficient of 0.959 for *JointNews* in column 2 means that a one standard deviation increase in joint news is associated with a 0.96% increase in abnormal search volumes.[19] In addition, the coefficient on the interaction term, $I_{JointNews} \times SelfNews$, is positive and significant, suggesting that the joint news coverage substantially strengthens the attentional effects of self news. Specifically, the impact of *SelfNews* on abnormal search volume is nearly doubled (from 0.81% to 1.56%) for firms in the top tertile of joint news coverage compared to those in the bottom tertiles.

The results are consistent with our hypothesis that joint news triggers a spillover of investor attention from connected firms to the focal firm. The result further suggests that joint news is more powerful in attracting investor attention than self news—joint news both strongly attracts investor attention directly and substantially increases investor attention to self news.

5.2. *Joint news and EDGAR downloads by unique IP addresses*

In this subsection, we use granular, individual-investor level data to provide direct evidence that joint news coverage is associated with a spillover of investor attention across firms. To this end, we explore downloads of 10-K and 10-Q filings in the EDGAR website by unique IPs. Motivated by studies that show EDGAR downloads are associated with information acquisition activities by investors (see, for example, Lee, Ma, and Wang, 2015; Chen et al., 2020a), we utilize the data to

[19]The coefficients of the control variables are consistent with those in Da, Engelberg, and Gao (2011).

analyze the effect of joint news on investor attention.[20]

Since 1996, the Securities and Exchange Commission (SEC) has required that all public domestic companies to submit their filings electronically via the EDGAR website. From the website, we obtain a sample that consists of over 230 million document requests by 5.97 million unique IPs for the period of 2003 through 2014.[21] We obtain the IP address of the EDGAR user, the filing firm, and the time-stamp for each request.

For each month, we proxy for a firm's investor base with the set of IPs that downloaded a firm's EDAGR filings in the past 18 months.[22] We then consider how joint news coverage of a firm-pair expands the firms' investor bases by identifying the number of unique *new* IPs that accessed information about one firm that also overlaps with the existing investor base of the other firm. The increases of such new IP activities thus proxies for the extent to which joint news triggers a spillover of investor attention across the covered firms.

We analyze the cross-sectional relation between joint news coverage and IP activities using the following Fama and MacBeth (1973) regression:

$$\begin{aligned}\log(\text{New IP}_{it}) = \alpha_t + \beta_t JointNews_{it} + \gamma_t SelfNews_{it} + \phi_t \mathrm{I}_{JointNews} \times SelfNews_{it} \\ + \theta_t X_{it} + \varepsilon_{it}, \qquad (14)\end{aligned}$$

where $\mathrm{I}_{JointNews}$ is the joint news indicator that equals one if the *JointNews* of a firm is above the cross-sectional top tertile, and zero otherwise. X is a set of control variables that may affect retail investor attention (Da, Engelberg, and Gao, 2011) as in previous analysis. All independent

[20]The set of investors as captured by EDGAR IP activities is likely an important component of a firm's potential investors, although we acknowledge that the EDGAR-based set is only a subset of a firm's investor base. Hence, the results that we document likely capture a lower bound of the effect of joint news on investor attention.

[21]Users are partially anonymized as the EDGAR log files show the first three octets of the IP address and replace the fourth with a unique string. Following previous studies (e.g., Lee, Ma, and Wang, 2015; Drake et al., 2020; Ryans, 2017; Li and Sun, 2021), we remove the records of users that download more than 50 unique firms' filings per day from the sample and keep only the successful request records (code = 200) and exclude records that refer to an index (idx = 1) since the index pages provide links to the firm's filings instead of the filings themselves.

[22]The choice of 18-month window to define the existing investor base follows from the literature convention of allowing sufficient window after the end of the fiscal year (up to 18 months) for the information in annual reports to become publicly available (e.g., Fama and French, 1993; Hou, Xue, and Zhang, 2015).

variables are standardized to have a zero mean and unit variance for easy comparison of economic magnitudes.

Columns 3 and 4 of Table 10 present the regression results and show that *JointNews* substantially outperforms *SelfNews* in attracting downloading activities by new investors. Economically, a coefficient of 0.049 of *JointNews* in column 4 means that a one standard deviation increase in *JointNews* attract 4.9% more new IPs that download a firm's EDGAR filings, all else equal. In contrast, *SelfNews* has a much weaker impact on attracting new investors to the focal firm, as evidenced by a smaller coefficient of 0.015. Consistent with the result for ASV in columns 1 and 2, joint news coverage strengthens the attentional effects of self news. Column 4 shows that the coefficient on the interaction term, $SelfNews \times I_{JointNews}$, is highly significant, at 0.039. This suggests that joint news coverage not only directly attracts new IPs, but it also substantially boosts investor attention to self news.

To further understand the source of new IPs, we classify news IPs attracted to a focal firm into the following two categories: those that overlaps with the investor bases of connected stocks via joint coverage, New IP_c, and those that do not, New IP_o. New IP_c therefore directly captures the spillover of investor attention from connected stocks to the focal stock due to joint news coverage.[23]

Table 10, column 5 presents the result for New IP_c. The coefficient on *JointNews* is 0.203 and highly significant. Economically, a one standard deviation increase in *JointNews* results in a substantial 20.3% increase in the EDGAR requests by new IPs from the investor bases of connected firms. *JointNews* also significantly boosts the new IP responses to self news coverage, as shown in the coefficient of 0.066 for the interaction term of $I_{JointNews}$ and *SelfNews*. The evidence provides direct support to our hypothesis that joint news coverage triggers an attention spillover to a focal firm from the other covered firms.

In addition, we present results in columns 6 that focus on New IP_o, the component of new IPs from investor bases of firms not covered by joint news. The result shows that *JointNews* is

[23]The average log(New IP) and log(Exist IP) per month is 5.587 and 5.456, which correspond to unlogged values of 267 and 234 per month, respectively. The numbers are comparable to Drake et al. (2016), who report that the average daily number of EDGAR requests per firm is 20.

still marginally significant even for this set of new IPs, and that joint news significantly boosts the effect of self news in attracting new IPs, as shown by the statistically significant coefficient of $I_{JointNews} \times SelfNews$. In contrast, *SelfNews* is insignificant. Finally, we turn to the number of EDGAR requests from the existing investors of a firm, Exist IP. Column 7 shows that *JointNews* consistently outperforms *SelfNews* in attracting EDGAR downloading activities and significantly strengthens the effects of self news. The results therefore suggest that the potential effects of joint news coverage in increasing investor attention is even broader, which includes but is not restricted to the attention spillover channel shown in column 5.

Taken together, the above findings provide strong supporting evidence for our hypothesis that joint news coverage is associated with a substantial attention spillover across covered firms and a significant increase in overall investor attention to the covered firms. In contrast, although self news can also attract attention from investors, the magnitude tends to be much smaller and relies heavily on joint news to reinforce its attentional effects.

5.3. *Cross-sectional return predictability*

Finally, we examine the effect of joint news on stock returns. We have shown that joint news coverage of a firm is associated with greater investor attention from a broader investor base. As shown in Da, Engelberg, and Gao (2011), heavy attention-driven buying by retail investors induces high valuations, followed by lower future returns. Therefore, in this subsection, we conduct cross-sectional analysis and investigate whether joint news can predict the subsequent returns of the firm's stocks.

We regress the future stock returns on the firm-level joint news coverage (*JointNews*) using the predictive Fama-MacBeth regression as follows:

$$\begin{aligned} R_{it} = \alpha_t + \beta_t JointNews_{it-1} + \gamma_t SelfNews_{it-1} + \phi_t \mathrm{I}_{JointNews} \times SelfNews_{it-1} \\ + \theta_t X_{it-1} + \varepsilon_{it}, \end{aligned} \tag{15}$$

where $\mathrm{I}_{JointNews}$ is the joint news indicator that equals one if the *JointNews* of a firm is above the cross-sectional top tertile, and zero otherwise. X is a set of control variables that includes the log book-to-market ratio, momentum (MOM, average returns from t-2 to t-12), short-term reversal (return in t-1), idiosyncratic volatility (IVOL), and controls as in Da, Engelberg, and Gao (2011), including log firm size, abnormal turnover, absolute characteristic-adjusted return as in Daniel et al. (1997), advertisement expenses, and log analyst coverage.

[Insert Table 11 here.]

Table 11 shows that the firms with more joint news tend to have lower future returns. For example, a coefficient of -13.031 in column 4 implies that a one standard deviation increase in a firm's abnormal joint news coverage significantly lowers the firm's next-month return, by 13 basis points. This finding corroborates the results of ASV of Google search and EDGAR IPs and provides further support to our hypothesis.[24]

To summarize, our cross-sectional analysis suggests that increases in joint news coverage is strongly associated with cross-firm attention spillover, more retail attention, and lower future returns of covered stocks. These firm-level and investor-level patterns provide useful micro-foundations to our time-series findings for aggregate stock market returns. These results are new and highlight the important role of joint news in generating systematic impacts on asset prices.

6. Conclusions

We propose a novel measure of aggregate joint news coverage of firms, $JointNews^M$, and find that it strongly predicts lower future market returns. A one standard deviation increase in $JointNews^M$ is associated with a substantially lower market return, by 89 basis points for the next month. The results are robust after controlling for an extensive list of alternative return predictors, both in

[24] Although *SelfNews* is significantly associated with ASV and EDGAR IP activities in Table 10, the variable does not predict stock returns. One reason could be that returns are noisier and, with the noisier dependent variable, only the strongest predictor, like *JointNews*, can survive whereas the weaker ones do not.

sample and out of sample, across expansion and recession periods, and lasts for more than six months. Moreover, the strong predictability corresponds to economically sizable values for mean-variance investors in asset allocation.

We provide identification using an instrumental variable approach based on exogenous distracting news shocks and show that the relationship between $JointNews^M$ and market returns is causal. Further, the predictability is stronger during periods of higher market uncertainty and greater market frictions, consistent with the predictability attributable to joint news-driven market overvaluations.

To dive deeper into the micro-foundations of our findings, we conduct cross-sectional analyses and examine the relation between joint news coverage, investor attention, and stock returns at the firm level. We show the joint news coverage is related to greater retail attention as measured by Google search activities. Further, taking advantage of the EDGAR search activities by unique IP addresses, we provide direct, individual investor-level evidence that the arrival of joint news is associated with substantial attention spillover. In addition, we show that joint news coverage significantly and negatively predicts future cross-sectional returns. In contrast, self news coverage has a much weaker relationship with investor attention and stock returns at the firm level and does not predict future market returns when aggregated.

The news and media sector is an important information intermediary that conveys the state of the economy and firm fundamentals to investors. At the same time, the sector can also be associated with distortions and subject to factors such as the confluence of consumer preferences, human biases, erroneous inferences, and unsubstantiated speculation (Mullainathan and Shleifer, 2005; Gentzkow and Shapiro, 2006). Our paper joins the emerging literature that provides insight into the ways in which the sector may influence investor behavior and market returns. Clearly, the channel that we document is one among many and more future work is called for.

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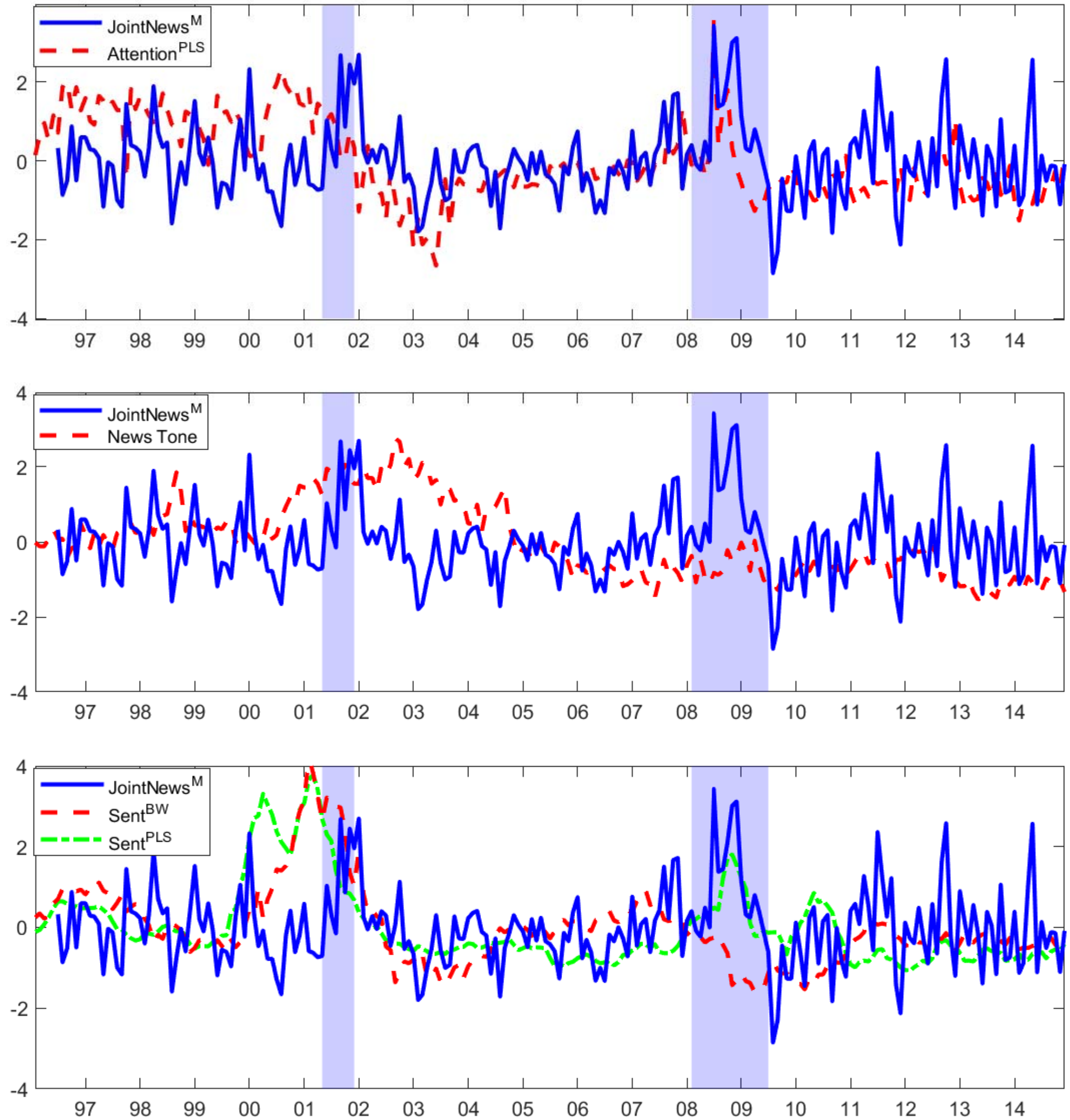

Fig. 1. Joint News. The figure plots the standardized time-series of *JointNews*^{M} with composite attention index, News Tone and investor sentiment indices. Panel A plots *JointNews*^{M} (solid line) and composite attention index by PLS (Chen et al., 2020b) (dashed line). Panel B plots *JointNews*^{M} (solid line) and value-weighted negative news tone measure (Tetlock, Saar-Tsechansky, and Macskassy, 2008) (dashed line). Panel C plots *JointNews*^{M} and investor sentiment measures Baker and Wurgler (2006) (Sent^{BW}, dashed line) and Huang et al. (2015) (Sent^{PLS}, dot-dashed line). All indices are standardized to have zero mean and unit variance. The shaded periods correspond to NBER-dated recessions. The sample period is February 1996 through December 2014.

Table 1 Summary Statistics and Correlation Coefficients

This table reports summary statistics and correlation coefficients for all the time-series variables. Panel A reports the temporal average (Mean), standard deviation (Stdev), skewness (Skew), 25 percentile (Q25), median (Med), 75 percentile (Q75), and first-order autocorrelation ($\rho(1)$) are reported. Panel B reports the Pearson correlation coefficients (in %) between all the time-series variables. The variable definitions are as following: R_m is the log return on the S&P 500 Index in excess of the risk-free rate; R_f is the risk-free rate, i.e., 1-month T-bill rate; $JointNews^M$ is the value-weighted aggregate joint news index; $JointNews^M_{ew}$ the equal-weighted aggregate joint news index; $SelfNews^M$ is the value-weighted aggregate self news index; News Tone is the value-weighted average of negative news tones of S&P500 stocks (Tetlock, Saar-Tsechansky, and Macskassy, 2008); Sent^{BW} and Sent^{PLS} are the investor sentiment index of Baker and Wurgler (2007) and Huang et al. (2015), respectively; Attn^{PLS} is the investor attention index of Chen et al. (2020b); DP is the log dividend-price ratio, DY is the log dividend-yield ratio; EP is the log earnings-price ratio; DE is the log dividend buyout ratio; SVAR is the stock return variance; BM is the book-to-market ratio; NTIS is the net equity expansion; TBL is the treasury bill rate; LTY is the long-term bond yield; LTR is the long-term bond return; TMS is the term spread; DFY is the default yield spread; DFR is the default return spread; INFL is the inflation rate. The sample period is February 1996 through December 2014.

Panel A: Summary statistics

Variables	Mean	Stdev	Skew	Q25	Med	Q75	$\rho(1)$
Returns							
R_m	0.004	0.045	−0.661	−0.022	0.013	0.037	0.084
R_f	0.002	0.002	0.198	1.422	0.000	0.006	0.978
News-based Measures							
$JointNews^M$	0.117	0.135	0.700	−0.614	−0.080	0.401	0.377
$JointNews^M_{ew}$	0.056	0.058	1.053	−0.653	−0.056	0.397	0.378
$SelfNews^M$	0.014	0.167	0.195	−0.113	−0.021	0.124	−0.208
News Tone, Investor Sentiment, and Composite Attention							
News Tone	0.008	0.002	0.688	0.006	0.007	0.009	0.947
Sent^{BW}	0.225	0.681	1.506	−0.120	0.100	0.460	0.964
Sent^{PLS}	−0.190	0.853	1.845	−0.724	−0.514	0.059	0.977
Attn^{PLS}	0.076	0.266	0.459	−0.102	0.009	0.301	0.803
Economic Predictors							
DP	−4.035	0.219	0.180	−4.137	−4.025	−3.903	0.976
DY	−4.030	0.219	0.063	−4.133	−4.015	−3.892	0.976
EP	−3.161	0.411	−1.876	−3.346	−3.011	−2.884	0.975
DE	−0.875	0.469	3.145	−1.118	−1.007	−0.853	0.983
SVAR	0.003	0.005	6.159	−0.322	−0.190	−0.095	0.699
BM	0.263	0.076	−0.102	0.195	0.271	0.326	0.960
NTIS	0.004	0.019	−1.283	−1.650	−0.991	0.719	0.973
TBL	2.462	2.138	0.178	−4.828	−1.730	−0.133	0.991
LTY	4.834	1.244	−0.186	−5.758	−4.840	−4.063	0.969
LTR	0.637	3.067	0.048	−1.333	0.830	2.485	−0.006
TMS	2.373	1.350	−0.235	1.275	2.440	3.590	0.975
DFY	1.000	0.452	2.906	0.743	0.900	1.130	0.961
DFR	0.000	1.831	−0.484	−0.670	0.040	0.590	0.019
INFL	0.002	0.004	−0.979	0.000	0.189	0.429	0.472

Table 1 (Cont'd) Summary Statistics and Correlation Coefficients

Panel B: Correlation Coefficients

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
$JointNews^{M}$																				
$JointNews^{M}_{ew}$	90																			
$SelfNews^{M}$	43	37																		
News Tone	2	3	4																	
Sent^{BW}	8	13	11	30																
Sent^{PLS}	12	7	9	34	59															
Attn^{PLS}	8	8	−3	10	54	53														
DP	9	10	−5	−50	−51	−36	−38													
DY	5	7	−7	−53	−53	−41	−39	98												
EP	−10	−11	−5	−36	5	−32	−5	−3	−3											
DE	12	14	2	8	−28	12	−14	49	48	−89										
SVAR	32	24	16	10	−10	30	8	32	24	−28	39									
BM	−4	−4	−9	−52	−55	−53	−60	70	69	42	−4	8								
NTIS	−21	−20	−4	41	5	−3	−2	−49	−46	9	−30	−33	−23							
TBL	−1	−4	12	26	60	42	67	−60	−60	−4	−24	−7	−70	17						
LTY	−1	−6	12	51	43	45	55	−59	−59	−27	−3	−3	−79	40	80					
LTR	11	9	−6	5	5	7	−1	4	0	5	−3	18	5	3	2	−9				
TMS	1	2	−7	5	−55	−26	−56	41	41	−18	35	9	39	9	−84	−35	−11			
DFY	25	20	−1	−5	−39	5	−25	64	61	−51	75	59	33	−57	−42	−34	0	35		
DFR	−8	−1	−1	3	−6	−5	−5	1	10	−20	18	−25	−3	4	−9	−2	−46	13	14	
INFL	−14	−9	8	1	9	−5	−8	−15	−15	3	−10	−35	−6	6	11	14	−24	−4	−22	−4

Table 2 In-Sample Forecasting of Market Returns

This table provides in-sample estimation results for the predictive regression

$$R_{m,t+1} = \alpha + \beta X_t + \varepsilon_{t+1},$$

where $R_{m,t+1}$ denotes the monthly excess market return (in %) and X_t is one of the return predictors. In Panel A, the return predictor is the value- and the equal-weighted aggregate joint news index ($JointNews^M$ and $JointNews^M_{ew}$) and the value-weighted aggregate self news index ($SelfNews^M$). In Panel B, the return predictor is the Tetlock, Saar-Tsechansky, and Macskassy (2008) News Tone, the investor sentiment measures proposed by Baker and Wurgler (2007) (Sent^{BW}) and Huang et al. (2015) (Sent^{PLS}), and the composite investor attention measure proposed by Chen et al. (2020b) (Attn^{PLS}). For Panel C, the return predictors are economic predictors following Goyal and Welch (2008): the log dividend price ratio (DP), log dividend yield (DY), log earnings-price ratio (EP), log dividend-payout ratio (DE), stock return variance (SVAR), book-to-market ratio (BM), net equity expansion (NTIS), Treasury bill rate (TBL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR) and inflation rate (INFL). The t-statistics are based on Newey-West standard errors with the six lags. *, **, and *** indicate significance at the 10%, 5% and 1% levels respectively. The sample period is February 1996 through December 2014.

Variables	$\hat{\beta}$	t-stat.	R^2	R^2_{up}	R^2_{down}
Panel A: News-based Measures					
$JointNews^M$	−0.891***	−2.868	3.929	2.249	3.312
$JointNews^M_{ew}$	−0.708**	−2.086	2.476	1.710	0.343
$SelfNews^M$	−0.325	−1.042	0.520	0.210	3.771
Panel B: News Tone, Investor Sentiment and Attention					
News Tone	−0.220	−0.665	0.241	0.337	0.026
Sent^{BW}	−0.595**	−2.187	1.779	1.728	0.812
Sent^{PLS}	−0.800***	−2.747	3.216	1.092	8.856
Attn^{PLS}	−0.658**	−2.112	2.179	0.699	12.223
Panel C: Economic Predictors					
DP	0.559	1.179	1.569	4.918	0.968
DY	0.635	1.562	2.026	4.135	3.027
EP	0.221	0.452	0.246	1.382	17.065
DE	0.068	0.137	0.023	0.005	11.411
SVAR	0.661*	1.905	2.194	0.003	4.006
BM	0.305	1.056	0.466	0.585	0.035
NTIS	−0.572	−1.200	1.645	0.083	1.051
TBL	0.188	0.647	0.177	0.326	2.986
LTY	0.307	1.142	0.466	0.654	0.687
LTR	0.113	0.457	0.065	0.001	1.003
TMS	0.015	0.048	0.001	0.022	4.796
DFY	−0.302	−0.558	0.458	0.001	0.412
DFR	0.350	0.707	0.615	0.168	2.146
INFL	0.431	1.003	0.916	0.378	17.737

Table 3 Market States and Return Predictability

This table provides in-sample estimation results for the predictive regression of monthly excess market returns on the aggregate joint news index, $JointNews^M$, under high/low market uncertainty and frictions periods. We construct the market uncertainty indicators (PCA-Uncertainty and EW-Uncertainty) by aggregating a set of uncertainty indices, including VIX from CBOE, the economic uncertain index (UNC), the treasury implied volatility index (TIV), the macro uncertainty (MU) and financial uncertainty (FU) index, the economic policy uncertainty index (EPU), and the disagreement index (DSA), through both PCA and equal-weighting. We also compute the market friction indicators (PCA-Friction and EW-Friction) using the equal-weighted short interest ratio (EWSI), value-weighted bid-ask spreads (BAS), and the price delay measure (DLY) in the same fashion. The overall market-state indicators (PCA-All and EW-All) use all the variables mentioned above, through both PCA and equal-weighting respectively. The market state is high (low) if the market indicator is in the top (bottom) 25%. The t-statistics reported in brackets are based on the Newey-West robust standard errors with six lags. The sample period is February 1996 through December 2014. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	High		Low		Diff	
Variables	$\hat{\beta}+\hat{\gamma}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\gamma}$	t-stat
Panel A. Market Uncertainty						
PCA-Uncertainty	−1.205**	−2.38	0.174	0.40	−1.379**	−2.08
EW-Uncertainty	−1.146**	−2.22	0.255	0.52	−1.401**	−1.99
Panel B. Market Frictions						
PCA-Friction	−1.483***	−5.11	−0.299	−0.37	−1.184*	−1.69
EW-Friction	−1.198**	−2.57	0.354	0.97	−1.552**	−2.34
Panel C. Overall						
PCA-All	−1.210**	−2.37	0.358	1.00	−1.568**	−2.55
EW-All	−1.018***	−3.06	0.381	1.01	−1.399***	−2.59

Table 4 Horse Race for In-Sample Forecasting of Market Returns

This table provides in-sample estimation results for the bivariate predictive regression of monthly excess market returns on $JointNews^M$ or $JointNews^M_{ew}$, and one of the other predictors, Z_t.

$$R_{m,t+1} = \alpha + \beta X_t + \phi Z_t + \varepsilon_{t+1},$$

where $R_{m,t+1}$ denotes the monthly excess market return (%), $JointNews^M$ and $JointNews^M_{ew}$ are the value- and the equal-weighted aggregate joint news indices, and Z is one of the other predictors (see Table 2 for the full list). The significance of the estimates are based on Newey-West t-statistics with the six lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. The sample period is February 1996 through December 2014.

	$JointNews^M$			$JointNews^M_{ew}$		
Variables	$\hat{\beta}$	$\hat{\phi}$	R^2	$\hat{\beta}$	$\hat{\phi}$	R^2
Controlling for Self News						
$SelfNews^M$	−0.871***	−0.067	3.949	−0.668**	−0.164	2.601
Controlling for News Tone, Investor Sentiment and Attention						
News Tone	−0.887***	−0.191	4.113	−0.701**	−0.188	2.652
$Sent^{BW}$	−0.849**	−0.516*	5.264	−0.641*	−0.500*	3.715
$Sent^{PLS}$	−0.809***	−0.697***	6.348	−0.653**	−0.742***	5.246
$Attn^{PLS}$	−0.843***	−0.576*	5.574	−0.663**	−0.595*	4.237
Controlling for Economic Predictors						
DP	−0.949***	0.667*	6.124	−0.770**	0.658	4.604
DY	−0.927**	0.710**	6.427	−0.754**	0.712*	4.978
EP	−0.876***	0.149	4.039	−0.690**	0.158	2.600
DE	−0.913***	0.178	4.088	−0.731**	0.166	2.613
SVAR	−0.750***	0.435	4.787	−0.576**	0.535	3.836
BM	−0.881***	0.266	4.286	−0.696*	0.269	2.839
NTIS	−0.806***	−0.463	4.955	−0.616**	−0.497	3.660
TBL	−0.897***	0.199	4.122	−0.722**	0.218	2.706
LTY	−0.894***	0.303	4.356	−0.726**	0.334	2.993
LTR	−0.916***	0.233	4.194	−0.723**	0.191	2.655
TMS	−0.893***	0.044	3.939	−0.710**	0.046	2.486
DFY	−0.865***	−0.105	3.980	−0.670**	−0.186	2.642
DFR	−0.870***	0.284	4.332	−0.707**	0.345	3.077
INFL	−0.845***	0.300	4.361	−0.669**	0.358	3.100

Table 5 Out-of-Sample Forecasting of Market Returns

This table reports the out-of-sample performance of monthly market excess return predictors. Panel A provides the results using the value- and the equal-weighted aggregate joint news index (*JointNews*^{M} and *JointNews*$^M_{ew}$), and the value-weighted aggregate self news index (*SelfNews*). Panel B shows results of the Tetlock, Saar-Tsechansky, and Macskassy (2008) News Tone, the investor sentiment measures proposed by Baker and Wurgler (2007) (Sent^{BW}) and Huang et al. (2015) (Sent^{PLS}), and the composite investor attention measure Chen et al. (2020b) (Attn^{PLS}). Panel C shows results using economic predictors (Goyal and Welch, 2008) (see Table 2 for the full list). All the predictors and regression slopes are estimated recursively using the data available at the forecast formation time t. R^2_{OS} is the out-of-sample R^2 with no constraints. $R^2_{OS,up}$ ($R^2_{OS,down}$) statistics are calculated over NBER-dated business-cycle expansions (recessions) based on the unconstrained model. CW test is the Clark and West (2007) MSFE-adjusted statistic calculated according to the prevailing mean model. DM test is the Diebold and Mariano (1995) statistic modified by McCracken (2007) for testing the equality of the MSFE of one forecast relative to another. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. The in-sample estimation period is February 1996 through December 2002 and the out-of-sample evaluation period is January 2003 through December 2014.

Variables	R^2_{OS}	CW test	p-value	DM test	p-value	$R^2_{OS,up}$	$R^2_{OS,down}$
Panel A: News-based Measures							
JointNews^M	6.518***	2.759	0.003	2.284**	0.011	5.780	7.517
JointNews$^M_{ew}$	3.686***	2.420	0.008	1.370*	0.085	3.029	4.577
SelfNews^M	0.423	0.841	0.200	0.432	0.333	0.354	0.515
Panel B: News Tone, Investor Sentiment and Attention							
News Tone	−2.281	−1.214	0.888	−1.808	0.965	−3.325	−0.867
Sent^{BW}	0.836	0.977	0.164	0.429	0.334	3.134	−2.277
Sent^{PLS}	4.284***	2.714	0.003	2.082**	0.019	3.331	5.575
Attn^{PLS}	3.569***	2.797	0.003	2.105**	0.018	3.634	3.482
Panel C: Economic Predictors							
DP	−3.760	−0.275	0.608	−1.112	0.867	3.243	−13.249
DY	−2.109	0.087	0.466	−0.682	0.752	4.435	−10.977
EP	−9.665	−0.318	0.625	−1.245	0.893	−5.140	−15.797
DE	−0.478	−1.172	0.879	−1.225	0.890	−0.407	−0.574
SVAR	1.074	0.979	0.164	0.273	0.392	2.066	−0.271
BM	−0.439	0.422	0.336	−0.438	0.669	0.612	−1.863
NTIS	−0.304	−1.647	0.950	−1.822	0.966	−0.104	−0.574
TBL	−0.066	−0.125	0.550	−0.271	0.607	0.309	−0.574
LTY	0.327	1.156	0.124	0.700	0.242	0.993	−0.574
LTR	−0.720	−1.961	0.975	−1.732	0.958	−0.652	−0.813
TMS	−0.321	−1.749	0.960	−1.929	0.973	−0.135	−0.574
DFY	−0.304	−1.647	0.950	−1.822	0.966	−0.104	−0.574
DFR	−4.537	−0.633	0.737	−1.031	0.849	0.318	−11.117
INFL	−0.189	0.415	0.339	−0.081	0.532	−5.605	7.149

Table 6 Long-horizon Return Predictability

This table reports the return 3- and 6-month return predictability of market excess return predictors. Panel A provides the in- and out-of-sample return predictability results using the value-weighted aggregate joint news index ($JointNews^M$). Panel B shows the in-sample results for the 3- and 6-month bivariate predictive regression of monthly excess market returns on $JointNews^M$ and one of the other predictors, Z_t (see Table 2 for the full list of other predictors). *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. The in-sample estimation period is February 1996 through December 2002 and the out-of-sample evaluation period is January 2003 through December 2014.

Panel A: In- and Out-of-sample Analysis

	In-Sample			Out-of-Sample		
Horizon	β	t-stat.	R^2	R^2_{OS}	CW test	p-value
$h = 3$	−0.816***	−2.702	8.98	13.362**	2.019	0.022
$h = 6$	−0.439**	−2.041	4.56	5.323*	1.488	0.068

Panel B: Horse Race

	$h = 3$			$h = 6$		
Variables	$\hat{\beta}$	$\hat{\phi}$	R^2	$\hat{\beta}$	$\hat{\phi}$	R^2
Controlling for Self News						
$SelfNews^M$	−0.854***	0.128	9.175	−0.464**	0.086	4.714
Controlling for News Tone, Investor Sentiment and Attention						
News Tone	−0.813***	−0.202	9.531	−0.437**	−0.165	5.204
$Sent^{BW}$	−0.777**	−0.491**	12.285	−0.391*	−0.612***	13.579
$Sent^{PLS}$	−0.746***	−0.608***	14.017	−0.378*	−0.543***	11.586
$Attn^{PLS}$	−0.770***	−0.574**	13.444	−0.399**	−0.513**	10.787
Controlling for Economic Predictors						
DP	−0.878**	0.694**	15.460	−0.503**	0.707***	16.355
DY	−0.854**	0.708**	15.754	−0.479**	0.714***	16.647
EP	−0.813***	0.036	8.996	−0.438**	0.016	4.569
DE	−0.852***	0.289	10.115	−0.478**	0.312	6.899
SVAR	−0.750***	0.206	9.501	−0.475**	−0.111	4.833
BM	−0.802**	0.418*	11.373	−0.421**	0.594***	12.934
NTIS	−0.712***	−0.566	13.187	−0.324*	−0.627*	13.617
TBL	−0.825***	0.242	9.753	−0.452**	0.306	6.697
LTY	−0.823***	0.327	10.303	−0.448**	0.371	7.482
LTR	−0.813***	−0.028	8.989	−0.453**	0.122	4.907
TMS	−0.820***	0.093	9.097	−0.446**	0.154	5.136
DFY	−0.827***	0.042	9.001	−0.487**	0.194	5.400
DFR	−0.802***	0.173	9.389	−0.428**	0.142	5.050
INFL	−0.863***	−0.292	10.087	−0.509**	−0.429**	8.741

Table 7 Asset Allocation Performance

This table reports the annualized CER gains (in %) and annualized Sharpe ratios for a mean-variance investor, who allocates assets between the market and risk-free bills using the out-of-sample forecasts based on the value–weighted aggregate joint news index ($JointNews^M$) over the prediction horizon h. $h = 1$ month, 3 months, and 6 months. The investor's risk-aversion (γ) varies from 1 to 5. We consider two scenarios: zero transaction cost and a proportional transaction cost of 50 basis points per transaction. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The in-sample estimation period is February 1996 through December 2002 and the out-of-sample evaluation period is January 2003 through December 2014.

	No Transaction Cost		50 bps Transaction Cost	
	CER Gains	Sharpe Ratio	CER Gains	Sharpe Ratio
Panel A: $h = 1$				
$\gamma = 1$	9.313***	1.053***	7.086**	0.850***
$\gamma = 3$	7.705***	0.902***	4.900**	0.577**
$\gamma = 5$	4.949***	0.795***	2.679**	0.446**
Panel B: $h = 3$				
$\gamma = 1$	8.480**	1.112***	7.995**	1.047***
$\gamma = 3$	7.189***	1.049***	6.478***	0.939***
$\gamma = 5$	4.814***	0.992***	4.162***	0.866**
Panel C: $h = 6$				
$\gamma = 1$	7.413*	1.016***	7.090*	0.956***
$\gamma = 3$	3.719**	0.796**	3.485**	0.718**
$\gamma = 5$	2.208**	0.619**	2.020*	0.534*

Table 8 Instrumental Variable Analysis

This table reports the instrumental variable analysis of market return predictability. $JointNews^M$ is the value-weighted aggregate joint news index. $\mathrm{I}_{\mathrm{Dist}}$ is a "distraction" indicator that equals one if the monthly Eisensee and Strömberg (2007) news pressure variable belongs to the top 20% of its annual distribution. Panel A reports the average of $JointNews^M$ during distraction and non-distraction months, respectively. Panel B reports the two-stage least squares results of regression (2) using $\mathrm{I}_{\mathrm{Dist}}$ as an instrument variable. The reported standard errors are Newey-West adjusted with six lags. The sample period is February 1996 through December 2014. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Univariate Contrast

Variables	Total	$\mathrm{I}_{\mathrm{Dist}} = 0$	$\mathrm{I}_{\mathrm{Dist}} = 1$	Diff
Average of $JointNews^M$	0.000	0.041	−0.441***	0.482***
t-statistic	0.00	0.58	−2.63	2.64
Observations	222	203	19	—

Panel B: Two-Stage Least Squares

	First Stage ($JointNews^M$)		Second Stage ($R_{m,t+1}$)	
Variables	β	t-stat	β	t-stat
Predicted $JointNews^M$			−3.595*	−1.73
$\mathrm{I}_{\mathrm{Dist}}$	−0.482***	−2.81		
Observations	221		221	
First-stage F-statistic	7.87		—	
Adj. R^2 (in %)	1.38		0.69	

Table 9 Additional Robustness Check with Other News-based Predictors

This table reports the in-sample predictive regression results of regressing monthly excess market returns on $JointNews^M$ after controlling for additional news-based return predictors. Panel A reports the results of controlling for lagged Calomiris and Mamaysky (2019) measures for the U.S. market: entropy, number of articles per month (ArtCount), and article sentiment (s[Topic]) and frequency (f[Topic]) for Topic in markets, commodities, corporate sector, credit, and government. Panel B reports the results of controlling for the five contemporaneous AR(1) innovations of Bybee et al. (2021) news attention measures: Recession, Problems, Record High, Option/VIX, and Convertible/preferred. $JointNews^M$ is the value-weighted aggregate joint news index. The t-statistics reported in brackets are based on the Newey-West robust standard errors with six lags. The sample period is February 1996 through December 2014. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Calomiris and Mamaysky (2019)			Panel B: Bybee et al. (2021)	
	(1)	(2)		(3)	(4)
$JointNews^M$		-0.962***	$JointNews^M$		-0.588**
		(-3.52)			(-2.32)
Entropy	3.473	4.170	Recession	-1.409***	-1.388***
	(0.37)	(0.46)		(-3.66)	(-3.86)
ArtCount	2.053*	2.031*	Problems	-1.076***	-1.028***
	(1.81)	(1.86)		(-3.10)	(-2.86)
sMkt	0.510	-0.201	Record High	0.629**	0.595**
	(0.38)	(-0.16)		(2.38)	(2.21)
fMkt	-0.790	-1.213	Option/VIX	-0.476*	-0.467*
	(-0.80)	(-1.23)		(-1.74)	(-1.71)
sComms	0.166	0.222	Convertible/preferred	-0.568**	-0.466*
	(0.31)	(0.41)		(-2.44)	(-1.93)
fComms	0.477	0.298			
	(0.82)	(0.53)			
sCorp	0.363	0.580			
	(0.34)	(0.56)			
fCorp	-0.074	0.047			
	(-0.11)	(0.07)			
sCredit	0.052	0.293			
	(0.05)	(0.32)			
fCredit	-0.594	-0.486			
	(-0.77)	(-0.59)			
sGovt	-0.723	-0.561			
	(-0.75)	(-0.58)			
Intercept	-8.283	-9.965	Intercept	0.415*	0.440*
	(-0.37)	(-0.45)		(1.76)	(1.94)
Observations	199	199	Observations	226	221
Adj. R^2 (in %)	0.54	4.11	Adj. R^2 (in %)	25.17	26.59

Note: fGovt is omitted due to collinearity issue in the data.

Table 10 Retail Investor Attention and EDGAR Search IPs

This table reports the Fama-MacBeth regression results of abnormal Google search volume (ASV, in %) and monthly numbers of unique IPs. Columns 1 and 2 report results for the abnormal Google search volume, Columns 3 and 4 report results for the log number of new IPs, Columns 5 reports the result for log number of new IPs from connected stocks (log(New IP_c)), Columns 6 presents the result for log number of new IPs from other sources (log(New IP_o)), and Column 7 presents the result for log number of existing IPs. New IP is the number of new IPs, where an IP as new if the IP address has not searched the focal stock in the past 18 months. New IP_c is the number of new IPs from connected stocks, where an IP has not searched the focal stock in the past 18 months but has searched the connected stocks in the past 18 months. Exist IP is the number of existing IPs, where an IP as existing if the IP address has searched the focal stock in the past 18 months. $I_{JointNews}$ equals one if the stock's $JointNews_i$ is above the cross-sectional top tertile, and zero otherwise. The control variables are the log firm size (log(Size)), abnormal turnover (Abn Turnover), absolute characteristic-adjusted returns (|Abn Ret|), advertisement expenses/sales ratio (AdExp/Sales), and log number of analysts (log(1+Analyst)). All the independent variables are also standardized (so the regression coefficients can be interpreted as the impact of a one standard deviation change). The t-statistics reported in brackets are based on the Newey-West robust standard errors with six lags. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is February 2005 through December 2014.

	ASV		log(New IP)		log(New IP_c)	log(New IP_o)	log(Exist IP)
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$JointNews_i$	0.971***	0.959***	0.091***	0.049***	0.203***	0.012*	0.030***
	(8.35)	(8.08)	(7.80)	(7.83)	(14.38)	(1.83)	(6.48)
$SelfNews_i$	0.898***	0.807***	0.006	0.015***	0.093***	0.001	0.014***
	(6.40)	(6.99)	(1.20)	(3.89)	(8.09)	(0.14)	(3.27)
$I_{JointNews} \times SelfNews_i$	0.927***	0.754***	0.029***	0.039***	0.066***	0.028***	0.016***
	(3.79)	(3.19)	(3.99)	(5.58)	(3.38)	(4.04)	(2.86)
log(Size)		2.407***		0.283***	0.372***	0.276***	0.218***
		(7.97)		(27.30)	(22.23)	(23.87)	(32.09)
Abn Turnover		-2.588***		0.150***	0.262***	0.133***	0.124***
		(-7.73)		(19.07)	(16.83)	(19.17)	(17.50)
|Abn Ret|		1.531***		0.040***	0.100***	0.031***	0.024***
		(6.97)		(8.55)	(12.78)	(6.03)	(7.34)
AdExp/Sales		0.206***		0.090***	0.110***	0.094***	0.030***
		(2.78)		(17.23)	(15.48)	(14.90)	(9.34)
log(1+Analyst)		-1.053***		-0.069***	0.062***	-0.089***	-0.044***
		(-4.82)		(-18.59)	(4.87)	(-21.76)	(-12.97)
Observations	58,985	55,191	32,464	29,279	29,279	29,279	29,279
Ave. R^2 (in %)	1.8	4.0	6.8	45.5	30.2	37.8	42.0

Table 11 Forecasting Cross-Sectional Returns

This table reports the Fama-MacBeth regression results of future stock returns (in bps) on firm-level abnormal joint news, $JointNews_i$, and self news, $SelfNews_i$. $I_{JointNews}$ equals one if the stock's *JointNews* is above the cross-sectional top tertile, and zero otherwise. The control variables include the lagged log firm size (log(Size)), lagged log book-to-market ratio (log(BM)), lagged momentum (MOM, average returns from $m-2$ to $m-12$), short-term reversal (Reversal, return in $m-1$), lagged idiosyncratic volatility (IVOL), lagged abnormal turnover (Abn Turnover), lagged absolute return (|Abn Return|), lagged advertisement expenses/sales ratio (AdExp/Sales), and lagged log analyst coverage (log(1+Analyst)). All the independent variables are also standardized (so the regression coefficients can be interpreted as the impact of a one standard deviation change). The t-statistics reported in brackets for Fama-MacBeth regressions are based on the Newey-West robust standard errors with six lags, and those for panel regressions are based on the stock-month double-clustered standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. The sample period is February 1996 through December 2014.

Variables	(1)	(2)	(3)	(4)
$JointNews_i$	-12.190**		-12.383**	-13.031***
	(-2.08)		(-2.14)	(-2.95)
$SelfNews_i$		-1.750	-0.617	8.130
		(-0.39)	(-0.10)	(1.39)
$I_{JointNews} \times SelfNews_i$			8.942	-1.700
			(1.01)	(-0.21)
log(Size)				-50.232***
				(-3.06)
log(BM)				-5.458
				(-0.62)
MOM				4.154
				(0.29)
Reversal				-2.973
				(-0.33)
IVOL				-12.534
				(-0.95)
Abn Turnover				-0.272
				(-0.02)
|Abn Ret|				-9.178*
				(-1.78)
AdExp/Sales				9.203**
				(2.02)
log(1+Analyst)				15.746*
				(1.69)
Observations	81,299	95,368	78,629	64,285
Ave. R^2 (in %)	0.5	0.3	1.2	14.8

Appendices

Appendix A presents all the variable definitions, summary statistics of variables used in Section 5, and the correlation coefficients between these variables. Appendix B contains the time series return predictability results for the CRSP value-weighted index.

A. Variable Definitions and Additional Summary Statistics

Table A1 Variable Definitions

Variable	Definition
Panel A: Returns	
R_m	Log return on the S&P 500 Index in excess of the risk-free rate
R_f	Risk-free rate, i.e., 1-month T-bill rate
Panel B: News-based Attention Measures	
$JointNews_i$	Firm-level average abnormal joint news coverage across all connected firms, weighted by the centrality of the connected firm.
$JointNews^M$	Aggregate joint news index, value-weighted across firms
$JointNews^M_{ew}$	Aggregate joint news index, equal-weighted across firms
$SelfNews_i$	Firm-level abnormal self news coverage.
$SelfNews^M$	Aggregate self news index, value-weighted across firms
Panel C: News Tones, Investor Sentiment, and Composite Attention	
News Tone	Value-weighted average of negative news tones of S&P500 stocks following (Tetlock, Saar-Tsechansky, and Macskassy, 2008)
Sent^{BW}	Investor sentiment index estimated as the first principle component of six individual sentiment proxies (Baker and Wurgler, 2006, 2007)
Sent^{PLS}	Investor sentiment index estimated by partial least squares (Huang et al., 2015)
Attn^{PLS}	Investor attention index estimated by partial least squares (Chen et al., 2020b)
Panel D: Economic Predictors (Goyal and Welch, 2008)	
DP	Log dividend-price ratio
DY	Log dividend-yield ratio
EP	Log earnings-price ratio
DE	Log dividend buyout ratio
SVAR	Stock return variance
BM	Book-to-market ratio
NTIS	Net equity expansion
TBL	Treasury bill rate

Table A1 (Cont'd) Variable Definitions

Variable	Definition
LTY	Long-term bond yield
LTR	Long-term bond return
TMS	Term spread
DFY	Default yield spread
DFR	Default return spread
INFL	Inflation rate
Panel E: Market Uncertainty and Frictions	
VIX	CBOE volatility index
UNC	Economic uncertainty index (Bali, Brown, and Caglayan, 2014)
TIV	Treasury implied volatility (Choi, Mueller, and Vedolin, 2017)
MU	Macro uncertainty index (Jurado, Ludvigson, and Ng, 2015)
FU	Financial uncertainty index (Jurado, Ludvigson, and Ng, 2015)
EPU	Economic policy uncertainty index (Baker, Bloom, and Davis, 2016)
DSA	Disagreement index (Huang, Li, and Wang, 2021)
EWSI	Equal-weighted short-interest ratio (Rapach, Ringgenberg, and Zhou, 2016)
BAS	Value-weighted average of bid-ask spreads across S&P500 firms
DLY	Value-weighted average of the second type of price delay measure (Hou and Moskowitz, 2005) across S&P500 firms
Panel F: Variables for Cross-Sectional Analysis	
ASV	Abnormal Google search volume. The log of SVI during the month minus the log of average SVI during the previous 12 months, skipping the most recent month
New IP	Number of new IPs in EDGAR search traffic, defined as the unique IP address that has not searched the focal stock in the past 18 months
New IP$_c$	Number of new IPs from connected stocks in EDGAR search traffic, defined as the unique IP address that has not searched the focal stock in the past 18 months but searched the connected stocks in the past 18 months
New IP$_o$	Number of new IPs from other stocks in EDGAR search traffic, defined as New IP net of New IP$_c$
Exist IP	The number of unique IP addresses that has searched the focal stock in the past 18 months
IVOL	Idiosyncratic volatility
MOM	Average returns from $m-2$ to $m-12$
log(Size)	Log market cap
log(BM)	Log book-to-market ratio
Abn Turnover	Standardized abnormal turnover as in Chordia, Huh, and Subrahmanyam (2007)
Abn Ret	Characteristic-adjusted return as in Daniel et al. (1997)
AdExp/Sales	Ratio between advertisement expense and sales in the previous fiscal year, where we set advertisement expenditure to zero if it is missing in Compustat
log(1+Analyst)	Log number of analysts in IBES

Table A2 Correlation Coefficients between Joint News and Topic-specific Measures

Panel A: Topic-specific Sentiment, Frequency, and Entropy

	1	2	3	4	5	6	7	8	9	10	11	12
JointNews^M												
Entropy	3											
ArtCount	9	−80										
sMkt	−34	−23	−8									
fMkt	−4	8	16	−14								
sComms	−1	28	9	1	69							
fComms	−20	−51	5	36	−45	−63						
sCorp	−26	−1	−7	74	39	46	4					
fCorp	10	−37	22	3	−46	−50	14	−43				
sCredit	−31	−21	−11	85	11	1	39	77	−11			
fCredit	4	−78	79	11	3	3	22	14	1	3		
sGovt	−3	−78	74	27	31	11	20	28	25	28	73	
fGovt	−1	84	−79	−14	−26	3	−29	−11	−39	−17	−77	−92

Panel B: Topic Attention

	1	2	3	4	5
JointNews^M					
Recession	−1				
Problems	12	38			
Record High	−16	−3	−24		
Option/VIX	0	4	−4	−20	
Convertible/preferred	17	−22	−5	−9	−4

Table A3 Summary Statistics for Cross-Sectional Variables

This table reports summary statistics for all the cross-sectional variables. We compute the temporal average of each variable first and then report its cross-sectional average (Mean), standard deviation (Stdev), skewness (Skew), 25 percentile (Q25), median (Med), and 75 percentile (Q75). The variable definitions are given in Table A1. The sample period is February 1996 through December 2014.

Variable	Mean	Stdev	Skew	Q25	Med	Q75
$JointNews_i$	0.000	0.999	1.759	−0.460	−0.221	0.155
$Selfnews_i$	0.000	0.999	−0.132	−0.600	0.027	0.624
ASV	−0.039	0.192	3.896	−0.128	−0.043	0.034
New IP	5.587	1.347	−1.627	5.043	5.687	6.433
New IP_c	3.942	1.700	−1.033	3.367	4.263	5.094
New IP_o	5.300	1.317	−1.545	4.771	5.394	6.111
Exist IP	5.456	1.289	−1.219	4.836	5.576	6.308
IVOL	0.000	0.999	1.729	−0.684	−0.251	0.401
MOM	0.000	0.998	0.810	−0.643	−0.102	0.513
log(Size)	0.000	0.999	0.086	−0.643	−0.033	0.625
log(BM)	0.000	0.998	0.789	−0.763	−0.190	0.610
Abn Turnover	0.000	0.999	0.240	−0.678	−0.049	0.621
Abn Ret	0.000	0.998	1.701	−0.717	−0.267	0.407
AdExp/Sales	0.000	0.998	3.002	−0.438	−0.421	−0.183
log(1+Analyst)	0.000	0.999	−0.857	−0.549	0.165	0.695

B. Additional Results for CRSP Value-Weighted Returns

Table B1 In-Sample Forecasting of Market Returns

This table provides in-sample estimation results for the predictive regression

$$R_{m,t+1} = \alpha + \beta X_t + \varepsilon_{t+1},$$

where $R_{m,t+1}$ denotes the monthly excess market return (in %) and X_t is one of the return predictors. In Panel A, X_t is the value- and the equal-weighted aggregate joint news index ($JointNews^M$ and $JointNews^M_{ew}$) and the value-weighted self news index ($SelfNews^M$). In Panel B, the return predictor is the Tetlock, Saar-Tsechansky, and Macskassy (2008) News Tone, the investor sentiment measures proposed by Baker and Wurgler (2007) (Sent^{BW}) and Huang et al. (2015) (Sent^{PLS}), and the investor attention measure proposed by Chen et al. (2020b) (Attn^{PLS}). For Panel C, the return predictors are economic predictors following Goyal and Welch (2008): the log dividend price ratio (DP), log dividend yield (DY), log earnings-price ratio (EP), log dividend-payout ratio (DE), stock return variance (SVAR), book-to-market ratio (BM), net equity expansion (NTIS), Treasury bill rate (TBL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR) and inflation rate (INFL). The t-statistics are based on Newey-West standard errors with the six lags. *, **, and *** indicate significance at the 10%, 5% and 1% levels respectively. The sample period is February 1996 through December 2014.

Variables	$\hat{\beta}$	t-stat.	R^2	R^2_{up}	R^2_{down}
Panel A: News-based Measures					
$JointNews^M$	−0.883***	−2.645	3.565	2.191	2.997
$JointNews^M_{ew}$	−0.731**	−1.973	2.438	1.822	0.474
$SelfNews^M$	−0.308	−0.924	0.429	0.109	4.674
Panel B: News Tone, Investor Sentiment and Attention					
News Tone	−0.204	−0.592	0.190	0.269	0.018
Sent^{BW}	−0.682**	−2.412	2.151	2.162	1.111
Sent^{PLS}	−0.835***	−2.798	3.224	1.280	8.777
Attn^{PLS}	−0.736**	−2.191	2.505	0.843	14.350
Panel C: Economic Predictors					
DP	0.592	1.190	1.623	4.485	1.153
DY	0.687	1.601	2.180	3.851	3.590
EP	0.138	0.275	0.087	1.213	18.231
DE	0.157	0.314	0.113	0.008	12.365
SVAR	0.693*	1.786	2.222	0.058	4.092
BM	0.319	1.047	0.468	0.597	0.013
NTIS	−0.522	−1.003	1.261	0.037	1.091
TBL	0.248	0.809	0.284	0.426	3.501
LTY	0.329	1.202	0.493	0.625	1.160
LTR	0.110	0.437	0.056	0.005	1.035
TMS	0.090	0.274	0.037	0.087	4.751
DFY	−0.173	−0.304	0.138	0.072	0.798
DFR	0.431	0.814	0.858	0.226	3.022
INFL	0.312	0.722	0.444	0.754	14.203

Table B2 Horse Race for In-Sample Forecasting of Market Returns

This table provides in-sample estimation results for the bivariate predictive regression of monthly excess market returns on $JointNews^M$ or $JointNews^M_{ew}$, and one of the other predictors, Z_t (see Table 2 for the full list of other predictors).

$$R_{m,t+1} = \alpha + \beta X_t + \phi Z_t + \varepsilon_{t+1},$$

where $R_{m,t+1}$ denotes the monthly excess market return (%). The significance of the estimates are based on Newey-West t-statistics with the six lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. The sample period is February 1996 through December 2014.

	$JointNews^M$			$JointNews^M_{ew}$		
Variables	$\hat{\beta}$	$\hat{\phi}$	R^2	$\hat{\beta}$	$\hat{\phi}$	R^2
Controlling for Self News						
$SelfNews^M$	−0.868***	−0.051	3.576	−0.698**	−0.140	2.522
Controlling for News Tone, Investor Sentiment and Attention						
News Tone	−0.879**	−0.173	3.703	−0.725*	−0.168	2.569
Sent^{BW}	−0.834**	−0.602**	5.244	−0.653	−0.583*	3.997
Sent^{PLS}	−0.798**	−0.729***	6.011	−0.674*	−0.772***	5.204
Attn^{PLS}	−0.829***	−0.652**	5.510	−0.680**	−0.669**	4.489
Controlling for Economic Predictors						
DP	−0.944**	0.703	5.816	−0.797**	0.697	4.643
DY	−0.923**	0.765**	6.241	−0.781*	0.769*	5.133
EP	−0.877***	0.065	3.585	−0.723*	0.071	2.462
DE	−0.917***	0.268	3.895	−0.767**	0.260	2.749
SVAR	−0.729**	0.477	4.516	−0.592**	0.567	3.845
BM	−0.873**	0.279	3.926	−0.719*	0.280	2.802
NTIS	−0.806***	−0.419	4.342	−0.649**	−0.448	3.324
TBL	−0.891***	0.257	3.861	−0.749**	0.277	2.783
LTY	−0.887***	0.318	4.000	−0.750**	0.350	2.965
LTR	−0.909**	0.235	3.814	−0.747*	0.196	2.612
TMS	−0.888***	0.119	3.631	−0.738**	0.122	2.508
DFY	−0.891***	0.030	3.569	−0.721**	−0.047	2.448
DFR	−0.856***	0.364	4.179	−0.730**	0.425	3.279
INFL	−0.856***	0.178	3.706	−0.706**	0.234	2.685

Table B3 Out-of-Sample Forecasting of Market Returns

This table reports the out-of-sample performance of monthly market excess return predictors. Panel A provides the results using the value- and the equal-weighted aggregate joint news index, *JointNews*^{M} and *JointNews*$^M_{ew}$, and the value-weighted aggregate self news index (*SelfNews*). Panel B shows results of the Tetlock, Saar-Tsechansky, and Macskassy (2008) News Tone, the investor sentiment measures proposed by Baker and Wurgler (2007) (Sent^{BW}) and Huang et al. (2015) (Sent^{PLS}), and the composite investor attention measure proposed by Chen et al. (2020b). Panel C shows results using economic predictors (Goyal and Welch, 2008) (see Table 2 for the full list). All the predictors and regression slopes are estimated recursively using the data available at the forecast formation time t. R^2_{OS} is the out-of-sample R^2 with no constraints. $R^2_{OS,up}$ ($R^2_{OS,down}$) statistics are calculated over NBER-dated business-cycle expansions (recessions) based on the unconstrained model. CW test is the Clark and West (2007) MSFE-adjusted statistic calculated according to the prevailing mean model. DM test is the Diebold and Mariano (1995) statistic modified by McCracken (2007) for testing the equality of the MSFE of one forecast relative to another. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. The in-sample estimation period is February 1996 through December 2002 and the out-of-sample evaluation period is January 2003 through December 2014.

Variables	R^2_{OS}	CW test	p-value	DM test	p-value	$R^2_{OS,up}$	$R^2_{OS,down}$
Panel A: News-based Measures							
JointNews^M	5.668***	2.598	0.005	1.984**	0.024	4.997	6.565
JointNews$^M_{ew}$	3.472**	2.306	0.011	1.230	0.109	2.630	4.600
SelfNews^M	0.246	0.660	0.255	0.283	0.389	0.250	0.241
Panel B: News Tone, Investor Sentiment and Attention							
News Tone	−2.120	−1.250	0.894	−1.849	0.968	−3.060	−0.863
Sent^{BW}	1.518	1.207	0.114	0.711	0.238	3.874	−1.636
Sent^{PLS}	4.177***	2.607	0.005	1.931**	0.027	3.032	5.709
Attn^{PLS}	4.041***	2.688	0.004	2.053**	0.020	3.501	4.765
Panel C: Economic Predictors							
DP	−2.866	−0.136	0.554	−0.873	0.809	3.858	−11.862
DY	−1.261	0.269	0.394	−0.404	0.657	4.986	−9.620
EP	−7.911	−0.336	0.631	−1.159	0.877	−3.125	−14.315
DE	−0.519	−0.758	0.776	−0.891	0.813	−0.471	−0.582
SVAR	0.144	0.932	0.176	0.032	0.487	2.082	−2.449
BM	−0.486	0.366	0.357	−0.438	0.669	0.760	−2.154
NTIS	−0.304	−1.573	0.942	−1.754	0.960	−0.097	−0.582
TBL	−0.196	−0.196	0.578	−0.496	0.690	0.193	−0.717
LTY	0.102	0.703	0.241	0.170	0.432	0.637	−0.615
LTR	−0.779	−1.998	0.977	−1.728	0.958	−0.695	−0.891
TMS	−0.561	−1.781	0.963	−2.087	0.982	−0.491	−0.655
DFY	−0.304	−1.573	0.942	−1.754	0.960	−0.097	−0.582
DFR	−4.350	−0.418	0.662	−0.858	0.805	0.341	−10.626
INFL	−0.663	0.007	0.497	−0.446	0.672	−4.250	4.137

Table B4 Long-horizon Return Predictability

This table reports the return 3- and 6-month return predictability of market excess return predictors. Panel A provides the in- and out-of-sample return predictability results using the value-weighted aggregate joint news index (*JointNews*^{M}). Panel B shows the in-sample results for the 3- and 6-month bivariate predictive regression of monthly excess market returns on *JointNews*^{M} and one of the other predictors, Z_t (see Table 2 for the full list of other predictors). *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. The in-sample estimation period is February 1996 through December 2002 and the out-of-sample evaluation period is January 2003 through December 2014.

Panel A: In- and Out-of-sample Analysis

	In-Sample			Out-of-Sample		
Horizon	β	t-stat.	R^2	R^2_{OS}	CW test	p-value
$h=3$	−0.828***	−2.612	8.31	9.317**	1.952	0.025
$h=6$	−0.451**	−2.015	4.49	5.162*	1.49	0.068

Panel B: Horse Race

	$h=3$			$h=6$		
Variables	$\hat{\beta}$	$\hat{\phi}$	R^2	$\hat{\beta}$	$\hat{\phi}$	R^2
Controlling for Self News						
SelfNews^M	−0.887***	0.175	8.753	−0.493**	0.118	4.886
Controlling for News Tone, Investor Sentiment and Attention						
News Tone	−0.833**	−0.163	8.749	−0.457**	−0.125	4.962
Sent^{BW}	−0.790**	−0.570**	12.410	−0.405*	−0.675***	14.809
Sent^{PLS}	−0.763***	−0.633***	13.303	−0.394*	−0.567***	11.737
Attn^{PLS}	−0.783***	−0.665**	13.795	−0.412**	−0.589**	12.247
Controlling for Economic Predictors						
DP	−0.902**	0.744**	15.093	−0.526**	0.752***	17.028
DY	−0.877**	0.758**	15.381	−0.500**	0.752***	17.064
EP	−0.839***	−0.036	8.443	−0.463**	−0.050	4.674
DE	−0.883***	0.375	10.147	−0.507**	0.390	8.010
SVAR	−0.793***	0.131	8.618	−0.523**	−0.200	5.423
BM	−0.821**	0.453*	10.938	−0.439**	0.628***	13.315
NTIS	−0.743***	−0.507	11.445	−0.351**	−0.588	12.024
TBL	−0.848***	0.307	9.540	−0.474**	0.366	7.445
LTY	−0.843***	0.355	9.830	−0.468**	0.403*	7.811
LTR	−0.831***	−0.045	8.451	−0.474**	0.131	4.988
TMS	−0.843***	0.167	8.771	−0.468**	0.217	5.676
DFY	−0.885***	0.199	8.883	−0.537***	0.316	6.693
DFR	−0.819***	0.216	9.000	−0.447**	0.149	5.115
INFL	−0.894***	−0.362	9.959	−0.538**	−0.488**	9.640

Table B5 Asset Allocation Performance

This table reports the annualized CER gains (in %) and annualized Sharpe ratios for a mean-variance investor, who allocates assets between the market and risk-free bills using the out-of-sample forecasts based on the value-weighted aggregate joint news index (*JointNews*^{M}) over the prediction horizon h. $h = 1$ month, 3 months, and 6 months. The investor's risk-aversion (γ) varies from 1 to 5. We consider two scenarios: zero transaction cost and a proportional transaction cost of 50 basis points per transaction. The in-sample estimation period is February 1996 through December 2002 and the out-of-sample evaluation period is January 2003 through December 2014.

	No Transaction Cost		50 bps Transaction Cost	
	CER Gains	Sharpe Ratio	CER Gains	Sharpe Ratio
Panel A: $h = 1$				
$\gamma = 1$	7.196**	1.192***	5.396*	1.037***
$\gamma = 3$	7.943***	0.996***	5.536**	0.763**
$\gamma = 5$	5.770***	0.883***	3.571**	0.602**
Panel B: $h = 3$				
$\gamma = 1$	7.423*	1.176***	6.935*	1.115**
$\gamma = 3$	7.813***	1.194***	7.115***	1.097***
$\gamma = 5$	5.571***	1.128***	4.936***	1.009***
Panel C: $h = 6$				
$\gamma = 1$	3.843	0.824***	3.510	0.786**
$\gamma = 3$	4.570**	0.891***	4.339**	0.830***
$\gamma = 5$	2.988**	0.776**	2.806**	0.708**