News Co-Occurrence, Attention Spillover and Return Predictability

Li Guo*

Singapore Management University

Lin Peng†

Baruch College

Yubo Tao‡

Singapore Management University

Jun Tu§

Singapore Management University

November, 2018

*Lee Kong Chian School of Business, Singapore Management University. 50 Stamford Road, Singapore, 178899. E-mail: liguo.2014@pbs.smu.edu.sg.

†Zicklin School of Business, Baruch College/CUNY. One Bernard Baruch Way, 10-225, New York, NY 10010. Email: lin peng@baruch.cuny.edu. Phone: (646) 312-3491.

‡School of Economics, Singapore Management University. 90 Stamford Road, Singapore, 178903. E-mail: yubo.tao.2014@phdecons.smu.edu.sg.

§We are grateful to Zhi Da, Tse-Chun LIN (discussant), Nancy Xu (discussant), Jorida Papakroni (discussant) and participants at the 2018 SMU Finance Summer Camp, the 2018 China International Conference in Finance and 2018 Financial Management Association Annual Conference, for their very helpful comments.

Corresponding author. Lee Kong Chian School of Business, Singapore Management University, 50 Stamford Road, Singapore, 178899. E-mail: tujun@smu.edu.sg. Phone: (65) 6828-0764.

Jun Tu acknowledges that the study was funded through a research grant from Sim Kee Boon Institute for Financial Economics. The usual disclaimer applies. A previous version of this paper has been circulated under the title, "Media Network Based Investors' Attention: A Powerful Predictor of Market Premium".

News Co-Occurrence, Attention Spillover and Return Predictability

Abstract

We examine the effect of investor attention spillover on stock return predictability. Using a novel measure, the News Network Triggered Attention index (NNTA), we find that NNTA negatively predicts market returns with a monthly in(out)-of-sample R^2 of 5.97% (5.80%). In the cross-section, a long-short portfolio based on news co-occurrence generates a significant monthly alpha of 68 basis points. The results are robust to the inclusion of alternative attention proxies, sentiment measures, other news- and information-based predictors, across recession and expansion periods. We further validate the attention spillover effect by showing that news co-mentioning leads to greater increases in Google and Bloomberg search volumes than unconditional news coverage. Our findings suggest that attention spillover in a news-based network can lead to significant stock market overvaluations, and especially when arbitrage is limited.

JEL Classification: G11, G12, G41.

Keywords: Investors attention; Network; Return predictability; Short-sales constraint; Media coverage; News tones; Heterogeneous belief.

Among numerous studies regarding the stock market return predictability, most of them are about information-based predictors, usually adopt hard information (e.g., fundamental economic variables in Goyal and Welch (2008)) and recently turn to soft information (e.g., news tones in Tetlock (2007)). However, without investor attention, information per se is unable to move stock prices. Given that investor attention has been documented as one of the most important driving forces of stock returns in recent literature, it is surprising that there is a lack of investigation on the impact of investor attention on market premium forecasting. In this paper, we construct a novel attention-based predictor, i.e., *news network triggered attention* (NNTA) index, for forecasting market equity premium.

There is evidence suggesting that attention is a scarce resource for investors, especially for individual investors [1]. Therefore, it is likely that investor recognition of a security is limited (Merton (1987)), and they may only attend to information regarding the stocks that they are aware of or hold while paying little attention to the others. When multiple stocks are mentioned in the same news story, investor recognition to one stock is spilled over to the co-mentioned stocks, thereby increasing the attention to all the mentioned stocks. The news network-based attention spillover, with the presence of short sale constraints, can lead to a stronger reaction to good news than bad news (Barber and Odean (2008)), which in turn results in overvaluation, and subsequent underperformance.

In this study, by aggregating the news about all the stocks in the market on monthly basis, we formulate the NNTA index using the adjacency matrix in network analysis to gauge the fraction of the attention for non-shareholders type of investors induced by the news co-occurrence triggered attention spillover. We expect that the higher NNTA index, the larger the overvaluation of the aggregate stock market. Consistently, we find that our proposed attention-based predictor, NNTA, can forecast the market premium with a significantly negative coefficient and 5.97% and 5.80% monthly in-sample and out-of-sample R^2 respectively. In addition, our findings are statistically as well as economically significant even when we control for alternative attention proxies, news-based predictors, and information-based predictors, including economic predictors used in Goyal and Welch (2008), media coverage

[1] Related work include Kahneman (1973), Shiller, Fischer and Friedman (1984), Merton (1987), Shiller (1999), Barberis and Shleifer (2003), Peng (2005), Peng and Xiong (2006), Gabaix, Laibson, Moloche and Weinberg (2006), Cohen and Frazzini (2008a), Hirshleifer, Lim and Teoh (2009), DellaVigna and Pollet (2009) and Van Nieuwerburgh and Veldkamp (2009).

following Fang and Peress (2009), Google search index[2], the 52-week high following George and Hwang (2004), analyst coverage and trading volume aggregated from individual S&P500 stocks using value weight, and news tones based on Loughran and McDonald (2011) dictionary (Engelberg, 2008; Gurun and Butler, 2012; Hillert *et al.*, 2014; Solomon *et al.*, 2014; Tetlock *et al.*, 2008). Under our empirical setting, NNTA shows the strongest in-sample and out-of-sample predictability of market premium among all the predictors. We also examine the performance of NNTA in predicting returns during the recession and expansion periods. It shows that NNTA obtains larger and positive R^2s in both recession and expansion periods comparing with alternative predictors. We further verify the investor attention channel by predicting cross-sectional portfolios and find more frequent news co-occurrence produces lower returns. The long-short portfolio based on abnormal connected news coverage generates a 0.68% monthly return with statistical significance at 1% level. The conventional risk factors such as Carhart (1997) four-factor, Hou *et al.* (2015) q-factor and Fama and French (2016) five-factor models are unable to explain the alphas generated by our news network triggered attention.

To source the economic interpretation of NNTA, we check the average correlation of Google and Bloomberg search volumes between the connected stock pairs. It shows that the stock pairs that are more frequently connected tend to enjoy higher correlation of Google and Bloomberg search volumes. In accordance to Da *et al.* (2011), correlated search activities directly support the conjecture that the NNTA constructed from news co-occurrence measures investor attention. Since investor attention needs heterogeneous belief or short-sales constraint to generate asymmetric buying pressure (Hong and Stein, 2007), we then check the return predictability performance of NNTA index under different scenarios of investor disagreement and short-sales constraint. Expectedly, the NNTA index shows significant return predictability only when investors' beliefs are highly divergent and the short-sales constraint is tight. We further illustrate that the NNTA index composed of the stocks with higher retail investor ownership has stronger return predictability as retail investors are more constrained to short-sales. These results are consistent with the intuition that stock mispricing is more profound when investor disagreement is high and short-sales constraint is more binding.

[2]We calculate the frequency of the search queries with key words "S&P500", "SP500", "S&P 500" or "SP 500" in Google over the sample period 2004:01-2014:12.

Our paper has shed new light on a different aspect of investor attention. In Peng and Xiong (2006), they documented that investors tend to process more market information than firm-specific information due to limited attention, which results in a return co-movement phenomenon. A follow-up work Peng *et al.* (2007) shows that under both limited attention and attention shifts assumptions, one can explain time-varying asset co-movement. In terms of news attention, Odean (1999) and Barber and Odean (2008) found that individual investors are more likely to trade the stocks that have grabbed their attention due to limited attention in searching what to trade, especially for buying stocks. Fang and Peress (2009) and Fang *et al.* (2014) further examined the cross-sectional return predictability and mutual funds' trading and performances using media coverage as the proxy of attention-grabbing events, and they also find evidence that both individual and institutional investors subject to limited attention. Different from those papers, we identify an efficient proxy for investor attention through media network formation. This proxy address the fact that non-shareholders' trading behaviour is more subject to short-sales constraint comparing to that of shareholders. Therefore, our proxy is more powerful in predicting the market premium than those proxies without distinguishing the roles of the investors.

We also contribute to the literature that studies financial media's role in return predictability. In the past decades, the literature that investigates the media's role in financial markets mainly examines how do the news tones between the lines predict stock prices. Tetlock (2007) presented that the linguistic tone, especially negative tones, can predict market excess returns. Tetlock *et al.* (2008) further explored the cross-sectional return predictability by processing firm-specific news. Similarly, Zhang *et al.* (2016) documented a sector-specific reaction based on their distilled sentiment measure. Jegadeesh and Wu (2013) further improved Tetlock (2007) with a term weighting scheme based on OLS and Naïve Ba, and they also find significant return predictability of news articles. Unlike these studies that focus on extracting information from firm-specific news, we isolate the connected news from this dataset and we show that these news possesses valuable information for predicting market premium.

Lastly, we contribute to the literature that applies network analysis in financial studies. Cohen and Frazzini (2008b) and Menzly and Ozbas (2010) find that economic links among certain individual firms and industries contribute to cross-firm and cross-industry return predictability. They interpret their results as evidence of gradual information diffusion across economically connected firms, in line with the theoretical model of Hong *et al.* (2007). Rapach *et al.* (2015) investigate the predictability of industry returns base on a wide range of industrial interdependencies. Different from the above literature, we are the first paper to construct the market-wide media network and provide direct evidence of its market return predictability.

The rest of the paper is organized as follows. In section 1, we review the literature exploring media network in financial markets and make some essential assumptions for subsequent analysis. In section 2, we show how to compose a comprehensive measure of media-network-based attention index. Then, we conduct some empirical tests and present our results in section 3. In section 4, we provide economic explanations to our NNTA. We conclude in section 5.

1 Media Connection and Media Network

Media connection, by definition, is an inter-relationship that is built via news stories which may through explicit mentions or implicit affections. The explicit mentions, also known as media co-occurrence, is the most natural way of formulating the connectivity of two entities. Özgür *et al.* (2008) first studied the social network inferred from the co-occurrence network of Reuters news. They show that the network exhibits small-world features with power-law degree distribution and it provides a better prediction of the ranking on "importance" of people involved in the news comparing to other algorithms. Scherbina and Schlusche (2015) studied the cross-predictability of stock returns by identifying the economic linkage from co-mentions in the news story. They constructed a linkage signal using the weighted average of the connected stock returns and they find that the linked stocks cross-predict one anothers returns in the future significantly, and the predictability increases with the number of the connected news.[3]

Complementary to explicit mentions, the connection may also be built through implicit af-

[3]The *connected news* we are referring to throughout this paper is defined as the news that mentions more than one firm.

fections. One of the most well-known channels is the industrial chain. As shown in Cohen and Frazzini (2008b), economic links among certain individual firms and industries contribute significantly to cross-firm and cross-industry return predictability. Rapach *et al.* (2015) extends the perspective of Cohen and Frazzini (2008b) by defining a connection between industries with the predictability of returns. Through these industrial interdependencies, the news that conveys information on one industry will also percolate into the other industries. Due to the competitive relationship of stocks within the industry, the good (bad) news to one stock will be bad (good) news to its competitors. Business interaction is another important channel news to travel from one firm to another.

Based on media connections, we can formulate a news network by taking the whole picture of the connected stocks as an undirected graph with firm size or centrality tagged on each stock. In network analysis context, all these information can be captured by the *adjacency matrix* or *weighted adjacency matrix*.[4] Apart from the adjacency matrix, we also need to make some essential and reasonable assumptions on news arrival and network structures in advance to simplify our analysis.

Assumption 1 (Random News Arrival)**.** *Connected news arrives randomly and investors have no prior information on the distribution of news arrival.*

In Daley and Green (2012) and Rubin *et al.* (2017), they presume the news arrival follows some stochastic process or is priori unanticipated. This assumption is reasonable as investors face two tiers of randomness. The first tier of randomness comes from the arrival of a firm-specific news event and the second tier comes from the news linkages. In reality, a news event is always unpredictable, and even though investors realize a news event will occur, the stocks that the news will mention are still mysterious to the investors.

Assumption 2 (Multi-degree Network)**.** *The attention that the connected news attracts not only affects the directly connected stocks but also indirectly connected stocks.*

To fit stocks into a network structure, the attention attracted by connected news could travel through the news linkages. Attention induced by news co-mentions will not only affect

[4]In graph theory and computer science, an *adjacency matrix* is a square matrix used to represent an unweighted graph. The elements of the matrix indicate whether pairs of vertices are adjacent or not in the graph. For *weighted adjacency matrix*, it is square matrix used to represent a weighted graph whose edges are tagged with a weight to denote some relationship between the nodes, e.g. distance. The elements of the matrix are just the weight of the edges.

the directly linked stocks but also the stocks with indirect connections. The importance of each node (stock) will depend on its connections with all the other nodes (stocks) in this news network. To account for this indirect effect, we use some measures to weigh the importance of a stock in the market and we will discuss them in detail in the rest of the paper.

2 Data and Methodology

In this section, we introduce the data sources and explain the intuition behind the news network triggered attention index[5]. Then, we introduce the alternative predictors that we can compete with and their corresponding data sources.

2.1 News network triggered attention

The data we use for constructing media network is the firm-specific news from the Thomson Reuters News Analytics and Archive dataset ranging from Jan-1996 to Dec-2014. The data contains various types of news, e.g. reviews, stories, analysis and reports etc., about markets, industries and corporations. It also provides three probabilities, namely, Pos^{NN} (the probability of the article being positive), Neg^{NN} (the probability of the article being negative), and Neu^{NN} (the probability of the article being neutral) for all the mentioned firms in each piece of news. These three probabilities sum up to 1 and are being computed from a neural-network-based sentiment engine. In subsequent analysis, we will use Neg^{NN} and Opt^{NN} ($Pos^{NN} - Neg^{NN}$) in addition to soft information predictors.

The news network triggered attention measure is constructed in three steps. We first classify the news into two categories: *connected news* that mentions more than one stock and the *self news* that only refer to one stock. Empiricists used to measure investor attention indirectly by counting the total number of mentions (news coverage) (Barber and Odean, 2008) or appearance in headlines (Yu, 2015) without distinguishing the subtle difference in these two type of news. Specifically, self news may only attract investors that care about this stock ex ante or have already held its shares, while connected news not only draws attention from relevent investors, but also may trigger those investor who only care about one stock mentioned to pay attention to other stocks co-mentioned. Therefore, connected news could

[5]A rigorous mathematical formulation about the construction of this index is provided appendix.

substantially enlarge the investor base comparing to self news. Based on this distinction, for any given pair of stocks, we separately calculate self news coverage of both stocks and the connected new coverage between them. Then, we rescale connected news coverage by its self news coverage to measure connected news' contribution to overall investor base. Lastly, we follow Da *et al.* (2011) to construct abnormal attention measure by taking the first difference of the rescaled connected news coverage, which may also help with detrending potentially nonstationary time series.

So far, we implicitly assume that each stock in the news network is equally important such that each stock's abnormal investor attention takes an equal weight. In reality, the more important firms are more easily to seize investor attention. Therefore, we propose to adjust abnormal connected news coverage by the importance of stocks. In this paper, we measure the importance of the stocks in two dimensions. One dimension is the firm's own characteristic, i.e, *firm size*, which determines how much investor attention the firm could attract by itself. The other dimension is the overall importance of the connected firms, i.e, *centrality*, which evaluates how much investor attention the firm could attract through connecting to other firms. In particular, centrality is a specialized measure that helps rank the importance of the vertices in the network using the edge information. As introduced in Newman (2010), there are various types of centrality measures applying in network analysis (e.g. degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, etc.), and we choose to use eigenvector centrality in our study. Specifically, we first define the adjacency matrix $\mathcal{A}_t$,

$$\mathcal{A}_t = \begin{array}{c} \\ stock_1 \\ stock_2 \\ \vdots \\ stock_N \end{array} \begin{array}{c} \begin{array}{cccc} stock_1 & stock_2 & \cdots & stock_N \end{array} \\ \begin{bmatrix} a_{11,t} & a_{12,t} & \cdots & a_{1N,t} \\ a_{21,t} & a_{22,t} & \cdots & a_{2N,t} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1,t} & a_{N2,t} & \cdots & a_{NN,t} \end{bmatrix} \end{array}. \tag{2.1}$$

where $a_{ij,t} = 1$ if there exists news that co-mentions stock i and j at time t, and 0 otherwise. Then, we calculate the eigenvector, $\mathbf{x}_t$, that corresponds to the largest eigenvalue[6] ($\lambda_{\max}$) of

[6]In this way, the corresponding eigenvector captures the most variations of the column vectors projected onto the eigenspace, which can be used to describe the informativeness of the links in a network context (Newman, 2010).

the adjacency matrix and define the values of $\mathbf{x}_t$ as our centrality score, i.e.,

$$\mathcal{A}_t\mathbf{x}_t = \lambda_{\max}\mathbf{x}_t, \text{ for each } t = 1, 2, \cdots, T, \tag{2.2}$$

where $\mathbf{x}_t = (Ctry_{1,t}, Ctry_{2,t}, \cdots, Ctry_{N,t})'$ and $Ctry_{i,t}$ stands for the eigenvector centrality score of stock i at time t.

Unlike the degree centrality that awards nodes according to its number of degrees, eigenvector centrality thinks not all vertices are equivalent: some are more relevant than others, and, reasonably, endorsements from important nodes count more. So, the eigenvector centrality indicates that a node is important if it connects to other important nodes. Take a simple network in Figure 1 as an example, each vertex in the network represents a firm and the edges indicate the media connections induced by news co-occurrence. The degree centrality suggests that firm 1 and 3, firm 2 and 6, or firm 4 and 5 are equally important since they have the same degrees. However, although firm 2 and 6 both have two degrees and connect to firm 1, firm 6 connects to firm 3 which has more degrees than firm 4. Therefore, we should expect firm 6 to be more important than firm 2 in terms of spreading the news as it has more second-degree connections. Similarly, we should also expect firm 1 and 5 to take a more central position than firm 3 and firm 4, respectively. This intuition is confirmed by the eigenvector centrality scores $[0.5641, 0.2960, 0.5454, 0.1268, 0.2337, 0.4753]$. Clearly, the eigenvector centrality scores fit the situation better in describing the propagation of news.

[Insert Figure 1 here.]

Evidently, the firm size and the centrality complete each other in describing the importance of a firm in the context of attention attraction and news diffusion. To combine these two aspects, we then formulate a composite news network triggered attention index, NNTA, as the simple average of the two standardized attention measures as in equation (2.3). Since both measures likely contain information about investors' attention as well as idiosyncratic non-attention noise, the composite NNTA measure helps to capture the common investor attention component in the connected news and diversify away the idiosyncratic noise.

$$NNTA_t = 0.5NNTA_t^{sz} + 0.5NNTA_t^{ctr}. \tag{2.3}$$

In Figure 2, we plot the composite NNTA index and the other two individual NNTA indices. Generally, the size-based index shows a similar pattern as centrality weighted attention index (with correlation coefficient 0.41), which means large stocks also tend to be those with high centrality scores and both indices reflect similar information content. However, these two indices still differ especially during the expansion period, which implies it would be beneficial to combine these two indices. By construction, NNTA correlates with NNTA^{sz} and NNTA^{ctr} at similar level, 0.72 and 0.78, respectively.

[Insert Figure 2 here.]

2.2 Alternative predictors

To ensure NNTA captures a different aspect of investor attention, we would like to control for some alternative attention measures in the predictive regression. According to Barber and Odean (2008) and Fang and Peress (2009), media coverage is a critical proxy for investor attention and has a significant impact on stock returns. Therefore, we construct market-wide news coverage from Dow Jones and Wall Street Journal articles by searching the keywords "S&P500", "SP500", "S&P 500" or "SP 500" on Factiva and obtain firm specific news coverage from Thomson Reuters News Archive. In addition, we take the first difference for these predictors to obtain the abnormal media coverages, labeled as ΔTRN, ΔDJI, and ΔWSJ.

Other than news coverage, we also construct various attention measures based on the literature, such as, Google search volume (*Google Search*) of keywords "S&P500", "SP500", "S&P 500" and "SP 500" in the spirit of Da *et al.* (2011), 52-week highest price indicator (Prc^{High}) following George and Hwang (2004), level and change of average number of analysts aggregated from individual S&P500 stocks using value weight (*Analyst* and Δ*Analyst*) and the residual of Analyst coverage regressing on Nasdaq index and firm size (*Analyst_r*) following Hong *et al.* (2000), and value-weighted trading volume of each stock (*TrdVol*) and the abnormal trading volume ($\Delta TrdVol$) in the spirit of Gervais *et al.* (2001).

In addition to attention proxies, other factors that possess strong return predictability are considered as controls to rule out other possible interpretations. The first set of the factors are news tones, e.g., negative news tone for individual stock i in month t is calculated as $Neg = \frac{\#\ of\ Neg\ Words_{i,t}}{Total\ \#\ of\ Words_{i,t}}$, and the optimistic news tone is $Opt = \frac{\#\ of\ Pos\ Words_{i,t} - \#\ of\ Neg\ Words_{i,t}}{Total\ \#\ of\ Words_{i,t}}$, where positive words and negative words follow Loughran and McDonald (2011) dictionary. The second set of factors are those that may affect investors' beliefs, namely, the sentiment indices (Baker and Wurgler, 2006; Huang *et al.*, 2014) and uncertainty indices, including VIX, economic uncertainty index (UNC) in Bali *et al.* (2014), treasury implied volatility (TIV) in Choi *et al.* (2017), economic policy uncertainty (EPU) in Baker *et al.* (2016), financial uncertainty (FU), and economy uncertainty (EU) in Jurado *et al.* (2015). The last set of factors are economic predictors that are linked directly to economic fundamentals. Specifically, we collect factors in Goyal and Welch (2008) from Amit Goyal's website: the log dividend-price ratio (D/P), log dividend yield (D/Y), log earnings-price ratio (E/P), log dividend payout ratio (D/E), stock return variance (SVAR), book-to-market ratio (B/M), 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 rates (INFL). Additionally, we follow Morck *et al.* (2000) to construct the *Earnings Co-movement Index* (ECI) for controlling fundamental correlations. We first run the regression

$$ROA_i = a_i + b_i \times ROA_m + \epsilon_i, \tag{2.4}$$

for each firm i in each period. ROA_i is a firms returns on assets, calculated as annual after-tax profit plus depreciation over total assets. ROA_m is the value-weighted average of the return on assets for all firms.

$$Earnings\ Co\text{-}movement\ Index = \frac{\sum_i R_i^2(ROA) \times SST_i(ROA)}{\sum_i SST_i(ROA)}, \tag{2.5}$$

where $R_i^2(ROA)$ and $SST_i(ROA)$ are the R^2 and the sum of squared total variations derived from regression (2.4) for firm i. A higher ECI indicates that the earnings frequently move together. All the variables used in the paper are summarized in Table 1.

[Insert Table 1 here.]

From the summary statistics in Table 1 we can observe that the monthly excess market return has a mean of 0.41% and a standard deviation of 4.49%, implying a monthly Sharpe ratio of 0.09. It also can be observed that most of the economic predictors are highly persistent while the excess market return has little autocorrelation. These summary statistics are generally consistent with the literature.

3 Predicting Stock Market Returns with News Co-occurrence

In this section, we provide a number of empirical results. Section 3.1 examines the time series return predictability of the NNTA index on the aggregate market level. Section 3.2 compares the in-sample return predictability of NNTA index with alternative predictors. Section 3.3 analyses the out-of-sample predictability. Lastly, Section 3.4 assesses the cross-sectional predictability of the NNTA index.

3.1 Forecasting the market

Consider the standard predictive regression model,

$$R^m_{t+1} = \alpha + \beta X_t + \epsilon_{t+1}, \tag{3.1}$$

where R^m_{t+1} is the excess market return, i.e., the monthly return on the S&P500 index in excess of the risk-free rate, and X_t is the NNTA index or other predictor. For comparison, we also run the same in-sample predictive regression with media coverage indices, alternative attention proxies, news tones, investor sentiment, uncertainty factors, earnings comovement index and equal-weighted short interest ratio. Specifically, we test the null hypothesis $\mathcal{H}_0 : \beta = 0$, which means NNTA has no predictability for stock returns, against the alternative $\mathcal{H}_1 : \beta \neq 0$. Under the null hypothesis, (3.1) reduces to the constant expected return model, $R^m_{t+1} = \alpha + \epsilon_{t+1}$.

[Insert Table 2 here.]

Table 2 reports the results of in-sample predictive regressions. Economically, the OLS coefficient suggests that a one-standard-deviation increase in NNTA is associated with an approximate 1.09% decrease in expected excess market return for the next month. On the one hand, recall that the average monthly excess market return during our sample period is 0.41%, thus the slope of -1.09% implies that the expected excess market return based on NNTA varies by 2.7 times of the magnitude of its average level, which indicates a strong economic impact. On the other hand, if we annualize the 1.09% decrease in one month with the multiplication of 12, the annualized level of 13.08% is somewhat large. In this case, one may interpret this as the model-implied expected change may not be identical to the reasonable level of expected change of the investors in the market. Empirically, this level is significantly larger than conventional macroeconomic predictors. For example, a one-standard-deviation increase in the D/P ratio, the CAY and the net payout ratio tends to increase the risk premium by 3.60%, 7.39%, and 10.2% per annum, respectively (see, e.g. Lettau and Ludvigson (2001) and Boudoukh *et al.* (2007)).

The R^2 of NNTA with OLS forecast is 5.97%, which is substantially greater than all alternative attention proxies as well as soft/hard information predictors. This implies that if this level of predictability can be sustained out-of-sample, it will be of substantial economic significance (Kandel and Stambaugh (1996)). Campbell and Thompson (2008) show that given the large unpredictable component inherent in the monthly market returns, a monthly out-of-sample R^2 of 0.5% can generate significant economic value and our findings in section 3.3 are consistent with this argument.

Apart from analyzing the predictability over the whole sample period, it is also important to check the predictability during business cycles so that we can gain a better understanding of the fundamental driving forces. Following Rapach *et al.* (2010), we compute the R^2 statistics separately for economic expansions (R^2_{up}) and recessions (R^2_{down}),

$$R_c^2 = 1 - \frac{\sum_{t=1}^{T} 1_{\{t\in\mathbb{T}_c\}} \cdot \epsilon_t^2}{\sum_{t=1}^{T} 1_{\{t\in\mathbb{T}_c\}} \cdot (R_t^m - \bar{R}^m)^2}, \quad c \in \{up, down\}, \tag{3.2}$$

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 in an NBER expansion (recession) period, i.e., $\mathbb{T}_{up}$ ($\mathbb{T}_{down}$), and zero otherwise; ϵ_t is the fitted residual based on the in-sample estimates of the predictive regression model in (3.1); $\bar{R}^m$ is the full-sample mean of R_t^m; and T is the number of observations for the full sample. Note that, unlike the full-sample R^2 statistic, the R^2_{up} (R^2_{down}) have no sign restrictions. Columns 4 and 5 of Table 2 report the R^2_{up} and R^2_{down} statistics. It is shown that NNTA gains return predictability over the recessions twice as large than over the expansions. In addition, NNTA has significant higher return predictability than all the other predictors over the expansion periods, and it only underperforms abnormal WSJ news coverage over the recessions. This confirms that our news-network-based attention proxy possesses a stable predictive power of market premium under all economic environments.

3.2 Comparison with economic predictors

In this subsection, we compare the forecasting power of NNTAs with alternative predictors and examine whether its forecasting power is driven by omitted attention proxies, soft information, or economic variables related to business cycle fundamentals. Specifically, we examine whether the forecasting power of NNTA remains significant after controlling for other predictors. To analyze the marginal forecasting power of NNTA, we conduct the following bivariate predictive regressions based on NNTAs and other predictors,

$$R_{t+1}^m = \alpha + \beta X_t + \phi Z_t + \epsilon_{t+1}, \tag{3.3}$$

where X_t is one of the NNTA indices, and Z_t is one of the alternative predictors described in section 2.2, and our main interest is the coefficient β, and to test $\mathcal{H}_0 : \beta = 0$ against $\mathcal{H}_1 : \beta \neq 0$.

[Insert Table 3 here.]

Table 3 shows that the estimates of β in (3.3) are negative and stable in magnitude, which is in line with the results of predictive regression (3.1) reported in Table 2. More importantly, β remains statistically significant when augmented by other predictors. These results illustrate that NNTA contains sizeable complementary forecasting information beyond what is contained in the media coverage, alternative attention proxies, and other mainstream return predictors. Noticing that controlling other predictors does not undermine NNTA's impact (β remains almost the same magnitude as reported in Table 2), we are confident to claim that the information content of news network based predictors are not overlapping with existing attention proxies.

3.3 Out-of-sample forecasts

The in-sample analysis provides more efficient parameter estimates and thus more precise return forecasts by utilizing all available data. Goyal and Welch (2008), among others, argue that out-of-sample tests seem more relevant for assessing genuine return predictability in real time and avoid the over-fitting issue, and are much less affected by 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 NNTA indices.

For out-of-sample forecasts at time t, we only use 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 (3.4) recursively based on our news network triggered attention index,

$$\hat{R}^m_{t+1} = \hat{\alpha}_t + \hat{\beta}_t X_{1:t;t}, \tag{3.4}$$

where $X_{1:t;t}$ is the recursively estimated composite NNTA index or individual NNTA indices, $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates from regressing $\{R^m_{r+1}\}_{r=1}^{t-1}$ with model (3.1) recursively. We also carry out out-of-sample regressions using the same alternative predictors as in previous sections. The corresponding results are summarized in Panel B to F of Table 4.

To assess the out-of-sample performance, we apply the widely used Campbell and Thompson (2008) R^2_{OS} statistics based on unconstrained forecast and truncated forecast that imposing non-negative equity premium constraint. The unconstrained R^2_{OS} statistic measures the proportional reduction in 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 individual economic variables typically fail to outperform the historical average. To compute R^2_{OS}, let r be a fixed number chosen for the initial sample training, so that the future expected return can be estimated at time $t = r+1, r+2, ..., T$. Then, we compute $s = T - r$ out-of-sample forecasts: $\{\hat{R}^m_{t+1}\}_{t=r}^{T-1}$. More specifically, we use first 1/3 data over 1996:01 to 2002:06 as the initial estimation period so that the forecast evaluation period spans from 2002:07 to 2014:12.

$$\hat{R}^2_{OS} = 1 - \frac{\sum_{t=r}^{T-1}(R^m_{t+1} - \hat{R}^m_{t+1})^2}{\sum_{t=r}^{T-1}(R^m_{t+1} - \bar{R}^m_{t+1})^2}, \tag{3.5}$$

where $\bar{R}^m_{t+1}$ denotes the historical average benchmark corresponding to the constant expected return model ($R^m_{t+1} = \alpha + \epsilon_{t+1}$), i.e.,

$$R^m_{t+1} = \frac{1}{t}\sum_{s=1}^{t} R^m_s. \tag{3.6}$$

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

The statistical significance of the out-of-sample R^2s we report is based on the MSFE-adjusted statistic of Clark and West (2007) (CW-test hereafter). It tests the null hypothesis that the historical average MSFE is not greater than the predictive regression forecast MSFE against the one-sided (right-tail) alternative hypothesis that the historical average MSFE is greater than the predictive regression forecast MSFE, corresponding to $\mathcal{H}_0 : R^2_{OS} \leq 0$ against $\mathcal{H}_1 : R^2_{OS} > 0$. Clark and West (2007) show that the test has a standard normal limiting distribution when comparing forecasts from the nested models. Intuitively, under the null hypothesis that the constant expected return model generates the data, the predictive regression model will produce a noisier forecast than the historical average benchmark as it estimates slope parameters with zero population values. We thus expect the benchmark models MSFE to be smaller than the predictive regression model's MSFE under the null. The MSFE-adjusted statistic accounts for the negative expected difference between the historical average MSFE and predictive regression MSFE under the null so that it can reject the null even if the R^2_{OS} statistic is negative.

[Insert Table 4 here.]

Panel A of Table 4 shows that NNTA index generates positive and significant R^2_{OS} statistics (5.80%) and delivers a lower MSFE than the historical average. Hence, it is safe to conclude that NNTA has strong out-of-sample predictability for market returns, which confirms our conjectures in previous in-sample results (Table 2). Comparing with NNTA, all the other predictors show much weaker out-of-sample predictability for market excess returns as shown in Panel B to F. In general, most of the alternative predictors have negative out-of-sample R^2s, and their CW-statistics are insignificant. Obviously, our NNTA index is a more powerful predictor of market returns amongst other attention proxies and news-related predictors. The last two columns of Table 4 show that the predictability of the NNTA index is significantly strong and stable over both expansion and recession periods.

In summary, out-of-sample analysis shows that, consistent with our previous in-sample results (Tables 2 and 3), NNTA index is a powerful and reliable predictor for the excess market returns, and consistently outperforms other state-of-the-art return predictors in out-of-sample sense.

3.4 Forecasting cross-section portfolio

The news co-occurrence generates excessive investor attention from enlarged investor base. Due to short-sales constraint, bullish investors can simply buy the connected stocks while bearish investors (especially the non-shareholders or retail investors) are hard to short-sell (Barber and Odean, 2008). Consequently, an increased news co-occurrence injects more buying pressure than selling pressure into the prices of connected stocks, hence pushing up the prices of the connected stocks above their fair values.

Based on this logic, we can construct a cross-sectional portfolio that generates positive returns through buying the stocks with low abnormal connected news coverage and sell those with high abnormal connected news coverage. In particular, we construct 10 value-weighted portfolios by sorting the stocks into deciles according to their total abnormal connected news coverage ratio, i.e., $\sum_j aw_{ij,t}$. Considering a significant number of stocks do not have any connected news, we label those stocks as the lowest attention portfolio. For the rest, we divide them into 9 groups. All portfolios are rebalanced monthly at the close price of next month. The performances of cross-sectional portfolios are shown in the second column of Table 5. Expectedly, the portfolio with lowest abnormal connected news coverage ratio (long lag) gains a significant higher portfolio return of 0.68% per month (t-statistic = 3.02) than the portfolio with highest abnormal connected news coverage.

[Insert Table 5 here.]

In the last three columns of Table 5, we also test if the cross-sectional portfolio returns can be explained by existing factor models. We apply Carhart (1997) four-factor model, Hou *et al.* (2015) q-factor model and Fama and French (2016) five-factor model to dissect risk adjusted alphas. The results show that our portfolio remains a consistently significant alpha of 0.47% per month at least. This is a strong evidence indicating that connected news indeed captures a different aspect of market excess returns that is hardly explained by conventional risk factors.

4 Economic Explanations

In this section, we explore the source of predictability of NNTA through different channels. First and foremost, we test if higher news co-occurrence induces more correlated search activities, which is an important proxy for investor attention (Da *et al.*, 2011). Then, we explore why connected news is powerful in predicting negative returns by relating it to investor base. Lastly, we examine the performance of NNTA in different environments of investor sentiment, belief divergence, and short-sales constraint.

4.1 Connected news and search activities

As discussed in Da *et al.* (2011), the attention proxies based on the media coverage heavily rely on the "investor recognition hypothesis", i.e., if a stock's name was mentioned in the news media, then investors should have paid attention to it. However, news coverage does not guarantee attention unless investors actually read it. To address this issue, Da *et al.* (2011) proposed an active attention measure, Google search volume (SVI), for investor attention. Therefore, if we find news co-occurrences can induce correlated search or even stronger, co-search activities, it is a clear evidence to show NNTA indeed reflects investor attention.

Considering connected news coverage between stocks is quite sparse, we classify stock pairs into 5 groups base on the range of connected news coverage to ensure sufficient observations in each group. Specifically, we assign stock pairs with no connected news to group 1, stock pairs with 1 to 5 connected news to group 2, stock pairs with 6 to 10 connected news to group 3, stock pairs with 11 to 15 connected news to group 4, and the rest pairs to group 5. Table 6 summarizes number of observations in each group from Jan, 2005 to Dec, 2014 and Figure 3 presents the log number of stock pairs in each group. According to Figure 3, our classification balances the number of observations in each group reasonably well after some scale transformations. Given the minimum number of pairs in group 4 is 13, in each month, we randomly select 5 pairs in each group and calculate the average correlation coefficient according to their Google and Bloomberg search volumes. The aggregated results are shown in Figure 4.

[Insert Figure 3 here.]

[Insert Figure 4 here.]

As shown in Figure 4, the average correlations of Google search volume and Bloomberg search volume both increase with the news co-occurrences significantly. In particular, the average correlation coefficients in group 5 that has the most news co-occurrences are 9% and 16.1% for Google and Bloomberg respectively which are significantly higher than those in group 1 (with t-stats 3.52 and 5.16 respectively). These results strongly support that news co-occurrence is associated with more correlated search behaviours.

Considering Google and Bloomberg search data only provides aggregated search volume, correlated search activity does not necessarily sources from investors' co-search behaviour. To provide more convincing evidence, we use a novel Edgar search dataset which identifies the users with their IP addresses. Thanks to this nice feature, we re-examine the relationship between the average number of connected news and the co-search frequency of each group of stock pairs. The results are illustrated in Figure 5.

[Insert Figure 5 here.]

Clearly, the more connected news for stock pairs induces more co-search activities. This strongly significant result concretes our hypothesis that more news co-occurrence will attract more investors attention to connected stocks.

4.2 Connected news and investor base

Merton (1987) proposes that an increase in a firm's investor base will reduce the firm's cost of capital and increases its market value. A stock's visibility is associated with its price, publicity and popularity of the core products and social image. In that regard, a stock potentially enjoys a larger investor base when it receives more news coverage than other stocks. Barber and Odean (2008) assert that more news coverage will attract more investor attention and individual investors are more likely to buy rather than sell those stocks that catch their attention. Therefore, an enlarged investor base will aggravate the excessive buying pressure caused by high news coverage and lead to more negative future returns.

To illustrate that more connected news help enlarge the investor base, we first proxy the investor base with abnormal Google search volume[7] (ASV):

$$ASV_{it} = \frac{SVI_{it}}{E(SVI_{i,t-120:t-21})}.$$

Then, we carry out a panel regression by regressing each stock's abnormal Google search volume on the dummy based on the abnormal connected news ratio ($\mathit{Connected\ News}_{it} = 1\{\sum_j aw_{ij,t} > \mathit{Median}(\sum_j aw_{ij,t})\}$), i.e.,

$$ASV_{it} = \alpha + \beta \mathit{Connected\ News}_{it} + \theta' Z_{it} + \varepsilon_{it}, \tag{4.1}$$

where Z_{it} is a set of controls for other attention proxies. In particular, we follow Da *et al.* (2011) by controlling for total number of news, firm size, stock turnover, absolute abnormal return, total number of news on other stocks, total number of analysts and advertisement expenditures. Time fixed effect is included to account for periodicity and the standard errors are clustered on both individual and time dimension. The results are presented in Table 7.

[Insert Table 7 here.]

[7]As pointed out by Da *et al.* (2011), the news coverage and publicity measures are all passive measures. Therefore, we use an active measure, search volume, to address this issue.

Evidently, the significant positive coefficient of *Connected News* in Table 7 strongly supports our hypothesis on the positive correlation between the connected news and investor base. The result is quite robust across regression with various controls. As a robustness check, we also conduct a Fama-Macbeth regression with the same set of regressors. As shown in Table 8, we can draw the same conclusion that when abnormal connected news coverage ratio is higher, the more initiative searching volume is generated which reflects a larger investor base.

[Insert Table 8 here.]

4.3 Belief divergence and short-sales constraint

Miller (1977) asserts that the stock prices in equilibrium will reflect only the optimists view and hence will more likely be overvalued when investors have divergent opinions and short-selling is not allowed. Similarly, Hong and Stein (2007) argue that heterogeneous belief and short-sales constraint are the two key ingredients for explaining stock's overpricing behaviour. Align with this argument, we would expect NNTA to have stronger return predictability when investor beliefs are more divergent and the short-sales constraint is tighter.

As high belief divergence means more disperse forecast errors, which is likely the result of large uncertainty fluctuations. We collect VIX and several other uncertainty indices (e.g. Bali *et al.*, 2014; Choi *et al.*, 2017; Baker *et al.*, 2016; Jurado *et al.*, 2015) to proxy the level of belief divergence of the stock market. Since the return predictability of disagreement fluctuates with investor sentiment (Kim *et al.*, 2014), we also collect some investor sentiment measures, e.g. Baker and Wurgler (2006) and Huang *et al.* (2014), to dissect the interaction between NNTA and investors belief divergence. For the short-sales constraint, we use the short interest ratio scaled by institutional investor ownership to proxy the tightness of the short-sales constraint. This construction is in the same spirit as Asquith *et al.* (2005) who double sort the stock returns on institutional investor ownerships and the short interest ratio.[8]

Specifically, we sort returns on the market environment indicator, i.e., market uncertainty,

[8]Asquith *et al.* (2005) define *short-sales constrained stocks* as those in the highest decile of short interest ratio as well as in the lowest tertile of institutional ownership. However, if we use a similar way to divide sample according to the median of short interest ratios and institutional ownership, the number of observations will be small for both subsample periods and hence lead to a weak statistical inference. Therefore, we modify the short-sales constraint with a new proxy (short interest ratio divided by institutional ownership) to retain enough subsample observations to derive Table 9.

investor sentiment or short-interest ratio, and divide the sample into High/Low groups according to its median. The in-sample return predictability results for both subsamples are summarized in Table 9.

[Insert Table 9 here.]

Evidently, NNTAs only show strong return predictability when investor beliefs are highly divergent and the short-sales constraint is tight. More formally, we estimate a predictive regression involving both the market indicators/short-sales constraint proxy, NNTA, and their interaction terms as below

$$R^m_{t+1} = \alpha + \beta NNTA_t + \phi Z_t + \gamma NNTA_t \times Z_t + \epsilon_{t+1}, \tag{4.2}$$

where Z_t is the market environment indicator/short-sales constraint proxy. For investor sentiment and market uncertainty proxies, we rank them from 1 to 10 to indicate the level of strength. For short-sale constraint, we rank sample periods from 1 to 3. It equals 1 (3) when the modified short interest ratio is in the lowest (highest) decile and aggregated institutional ownership is in the highest (lowest) tercile, and equals 2 for the rest sample periods. The results are reported in Table 10.

[Insert Table 10 here.]

The significantly negative coefficients of the interaction terms in Table 10 forcefully support that the tight short-sales constraint and high belief divergence exaggerates the overvaluation caused by news co-occurrence. It is also an evidence to prove that media coverage of multiple stocks, in an environment of high belief divergence and tight short-sales constraint, can lead to correlated stocks over-valuation.

4.4 Connected news and retail investors

Considering retail investors are more subjected to the short-sales constraint, the overpricing caused by abnormal investor attention should be amplified in the stocks with a higher level of retail investor ownership. To justify this argument, we split the sample into two subsamples according to the stocks' retail investor ownership level and re-check the cross-sectional portfolio results in each subsample. The results are summarized in Table 11.

[Insert Table 11 here.]

Expectedly, only the stocks with a higher level of retail investor ownership generates a significant risk adjusted alpha in cross-sectional portfolio. To show the excessive buying pressure comes from the retail investors, we check the retail order imbalance of each stock during the good news period and the bad news period. In particular, when good news arrives, the retail order imbalance should be higher for stocks with more connected news and thus generates excessive high buying pressure. On the contrary, when bad news occurs, due to the short-sales constraint, the retail investors are unable to generate significantly higher selling pressure for stocks with more connected news provided they are exposed to retail investors attention. In Figure 6, we conduct this test and defines the arrival of good (bad) news with $r_{it} > 0$ ($r_{it} < 0$). The results shown in the figure provide concrete evidence to support our conjectures.

[Insert Figure 6 here.]

Combining these results with those in Table 9, we verify that the return predictability of NNTA index particularly sources from the retail investor attention which is more short-sales constrained and divergent in beliefs.

5 Conclusions

Investors attention affects market reactions to new information and has been documented as an important driving force of stock returns. Existing literature has constructed predictors using both hard information and soft information, while investors' attention effect seems to be underexplored. Based on the news network, we propose a novel predictor, news network triggered attention index (NNTA), which proxies abnormal investor attention with news co-occurrence. In general, we find NNTA consistently provides negative return forecasts for both time-series and cross-sectional portfolios. Using a sample of S&P500 stocks from 1996 to 2014, we first document NNTA can provide significant in-sample and out-of-sample return predictability. Then, we justify the investor attention interpretation of the NNTA index by showing that abnormal connected news coverage ratio can significantly predict correlated Google/Bloomberg search and Edgar co-search activities. In the end, we source the return predictability of NNTA from the retail investors' trading behaviors through the channel of short-sales constraint and belief divergence.

References

Asquith, P., Pathak, P. A. and Ritter, J. R. (2005). Short interest, institutional ownership, and stock returns. *Journal of Financial Economics*, **78** (2), 243–276.

Baker, M. and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, **61** (4), 1645–1680.

Baker, S. R., Bloom, N. and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, **131** (4), 1593–1636.

Bali, T. G., Brown, S. J. and Caglayan, M. O. (2014). Macroeconomic risk and hedge fund returns. *Journal of Financial Economics*, **114** (1), 1–19.

Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, **21** (2), 785–818.

—, — and Zhu, N. (2008). Do retail trades move markets? *The Review of Financial Studies*, **22** (1), 151–186.

Barberis, N. and Shleifer, A. (2003). Style investing. *Journal of financial Economics*, **68** (2), 161–199.

Boudoukh, J., Michaely, R., Richardson, M. and Roberts, M. R. (2007). On the importance of measuring payout yield: Implications for empirical asset pricing. *The Journal of Finance*, **62** (2), 877–915.

Busetti, F. and Marcucci, J. (2013). Comparing forecast accuracy: a monte carlo investigation. *International Journal of Forecasting*, **29** (1), 13–27.

Campbell, J. Y. and Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *The Review of Financial Studies*, **21** (4), 1509–1531.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, **52** (1), 57–82.

Choi, H., Mueller, P. and Vedolin, A. (2017). Bond variance risk premiums. *Review of Finance*, **21** (3), 987–1022.

Clark, T. E. and West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, **138** (1), 291–311.

Cohen, L. and Frazzini, A. (2008a). Economic links and predictable returns. *The Journal of Finance*, **63** (4), 1977–2011.

— and — (2008b). Economic links and predictable returns. *The Journal of Finance*, **63** (4), 1977–2011.

Da, Z., Engelberg, J. and Gao, P. (2011). In search of attention. *The Journal of Finance*, **66** (5), 1461–1499.

Daley, B. and Green, B. (2012). Waiting for news in the market for lemons. *Econometrica*, **80** (4), 1433–1504.

Daniel, K., Grinblatt, M., Titman, S. and Wermers, R. (1997). Measuring mutual fund performance with characteristicbased benchmarks. *The Journal of finance*, **52** (3), 1035–1058.

DellaVigna, S. and Pollet, J. M. (2009). Investor inattention and friday earnings announcements. *The Journal of Finance*, **64** (2), 709–749.

Engelberg, J. (2008). Costly information processing: Evidence from earnings announcements. *AFA 2009 San Francisco Meetings Paper*.

Fama, E. F. and French, K. R. (2016). Dissecting anomalies with a five-factor model. *The Review of Financial Studies*, **29** (1), 69–103.

Fang, L. and Peress, J. (2009). Media coverage and the cross-section of stock returns. *The Journal of Finance*, **64** (5), 2023–2052.

Fang, L. H., Peress, J. and Zheng, L. (2014). Does media coverage of stocks affect mutual funds' trading and performance? *The Review of Financial Studies*, **27** (12), 3441–3466.

GABAIX, X., LAIBSON, D., MOLOCHE, G. and WEINBERG, S. (2006). Costly information acquisition: Experimental analysis of a boundedly rational model. *American Economic Review*, **96** (4), 1043–1068.

GEORGE, T. J. and HWANG, C.-Y. (2004). The 52-week high and momentum investing. *The Journal of Finance*, **59** (5), 2145–2176.

GERVAIS, S., KANIEL, R. and MINGELGRIN, D. H. (2001). The high-volume return premium. *The Journal of Finance*, **56** (3), 877–919.

GOYAL, A. and WELCH, I. (2008). A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, **21** (4), 1455–1508.

GURUN, U. G. and BUTLER, A. W. (2012). Don't believe the hype: Local media slant, local advertising, and firm value. *The Journal of Finance*, **67** (2), 561–598.

HILLERT, A., JACOBS, H. and MÜLLER, S. (2014). Media makes momentum. *The Review of Financial Studies*, **27** (12), 3467–3501.

HIRSHLEIFER, D., LIM, S. S. and TEOH, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, **64** (5), 2289–2325.

HONG, H., LIM, T. and STEIN, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance*, **55** (1), 265–295.

— and STEIN, J. C. (2007). Disagreement and the stock market. *Journal of Economic Perspectives*, **21** (2), 109–128.

—, TOROUS, W. and VALKANOV, R. (2007). Do industries lead stock markets? *Journal of Financial Economics*, **83** (2), 367–396.

HOU, K., XUE, C. and ZHANG, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*, **28** (3), 650–705.

HUANG, D., JIANG, F., TU, J. and ZHOU, G. (2014). Investor sentiment aligned: A powerful predictor of stock returns. *The Review of Financial Studies*, p. hhu080.

Jegadeesh, N. and Wu, D. (2013). Word power: A new approach for content analysis. *Journal of Financial Economics*, **110** (3), 712–729.

Jurado, K., Ludvigson, S. C. and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, **105** (3), 1177–1216.

Kahneman, D. (1973). *Attention and effort*, vol. 1063. Citeseer.

Kandel, S. and Stambaugh, R. F. (1996). On the predictability of stock returns: an asset-allocation perspective. *The Journal of Finance*, **51** (2), 385–424.

Kelly, B. and Pruitt, S. (2013). Market expectations in the cross-section of present values. *The Journal of Finance*, **68** (5), 1721–1756.

Kim, J. S., Ryu, D. and Seo, S. W. (2014). Investor sentiment and return predictability of disagreement. *Journal of Banking & Finance*, **42**, 166–178.

Lee, C. M. C. and Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance*, **46** (2), 733–746.

Lettau, M. and Ludvigson, S. (2001). Consumption, aggregate wealth, and expected stock returns. *The Journal of Finance*, **56** (3), 815–849.

Loughran, T. and McDonald, B. (2011). When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *The Journal of Finance*, **66** (1), 35–65.

Menzly, L. and Ozbas, O. (2010). Market segmentation and cross-predictability of returns. *The Journal of Finance*, **65** (4), 1555–1580.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, **42** (3), 483–510.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *The Journal of Finance*, **32** (4), 1151–1168.

Morck, R., Yeung, B. and Yu, W. (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics*, **58** (1-2), 215–260.

Newman, M. (2010). *Networks: an introduction*. Oxford University Press.

Odean, T. (1999). Do investors trade too much? *American Economic Review*, **89** (5), 1279–1298.

Özgür, A., Cetin, B. and Bingol, H. (2008). Co-occurrence network of reuters news. *International Journal of Modern Physics C*, **19** (05), 689–702.

Peng, L. (2005). Learning with information capacity constraints. *Journal of Financial and Quantitative Analysis*, **40** (2), 307–329.

— and Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, **80** (3), 563–602.

—, — and Bollerslev, T. (2007). Investor attention and time-varying comovements. *European Financial Management*, **13** (3), 394–422.

Rapach, D., Strauss, J., Tu, J. and Zhou, G. (2015). Industry interdependencies and cross-industry return predictability. *Working Paper*.

Rapach, D. E., Ringgenberg, M. C. and Zhou, G. (2016). Short interest and aggregate stock returns. *Journal of Financial Economics*, **121** (1), 46–65.

—, Strauss, J. K. and Zhou, G. (2010). Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *The Review of Financial Studies*, **23** (2), 821–862.

Rubin, A., Segal, B. and Segal, D. (2017). The interpretation of unanticipated news arrival and analysts skill. *Journal of Financial and Quantitative Analysis*, **52** (4), 1491–1518.

Scherbina, A. and Schlusche, B. (2015). Economic linkages inferred from news stories and the predictability of stock returns. *Working Paper*.

Shiller, R. J. (1999). Human behavior and the efficiency of the financial system. *Handbook of macroeconomics*, **1**, 1305–1340.

—, Fischer, S. and Friedman, B. M. (1984). Stock prices and social dynamics. *Brookings papers on economic activity*, **1984** (2), 457–510.

Solomon, D. H., Soltes, E. and Sosyura, D. (2014). Winners in the spotlight: Media coverage of fund holdings as a driver of flows. *Journal of Financial Economics*, **113** (1), 53–72.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, **62** (3), 1139–1168.

—, Saar-Tsechansky, M. and Macskassy, S. (2008). More than words: Quantifying language to measure firms' fundamentals. *The Journal of Finance*, **63** (3), 1437–1467.

Van Nieuwerburgh, S. and Veldkamp, L. (2009). Information immobility and the home bias puzzle. *The Journal of Finance*, **64** (3), 1187–1215.

Yu, Y. (2015). Market-wide attention, trading, and stock returns. *Journal of Financial Economics*, **116** (3), 548–564.

Zhang, J. L., Härdle, W. K., Chen, C. Y. and Bommes, E. (2016). Distillation of news flow into analysis of stock reactions. *Journal of Business & Economic Statistics*, **34** (4), 547–563.

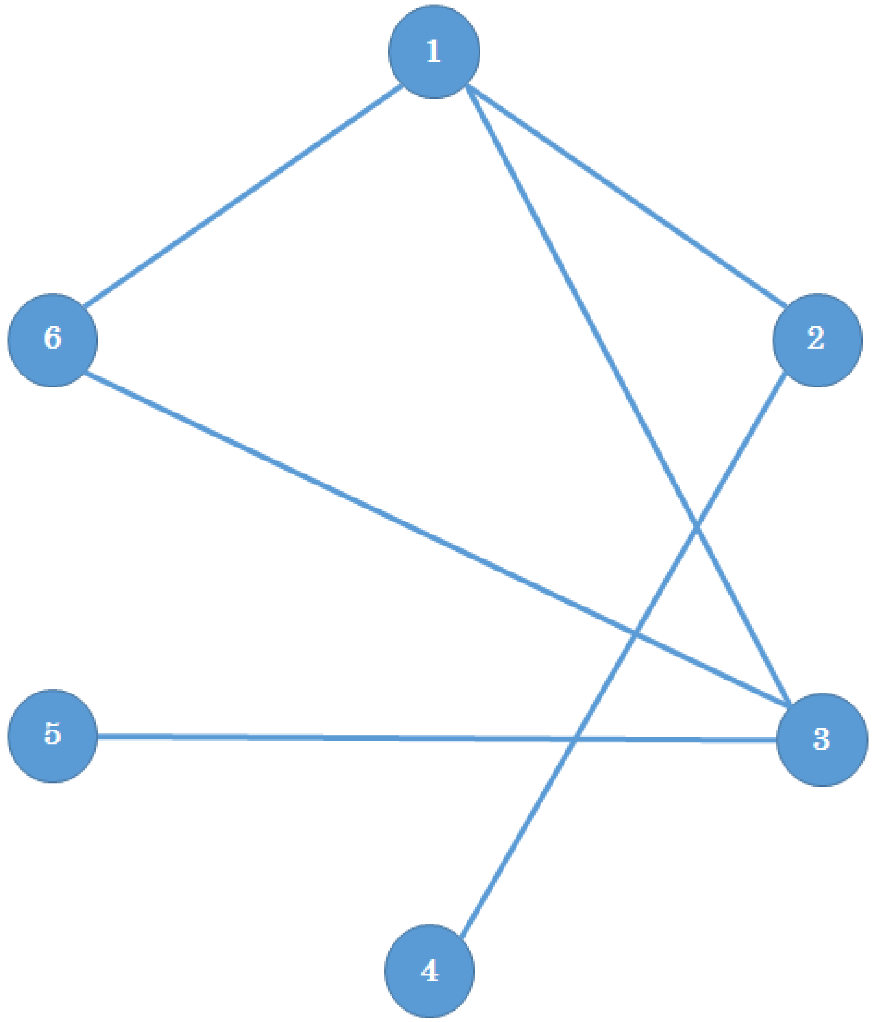

Figure 1: This figure is a simple network example to illustrate how eigenvector centrality differs from degree centrality. Each node in the network represents a stock and each edge denotes the existence of connected news between two stocks.

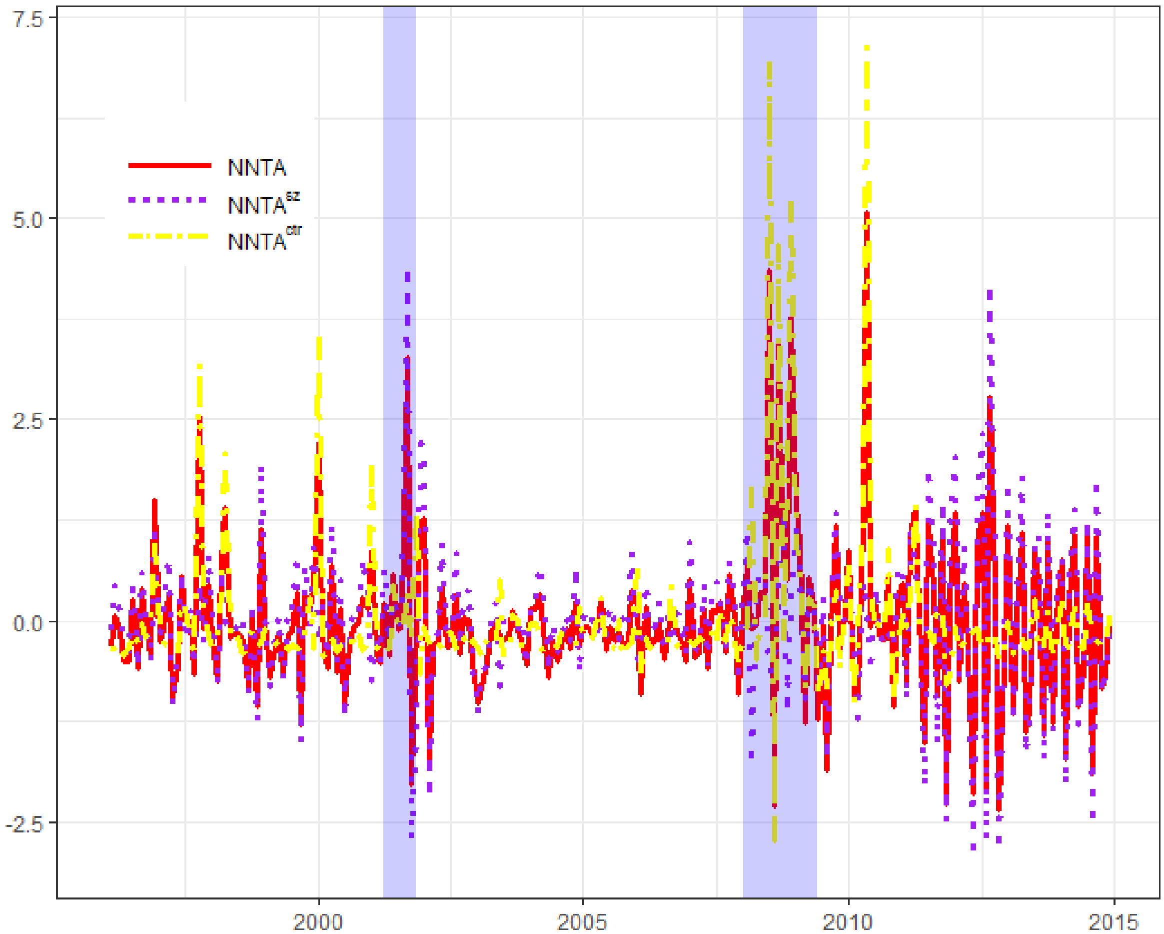

Figure 2: This figure plots the composite news network triggered attention index, size-based news network triggered attention index, and the centrality-based news network triggered attention index. The red line depicts the composite news network triggered attention index, the dotted dashed yellow line depicts the centrality-based news network triggered attention index, and the dotted purple line depicts the size-based news network triggered attention index. All indices are standardized to have zero mean and unit variance. The shaded periods correspond to NBER-dated recessions. The sample period is 1996:02–2014:12.

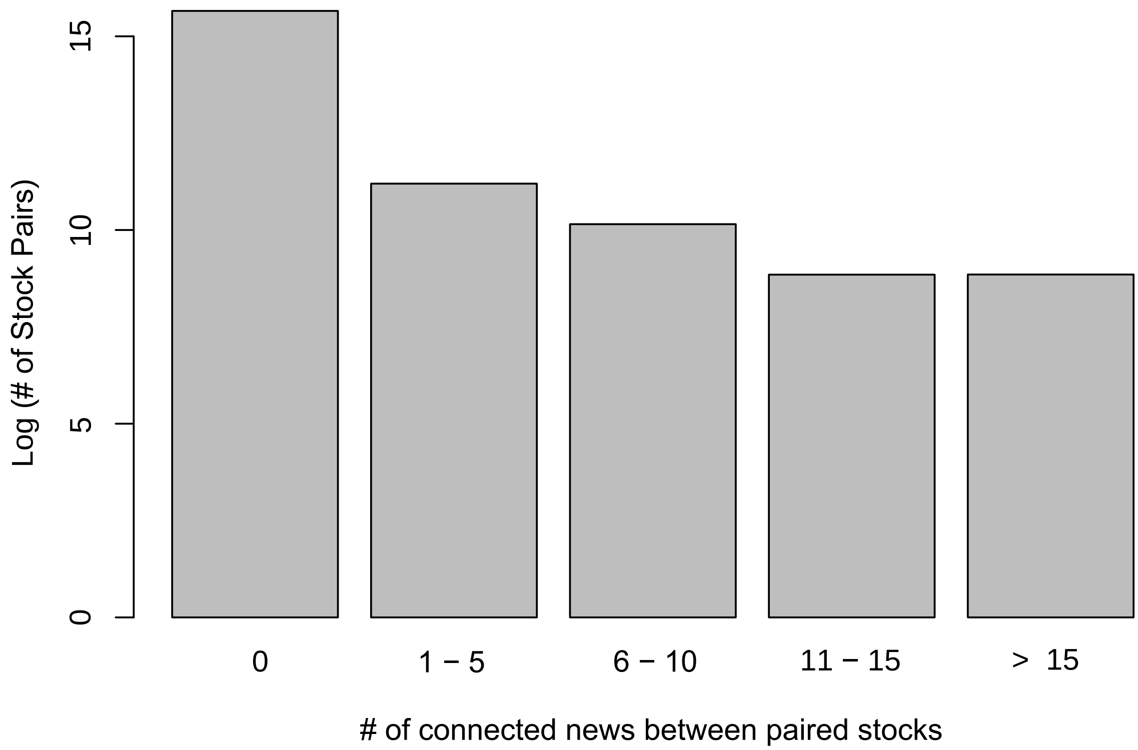

Figure 3: This histogram shows the log number of stock pairs in different bins according to the number of connected news between pair stocks. Stock pairs in the first (last) bin have no (more than 15) connected news. The middle three bins account for number of connected news between pair stocks within the range [1, 5], [6, 10] and [11, 15] respectively. The sample period is 2005:01–2014:12.

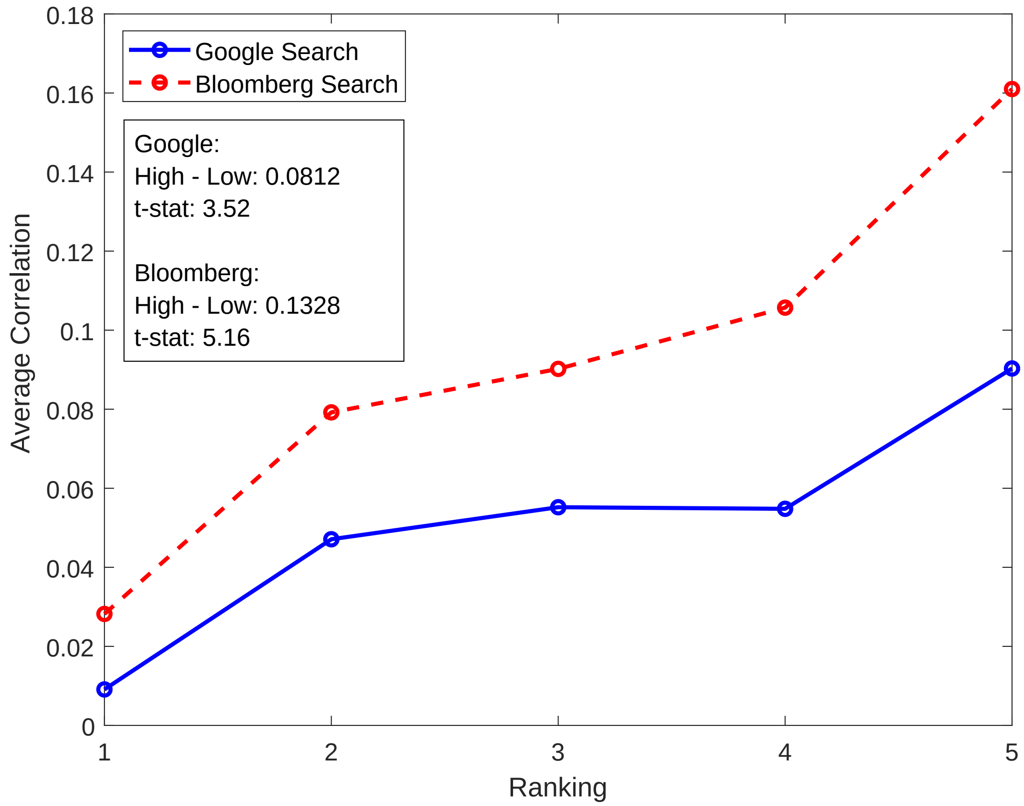

Figure 4: This figure plots the average correlation coefficient of Google and Bloomberg search volumes within 5 groups of stock pairs. Stock pairs in the first (last) group have no (more than 15) connected news. The middle three groups require the number of connected news between pair stocks within the range [1, 5], [6, 10] and [11, 15] respectively. Then, we randomly select 5 pairs of stocks in each group and calculate the corresponding average correlations based on their Google and Bloomberg search volumes over the sample period. The sample period is 2005:01–2014:12 for Google and 2010:01–2014:12 for Bloomberg.

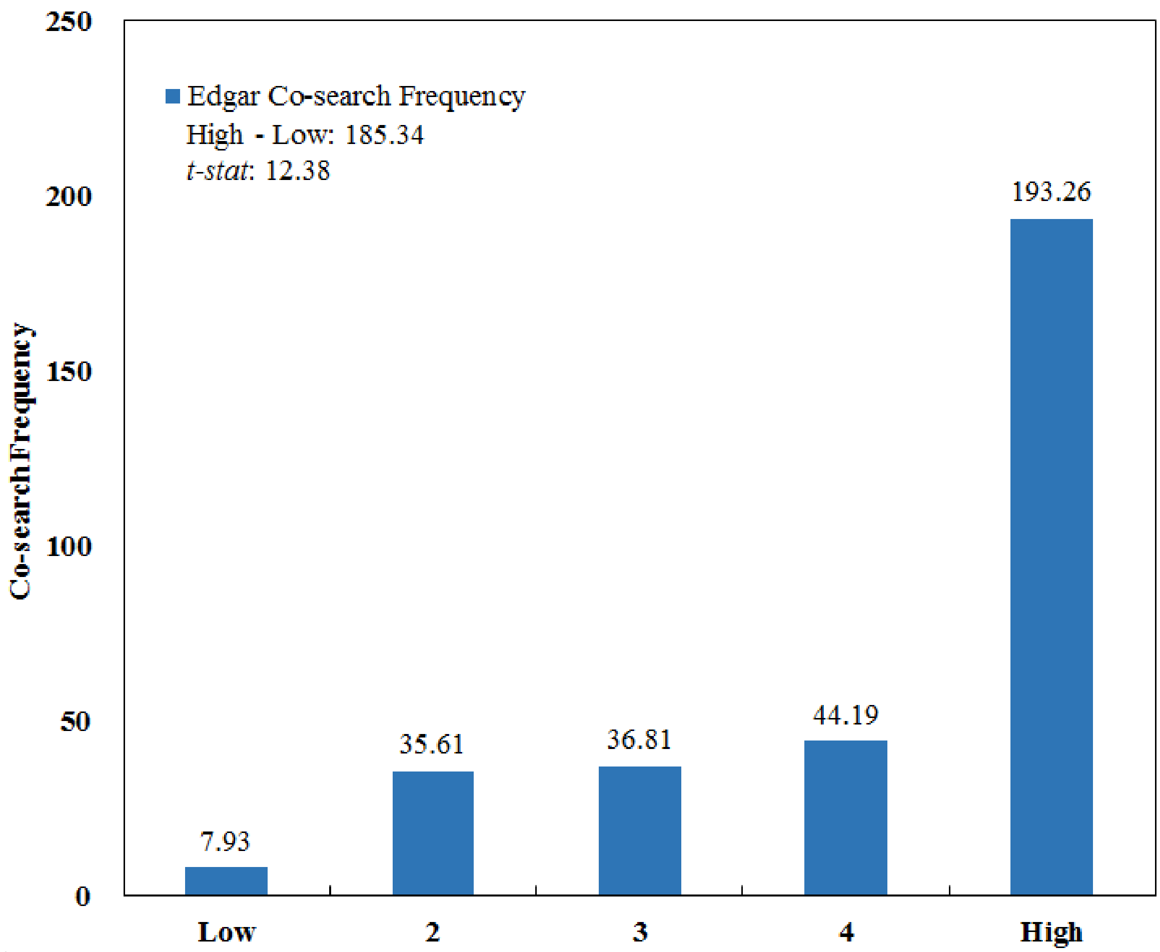

Figure 5: This figure presents the average co-search frequency from Edgar for each group of stock pairs. The stock pairs are sorted into quintiles according to the number of connected news between them. The sample period is 2005-2014.

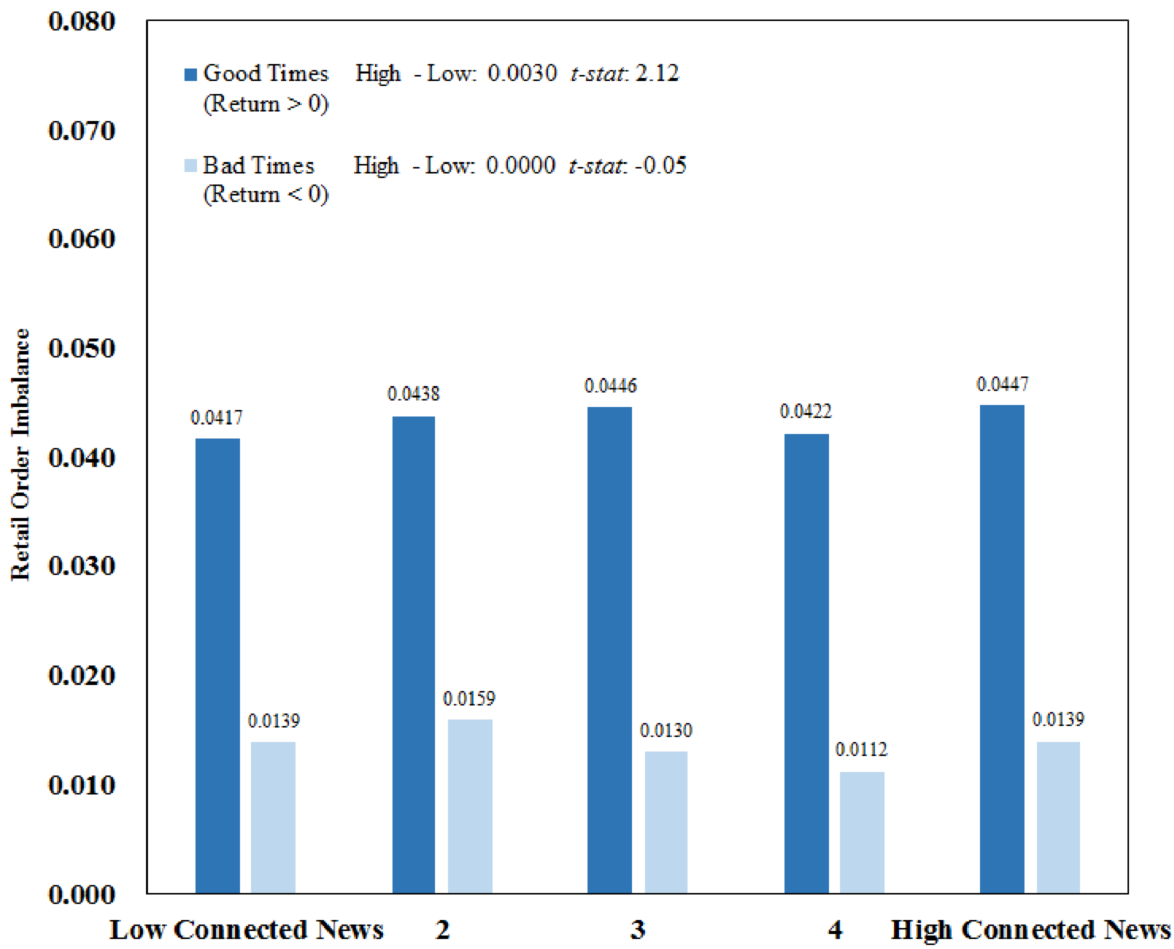

Figure 6: This figure shows the average retail order imbalance for each group of stocks under good/bad news period. The stocks are sorted into quintiles according to the number of connected news. The good (bad) news period is characterized by the return performance on the news event day, i.e., $r_{it} > 0$ ($r_{it} < 0$). We follow Barber *et al.* (2008) method for detecting retail order flows. Lee and Ready (1991) algorithm is applied to infer trading directions. The sample period is 1996-2011.

Table 1: Summary Statistics

This table reports summary statistics for the excess aggregate stock market return defined as the return on the value-weighted S&P500 stocks in excess of the risk-free rate (R_m), risk-free rate (R_f), size based news network triggered attention (NNTA^{sz}), eigenvector centrality based news network triggered attention, (NNTA^{ctr}), and naïvely combined news network triggered attention (NNTA); Both level and change of average number of firm specific news using value weight from Thomson Reuters News Analytics (*TRN* and Δ*TRN*); Level and change of Dow Jones News/Wall Street Journal related to S&P 500 index (*DJI*/*WSJ* and Δ*DJI*/Δ*WSJ*); Log of Google search index (*Google Search*), (Prc^{High}) following George and Hwang (2004), level and change of average number of analysts aggregated from individual S&P500 stocks using value weight (*Analyst* or Δ*Analyst*), residual of Analyst coverage regressing on size and Nasdaq index following Hong *et al.* (2000) (*Analyst_r*), value-weighted trading volume (*TrdVol* and Δ*TrdVol*); Negative and optimistic news tones based on Thomson Reuters News Analytics (Neg^{NN} and Opt^{NN}), and Loughran and McDonald (2011) dictionary with value weight (*Neg* and *Opt*); Investor sentiment index ($Sent^{BW}$) of Baker and Wurgler (2006) and investor sentiment aligned index ($Sent^{PLS}$) of Huang *et al.* (2014); VIX from CBOE, economic uncertainty index (UNC) in Bali *et al.* (2014), treasury implied volatility (TIV) in Choi *et al.* (2017), economic policy uncertainty (EPU) in Baker *et al.* (2016), financial uncertainty (FU), and economy uncertainty (EU) in Jurado *et al.* (2015); Morck *et al.* (2000) earnings co-movement index (ECI), Rapach *et al.* (2016) equal-weighted short interest ratio (EWSI), and 14 economic variables from Amit Goyals website: the log dividend-price ratio (D/P), the log dividend-yield ratio (D/Y), log earnings-price ratio (E/P), log dividend payout ratio (D/E), stock return variance (SVAR), book-to-market ratio (B/M), 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), inflation rate (INFL). For each variable, the time-series average (Mean), standard deviation (Std. Dev.), skewness (Skew.), kurtosis (Kurt.), minimum (Min.), maximum (Max.), and first-order autocorrelation ($\rho(1)$) are reported. The sample period is 1996:02–2014:12. (Google Search is from 2004:01 – 2014:12)

Variable	Mean	Std.	Skew.	Kurt.	Min.	Max.	$\rho(1)$
Panel A: Returns							
R_m	0.004	0.045	-0.661	3.965	-0.170	0.108	0.084
R_f	0.002	0.002	0.215	1.429	0.000	0.006	0.978
Panel B: News Network Triggered Attention							
NNTA	0.001	0.727	1.354	8.328	-1.700	3.676	-0.180
NNTA^{sz}	0.000	0.002	0.252	5.970	-0.005	0.007	-0.357
NNTA^{ctr}	0.277	0.648	2.577	18.880	-1.374	5.226	-0.163
Panel C: Media Coverage							
TRN	3.776	1.493	0.329	2.870	0.000	7.649	0.753
DJI	22.350	17.482	0.729	2.645	0.263	71.409	0.926
WSJ	5.507	4.429	0.624	2.193	0.136	17.087	0.939
Δ*TRN*	0.005	1.042	0.038	4.300	-3.155	4.273	-0.345
Δ*DJI*	0.133	6.569	-0.498	11.452	-36.000	29.577	0.066
Δ*WSJ*	0.045	1.472	1.185	8.970	-4.386	7.896	-0.217

Table 1 (Continued): Summary Statistics

Variable	Mean	Std.	Skew.	Kurt.	Min.	Max.	$\rho(1)$
Panel D: Attention Proxies							
Google Search	3.421	0.394	0.189	2.039	2.708	4.357	0.797
Prc^{High}	0.925	0.098	-1.880	6.141	0.531	0.998	0.946
Analyst	25.008	1.606	0.149	1.681	22.397	27.952	0.979
$\Delta Analyst$	0.017	0.268	1.670	13.920	-0.799	1.876	0.014
$Analyst\_r$	-0.169	0.040	-0.200	2.706	-0.266	-0.060	0.954
TrdVol	19.759	0.541	-0.995	4.051	17.978	20.738	0.942
$\Delta TrdVol$	0.009	0.155	0.328	3.462	-0.428	0.537	-0.196
Panel E: Soft Information – News Tones							
Neg	0.008	0.002	0.686	2.511	0.005	0.013	0.946
Opt	0.004	0.001	1.141	3.607	0.002	0.009	0.876
Neg^{NN}	0.006	0.002	0.561	2.918	0.003	0.010	0.725
Opt^{NN}	-0.003	0.001	-0.532	3.250	-0.007	0.001	0.557
Panel F: Investor Sentiment and Market Uncertainty							
$Sent^{BW}$	0.223	0.681	1.513	6.311	-0.87	3.08	0.964
$Sent^{PLS}$	-0.191	0.853	1.847	6.033	-1.107	3.027	0.977
VIX	21.278	8.143	1.822	8.439	10.820	62.640	0.876
UNC	0.374	2.229	2.176	7.957	-1.680	9.051	0.975
TIV	7.189	1.874	0.769	3.898	3.970	14.330	0.859
MU	0.663	0.094	2.034	8.111	0.554	1.063	0.987
FU	0.939	0.191	0.619	2.892	0.637	1.546	0.981
EPU	150.147	46.953	1.345	4.957	84.902	350.712	0.695
Panel G: Hard Information – Fundamentals							
ECI	0.147	0.066	0.490	2.535	0.035	0.310	0.957
EWSI	0.02%	0.266	0.397	2.542	-0.421	0.705	0.978
D/P	-4.014	0.398	8.666	109.093	-4.524	0.953	0.307
D/Y	-4.026	0.229	0.402	4.814	-4.531	-3.006	0.897
E/P	-3.169	0.425	-1.896	7.399	-4.836	-2.566	0.904
D/E	-0.845	0.644	5.945	52.942	-1.244	5.756	0.514
SVAR	0.003	0.005	6.124	52.661	-0.002	0.058	0.698
B/M	0.262	0.078	-0.222	2.354	0.000	0.441	0.900
NTIS	0.004	0.019	-1.276	4.478	-0.058	0.031	0.973
TBL	2.457	2.134	0.181	1.377	0.010	6.170	0.986
LTY	4.808	1.270	-0.292	2.716	0.564	7.260	0.946
LTR	0.666	3.046	0.045	5.629	-11.240	14.430	-0.004
TMS	2.350	1.400	-0.448	2.727	-3.226	4.530	0.903
DFY	0.987	0.501	0.960	17.140	-2.280	3.380	0.787
DFR	-0.013	1.832	-0.467	9.264	-9.750	7.370	0.021
INFL	0.002	0.004	0.520	13.794	-0.019	0.029	0.327

Table 2: Forecasting Market Return with News Co-occurrence

This table provides in-sample estimation results for the predictive regression of monthly excess market return on news network triggered attention indices, media coverage, alternative attention proxies, news tones, investor sentiment, market uncertainty, and fundamental predictors.

$$R^m_{t+1} = \alpha + \beta X_t + \epsilon_{t+1},$$

where R^m_{t+1} denotes the monthly excess market return (%). The t-statistics are based on Newey-West standard errors with 4 lags. *, **, and *** indicate significance at the 10%, 5% and 1% levels respectively. The sample period is 1996:02–2014:12 (Google Search is from 2004:01 – 2014:12).

Predictor	$\hat{\beta}$	t-stat.	R^2	R^2_{up}	R^2_{down}
Panel A: News Network Triggered Attention					
NNTA	-1.089***	-3.770	5.966	3.825	7.045
NNTA^{sz}	-0.749**	-2.548	2.817	2.149	3.807
NNTA^{ctr}	-0.831***	-2.839	3.473	2.100	3.179
Panel B: Media Coverage					
TRN	-0.149	-0.500	0.112	0.076	0.585
DJI	0.262	0.881	0.345	0.223	0.262
WSJ	0.153	0.511	0.116	0.316	0.335
ΔTRN	-0.259	-0.870	0.337	0.058	2.332
ΔDJI	0.035	0.118	0.006	0.269	4.363
ΔWSJ	-0.622**	-2.109	1.946	0.140	14.146
Panel C: Attention Proxies					
Google Search	-0.716**	-2.015	3.050	1.561	0.005
Prc^{High}	0.223	0.749	0.250	0.012	6.609
Analyst	-0.049	-0.165	0.012	0.420	0.248
$\Delta Analyst$	-0.119	-0.401	0.072	0.005	4.550
Analyst_r	0.187	0.628	0.176	0.628	0.192
TrdVol	-0.505*	-1.702	1.277	0.588	0.045
$\Delta TrdVol$	-0.446	-1.503	0.998	1.898	0.924
Panel D: Soft Information – News Tones					
Neg	-0.213	-0.713	0.227	0.843	0.023
Opt	0.302	1.012	0.455	0.307	0.032
Neg^{NN}	-0.290	-0.966	0.415	1.073	0.905
Opt^{NN}	0.455	1.526	1.029	1.174	0.039
Panel E: Investor Sentiment and Market Uncertainty					
$Sent^{BW}$	-0.595**	-2.014	1.779	2.811	0.357
$Sent^{PLS}$	-0.800***	-2.728	3.216	2.057	5.906
VIX	0.006	0.022	0.000	0.641	1.696
UNC	-0.102	-0.343	0.052	0.160	3.618
TIV	-0.420	-1.412	0.882	0.052	3.416
MU	-0.894***	-3.061	4.014	0.899	2.471
FU	-0.742**	-2.522	2.761	0.945	1.805
EPU	-0.074	-0.247	0.027	0.187	0.024
Panel F: Hard Information – Fundamentals					
ECI	-0.021	-0.069	0.002	0.117	6.456
EWSI	-0.644**	-2.173	2.064	0.162	2.312

Table 3: Comparison with Alternative Predictors

This table provides in-sample estimation results for the bivariate predictive regression of monthly excess market return on one of the NNTA indices, X_t and one of the other predictor, Z_t,e.g. media coverage predictors, the alternative attention proxies, the news tones, the investor sentiment indices, the uncertainty indices, or fundamental predictors.

$$R^m_{t+1} = \alpha + \beta X_t + \phi Z_t + \epsilon_{t+1},$$

where R^m_{t+1} denotes the monthly excess market return (%). The significance of the estimates are based on Newey-West t-statistics with 4 lags. *, **, and *** indicate significance at the 10%, 5% and 1% levels respectively. The sample period is 1996:02–2014:12 (Google Search is from 2004:01 – 2014:12).

	NNTA			NNTA^{sz}			NNTA^{ctr}		
Predictor	$\hat{\beta}$	$\hat{\phi}$	R^2	$\hat{\beta}$	$\hat{\phi}$	R^2	$\hat{\beta}$	$\hat{\phi}$	R^2
Panel A: Media Coverage									
TRN	-1.116***	0.113	6.026	-0.742**	-0.057	2.833	-0.838***	0.032	3.478
DJI	-1.105***	0.316	6.466	-0.747**	0.258	3.151	-0.856***	0.327	4.009
WSJ	-1.115***	0.264	6.310	-0.756**	0.183	2.984	-0.856***	0.242	3.762
ΔTRN	-1.184***	0.230	6.185	-0.764**	0.040	2.824	-0.812***	-0.090	3.512
ΔDJI	-1.108***	0.162	6.096	-0.759**	0.106	2.873	-0.838***	0.096	3.519
ΔWSJ	-0.998***	-0.389	6.685	-0.642**	-0.479	3.913	-0.770**	-0.533*	4.884
Panel B: Attention Proxies									
Google Search	-1.216***	-0.618*	11.814	-0.707**	-0.697**	6.032	-1.050***	-0.624*	9.575
Prc^{High}	-1.078***	0.104	6.019	-0.751**	0.231	3.084	-0.817***	0.084	3.507
Analyst	-1.103***	-0.152	6.079	-0.749**	-0.054	2.832	-0.851***	-0.158	3.596
$\Delta Analyst$	-1.105***	-0.204	6.173	-0.756**	-0.156	2.940	-0.842***	-0.171	3.620
Analyst_r	-1.108***	0.265	6.317	-0.746**	0.178	2.977	-0.864***	0.285	3.878
TrdVol	-1.041***	-0.367	6.631	-0.727**	-0.471	3.928	-0.774***	-0.392	4.228
$\Delta TrdVol$	-1.078***	-0.029	5.969	-0.675**	-0.221	3.036	-0.770**	-0.271	3.822
Panel C: Soft Information – News Tones									
Neg	-1.098***	-0.250	6.277	-0.749**	-0.214	3.047	-0.843***	-0.253	3.792
Opt	-1.093***	0.313	6.456	-0.752**	0.309	3.295	-0.833***	0.306	3.941
NegNN	-1.103***	-0.335	6.521	-0.762***	-0.323	3.331	-0.836***	-0.304	3.929
Opt^{NN}	-1.087***	0.449	6.967	-0.755***	0.466	3.897	-0.821***	0.436	4.418

Table 3 (Continued): Comparison with Alternative Predictors

	NNTA			NNTA^{sz}			NNTA^{ctr}		
Predictor	$\hat{\beta}$	$\hat{\phi}$	R^2	$\hat{\beta}$	$\hat{\phi}$	R^2	$\hat{\beta}$	$\hat{\phi}$	R^2
Panel D: Investor Sentiment and Market Uncertainty									
$Sent^{BW}$	-1.097***	-0.610**	7.834	-0.723**	-0.561*	4.398	-0.874***	-0.653**	5.604
$Sent^{PLS}$	-0.991***	-0.651**	8.045	-0.727**	-0.780***	5.874	-0.704**	-0.665**	5.616
VIX	-1.126***	0.207	6.175	-0.749**	0.011	2.818	-0.889***	0.231	3.723
UNC	-1.094***	0.040	5.973	-0.747**	-0.090	2.858	-0.838***	0.042	3.482
TIV	-1.048***	-0.192	6.141	-0.734**	-0.393	3.588	-0.775**	-0.204	3.666
MU	-0.939***	-0.689**	8.238	-0.720**	-0.870***	6.619	-0.628**	-0.715**	5.840
FU	-0.981***	-0.548*	7.410	-0.729**	-0.722**	5.429	-0.685**	-0.564*	4.960
EPU	-1.108***	0.111	6.025	-0.750**	0.013	2.818	-0.835***	0.032	3.478
Panel E: Hard Information − Fundamentals									
ECI	-1.090***	0.019	5.967	-0.748**	-0.009	2.818	-0.832***	0.011	3.474
EWSI	-1.049***	-0.566*	7.583	-0.751**	-0.651**	4.941	-0.769***	-0.564*	5.040
D/P	-1.144***	1.189**	8.112	-0.744**	1.003*	4.356	-0.920***	1.231**	5.753
D/Y	-1.122***	0.722**	8.349	-0.735**	0.648**	4.742	-0.897***	0.752**	6.044
E/P	-1.083***	0.194	6.142	-0.750**	0.234	3.074	-0.822***	0.185	3.634
D/E	-1.099***	0.194	6.065	-0.748**	0.083	2.836	-0.848***	0.217	3.597
SVAR	-0.992***	-0.443	6.901	-0.715**	-0.624**	4.757	-0.705**	-0.474	4.520
B/M	-1.104***	0.359	6.582	-0.744**	0.299	3.244	-0.860***	0.381	4.162
NTIS	-1.037***	0.474	7.080	-0.732**	0.567*	4.432	-0.767***	0.487*	4.647
TBL	-1.097***	-0.226	6.221	-0.746**	-0.178	2.977	-0.846***	-0.241	3.763
LTY	-1.088***	-0.313	6.434	-0.741**	-0.295	3.234	-0.839***	-0.337	4.014
LTR	-1.088***	0.113	6.029	-0.747**	0.014	2.818	-0.862***	0.236	3.747
TMS	-1.094***	0.079	5.994	-0.749**	0.018	2.819	-0.837***	0.081	3.503
DFY	-1.070***	-0.122	6.025	-0.736**	-0.295	3.171	-0.803***	-0.147	3.557
DFR	-1.088***	0.329	6.508	-0.804***	0.436	3.754	-0.801***	0.226	3.725
INFL	-1.086***	0.157	6.065	-0.756**	0.216	3.005	-0.824***	0.119	3.530

Table 4: Out-of-sample Forecasting

This table reports the out-of-sample performances of various measures of News Network Triggered Attention Indices in predicting the monthly excess market return. Panel A provides the results using the NNTA indices; Panel B are results of media coverage; Panel C are results using alternative attention proxies; Panel D reports results using news tones; Panel E is the results of investor sentiment indices (Baker and Wurgler, 2006; Huang *et al.*, 2014) and market uncertainty indices (Bali *et al.*, 2014; Choi *et al.*, 2017; Baker *et al.*, 2016; Jurado *et al.*, 2015); and Panel F reports the results of fundamental predictors including earning comovement index in Morck *et al.* (2000), short interest ratio in Rapach *et al.* (2016), and combined economic predictors in Rapach *et al.* (2010). 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. CW-test is the Clark and West (2007) MSFE-adjusted statistic calculated according to prevailing mean model. $R^2_{OS,up}$ ($R^2_{OS,down}$) statistics are calculated over NBER-dated business-cycle expansions (recessions) based on the no constraint model. The out-of-sample evaluation period is 2002:07–2014:12 (Google Search is from 2009:01 – 2014:12).

Predictor	R^2_{OS}	CW-test	p-value	$R^2_{OS,up}$	$R^2_{OS,down}$
Panel A: News Network Triggered Attention					
NNTA	5.800	2.658	0.004	4.496	8.184
NNTA^{sz}	2.607	2.549	0.005	0.786	5.936
NNTA^{ctr}	2.227	1.295	0.098	3.812	-0.670
Panel B: Media Coverage					
TRN	-4.298	-0.371	0.645	-7.543	1.635
DJI	-0.217	-0.109	0.544	-0.291	-0.083
WSJ	-5.251	0.291	0.385	-7.088	-1.892
ΔTRN	-2.248	-0.373	0.646	-0.805	-4.885
ΔDJI	-1.051	-0.939	0.826	-1.048	-1.057
ΔWSJ	-3.001	0.279	0.390	-1.863	-5.081
Panel C: Attention Proxies					
Google Search	2.438	1.807	0.035	3.662	-0.735
Prc^{High}	-2.537	-0.032	0.513	-1.950	-3.610
Analyst	-2.362	-0.766	0.778	-1.248	-4.398
$\Delta Analyst$	-0.412	-0.447	0.673	-1.163	0.960
Analyst_r	-0.888	0.235	0.407	-0.353	-1.865
TrdVol	-0.659	0.489	0.312	-5.320	7.862
$\Delta TrdVol$	-0.655	-0.098	0.539	0.022	-1.892

Table 4 (Continued): Out-of-sample Forecasting

Predictor	R^2_{OS}	CW-test	p-value	$R^2_{OS,up}$	$R^2_{OS,down}$
Panel D: Soft Information – News Tones					
Neg	-2.045	-0.171	0.568	-2.825	-0.618
Opt	-1.102	0.002	0.499	-1.571	-0.246
Neg^{NN}	-0.833	0.006	0.498	-1.108	-0.330
Opt^{NN}	0.139	0.567	0.285	0.228	-0.022
Panel E: Investor Sentiment and Market Uncertainty					
$Sent^{BW}$	-0.396	0.510	0.305	1.285	-3.469
$Sent^{PLS}$	2.062	1.874	0.030	0.439	5.029
VIX	-5.120	-0.833	0.798	-3.551	-7.987
UNC	-8.258	0.632	0.264	-2.965	-17.933
TIV	-1.657	-0.232	0.592	-1.865	-1.277
MU	0.610	1.321	0.093	-3.277	7.715
FU	1.608	1.256	0.105	-1.211	6.761
EPU	-2.461	-0.886	0.812	-1.799	-3.670
Panel F: Hard Information – Fundamentals					
ECI	-1.225	-0.077	0.531	-1.197	-1.277
EWSI	1.968	2.041	0.021	1.101	3.551
Mean	-0.669	0.003	0.499	-0.330	1.350
Median	0.052	0.224	0.411	0.178	2.423
Trimmed Mean	-0.493	-0.001	0.500	-0.328	1.836
DMSPE, $\theta = 1.0$	-0.693	0.020	0.492	-0.211	1.130
DMSPE, $\theta = 0.9$	-0.606	0.097	0.461	-0.239	1.370

Table 5: Performance of Sorted Portfolios Based on Abnormal News Co-occurrence

This table reports excess portfolio return and risk adjusted alpha of value weighted portfolio using S&P 500 stocks based on the abnormal connected news coverage in last month. The sample period is from 1996-02 to 2014-12. We first sort stocks into 10 groups according to firms i's abnormal connected news coverage, $\sum_j aw_{ij,t}$. Stocks in the top (bottom) group are regarded as short (long) leg. We hold each group of stocks for 1 month and rebalance them at the close price of next month. Three types of risk factors are considered: Carhart (1997) four-factor model, Hou *et al.* (2015) q-factor model, and Fama and French (2016) five-factor model. t-statistics are reported below the portfolio returns (risk adjusted alpha).

Portfolios	*ExcRet*	Cahart-4	HXZ-q	FF-5
Long	1.04%	0.39%	0.24%	0.15%
	(3.18)	(2.39)	(1.49)	(0.96)
2	0.64%	0.03%	0.08%	0.06%
	(1.75)	(0.19)	(0.46)	(0.31)
3	0.37%	-0.20%	-0.21%	-0.22%
	(1.17)	(-1.33)	(-1.34)	(-1.39)
4	0.60%	0.11%	0.11%	0.12%
	(1.77)	(0.60)	(0.59)	(0.65)
5	0.58%	0.09%	0.00%	0.05%
	(1.74)	(0.50)	(0.00)	(0.26)
6	0.35%	-0.14%	-0.13%	-0.17%
	(1.08)	(-1.02)	(-0.87)	(-1.15)
7	0.33%	-0.15%	-0.13%	-0.18%
	(0.98)	(-0.88)	(-0.77)	(-1.03)
8	0.39%	-0.12%	-0.12%	-0.15%
	(1.18)	(-0.72)	(-0.69)	(-0.83)
9	0.66%	0.13%	0.05%	0.07%
	(1.88)	(0.70)	(0.25)	(0.40)
Short	0.36%	-0.24%	-0.28%	-0.31%
	(1.01)	(-1.31)	(-1.54)	(-1.65)
Long - Short	**0.68%**	**0.63%**	**0.52%**	**0.47%**
	(3.02)	(2.79)	(2.24)	(2.01)

Table 6: Distribution Quantiles of the Number of Stock Pairs

This table reports the distribution quantiles of the number of stocks pairs in each group. We assign stock pairs without connected news to group 1, stock pairs with 1 to 5 pieces of connected news to group 2, stock pairs with 6 to 10 pieces of connected news to group 3, stock pairs with 11 to 15 pieces of connected news to group 4, and the rest pairs to group 5. The sample period is 2005:01 – 2014:12.

Groups	Min	25%	Median	Mean	75%	Max
Group 1	38393	43128.25	49697	51994.82	59347	74681
Group 2	542	801.5	967	1078.63	1250	2666
Group 3	36	92.75	175	213.32	284.5	728
Group 4	13	33	49	57.97	72	221
Group 5	19	36	52.5	58.15	73	145

Table 7: Abnormal Google Search Volume and Connected News: Panel Regression

This table reports the panel regression results of regressing each stock's abnormal google search volume (ASV) on connected news dummy controlling for some alternative attention measures. The ASV is defined as SVI devided by the average SVI over from -120 to -21 weekday, with SVI introduced in Da *et al.* (2011). The connected news dummy equals 1 if $\sum_j aw_{ij,t}$ is above the median and 0 otherwise. In the regression, we sort stocks into deciles based on the abnormal connected news ratio Δ(# Connected News/# Total News) and conduct the panel regression with time fixed effect. The controls include log total number of news, log firm size, turnover, absolute abnormal return (Daniel *et al.*, 1997), log total number of other firms' news, log number of analysts, advertisement expenses. Both month fixed effect and ranking fixed effect are controlled. The reported standard errors are double clustered on time and individual firm. The sample period is 1996:02–2014:12. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Connected News	0.00319**	0.00290**	0.00374***	0.00315**	0.00290**	0.00343**	0.00342**	0.00320**	0.00322**
	(2.35)	(2.14)	(2.76)	(2.32)	(2.08)	(2.53)	(2.52)	(2.35)	(2.31)
Log(All News+1)		0.01235***							0.00445***
		(18.36)							(3.11)
Log(Size)			0.00381***						0.00415***
			(7.69)						(4.10)
Turnover				0.00635***					0.00405***
				(9.38)					(5.95)
|Abn Return|					0.20841***				0.14987***
					(10.52)				(9.49)
Log(# of Other News)						-8.74146***			-4.61788***
						(-10.78)			(-3.86)
Log(# of Analyst+1)							0.00607***		-0.00663***
							(5.24)		(-3.76)
Ad. Expense								0.02811	-0.01081
								(1.23)	(-0.47)
Month Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	77089	77089	76843	77019	73533	77089	76044	77089	72784
Adj. R-square	0.016	0.021	0.017	0.022	0.022	0.023	0.017	0.016	0.029

Table 8: Abnormal Google Search Volume and Connected News: Fama-Macbeth Regression

This table reports the Fama-Macbeth regression results of regressing each stock's abnormal google search volume (ASV) on connected news dummy controlling for some alternative attention measures. The ASV is defined as SVI devided by the average SVI over from -120 to -21 weekday, with SVI introduced in Da *et al.* (2011). The connected news dummy equals 1 if $\sum_j aw_{ij,t}$ is above the median and 0 otherwise. In the regression, we sort stocks into deciles based on the abnormal connected news ratio Δ(# Connected News/# Total News) and conduct the panel regression with time fixed effect. The controls include log total number of news, log firm size, turnover, absolute abnormal return (Daniel *et al.*, 1997), log total number of other firms' news, log number of analysts, advertisement expenses. Both month fixed effect and ranking fixed effect are controlled. The reported standard errors are Newey-West adjusted with 4 lags. The sample period is 1996:02–2014:12. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Connected News	0.00321**	0.00296**	0.00385**	0.00322**	0.00290**	0.00337**	0.00348**	0.00317**	0.00307**
	(2.17)	(2.00)	(2.58)	(2.19)	(2.03)	(2.30)	(2.23)	(2.17)	(2.00)
Log(All News+1)		0.01244***							0.00574***
		(11.03)							(4.93)
Log(Size)			0.00388***						0.00539***
			(4.42)						(3.32)
Turnover				0.00688***					0.00532***
				(6.02)					(3.66)
|Abn Return|					0.22494***				0.15858***
					(9.54)				(8.74)
Log(# of Other News)						-8.41642***			-2.99719***
						(-8.78)			(-2.73)
Log(# of Analyst+1)							0.00520**		-0.00934***
							(2.37)		(-3.36)
Ad. Expense								0.03703	-0.00193
								(1.21)	(-0.07)
Month Fixed Effect									
Obs.	77089	77089	76843	77019	73533	77089	76044	77089	72784
Adj. R-sq	0.0018	0.0103	0.017	0.016	0.0118	0.0128	0.0053	0.0031	0.0385

Table 9: Return Predictability of NNTA under Different Market Environment and Different Tightness of Short-sales Constraint

This table provides in-sample estimation results for the predictive regression of monthly excess market return on news network triggered attention indices under different market environment as well as different tightness of short-sales constraint periods. We use investor sentiment, market uncertainty indices to describe the market environment and use value weighted short interest ratio divided by institutional ownerships of S&P500 stocks to proxy the short-sales contraint. A high market environment indicator equals one if the market environment index in the previous month is above the median of the whole sample and 0 otherwise. The sample period is 1996:02–2014:12. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Environment		NNTA			NNTA^{sz}			NNTA^{ctr}		
		$\hat{\beta}$	t-stat.	R^2	$\hat{\beta}$	t-stat.	R^2	$\hat{\beta}$	t-stat.	R^2
Panel A: Investor Sentiment										
$Sent^{BW}$	High	-0.582	-1.059	0.010	-0.865*	-1.831	0.029	0.402	0.635	0.004
	Low	-1.332***	-4.014	0.127	-0.669*	-1.776	0.028	-1.237***	-3.883	0.120
$Sent^{PLS}$	High	-1.366***	-3.156	0.082	-1.264**	-2.394	0.049	-0.798**	-2.116	0.039
	Low	-0.325	-0.886	0.007	-0.260	-0.938	0.008	-0.120	-0.120	0.000
Panel B: Market Uncertainty										
VIX	High	-1.363***	-3.290	0.089	-1.136**	-2.317	0.046	-0.840**	-2.296	0.045
	Low	-0.531	-1.288	0.015	-0.344	-1.072	0.010	-1.199	-1.190	0.013
UNC	High	-1.424***	-3.584	0.104	-1.114**	-2.536	0.055	-0.913**	-2.456	0.052
	Low	-0.239	-0.560	0.003	-0.214	-0.575	0.003	-0.122	-0.207	0.000
TIV	High	-1.495***	-3.652	0.107	-1.294***	-2.684	0.061	-0.881**	-2.423	0.050
	Low	-0.363	-0.888	0.007	-0.243	-0.714	0.005	-0.477	-0.706	0.004
MU	High	-1.463***	-3.749	0.112	-1.269***	-2.596	0.057	-0.884***	-2.630	0.059
	Low	-0.356	-0.816	0.006	-0.379	-1.087	0.011	0.260	0.317	0.001
FU	High	-1.431***	-3.298	0.089	-1.363***	-2.637	0.059	-0.810**	-2.101	0.038
	Low	-0.125	-0.368	0.001	-0.115	-0.440	0.002	0.089	0.102	0.000
EPU	High	-1.513***	-4.294	0.144	-0.869**	-2.339	0.047	-1.253***	-3.574	0.104
	Low	0.081	0.148	0.000	-0.422	-0.788	0.006	0.684	1.133	0.011
Panel C: Short-sales Constraint										
SI/IO	High	-1.234***	-3.497	0.099	-0.712*	-1.758	0.027	-1.011***	-3.096	0.079
	Low	-0.740	-1.376	0.017	-0.805*	-1.844	0.030	0.290	0.361	0.001

Table 10: Test for Interactions between NNTA and Market Environment/Short-sales Constraint

This table provides in-sample estimation results for the predictive regression of monthly excess market return on news network triggered attention indices, market environment indicators/short-sales constraint proxy, and the interaction terms between the NNTA index and the market environment indicators/short-sales constraint proxy. For market uncertainty and investor sentiment, we use rankings (from 1 to 10) to indicate the level of strength. For short-sale constraint, we rank sample periods from 1 to 3. It equals 1 (3) when aggregated short interest ratio is in the lowest (highest) decile and aggregated institutional ownership is in the highest (lowest) tercile, and equals 2 for the rest sample periods.

$$R^m_{t+1} = \alpha + \beta NNTA_t + \phi Z_t + \gamma NNTA_t \times Z_t + \epsilon_{t+1}.$$

The sample period is 1996:02–2014:12. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Predictor	$\hat{\beta}$	$\hat{\phi}$	$\hat{\gamma}$	*Predictor*	$\hat{\beta}$	$\hat{\phi}$	$\hat{\gamma}$
Panel A: Market Uncertainty				**Panel B: Investor Sentiment**			
VIX	0.012	-0.009**	-0.004***	$Sent^{BW}$	-0.029***	-0.010**	0.003**
	(1.151)	(-2.211)	(-2.811)		(-3.865)	(-2.326)	(2.143)
UNC	0.005	-0.009**	-0.003**	$Sent^{PLS}$	0.008	-0.010**	-0.003**
	(0.446)	(-2.245)	(-1.984)		(0.778)	(-2.333)	(-2.538)
TIV	0.006	-0.009**	-0.003**				
	(0.647)	(-2.248)	(-2.548)				
MU	0.002	-0.009**	-0.003**				
	(0.187)	(-2.239)	(-2.166)	**Panel C: Short-sales Constraint**			
FU	0.008	-0.009**	-0.003**	*SI/IO*	0.080	-0.009**	-0.047*
	(0.765)	(-2.229)	(-2.390)		(1.504)	(-2.198)	(-1.793)
EPU	0.021*	-0.009**	-0.005***				
	(1.760)	(-2.179)	(-3.191)				

Table 11: Performance of the Sorted Portfolios Based on Retail Investors' Ownership and Abnormal News Co-occurrence

This table reports excess portfolio return and risk adjusted alpha of value weighted portfolio using S&P 500 stocks based on the abnormal connected news coverage in last month. We first sort stocks into 10 groups according to firms i's abnormal connected news coverage, $\sum_j aw_{ij,t}$. Stocks in the top (bottom) group are regarded as short (long) leg. We hold each group of stocks for 1 month and rebalance them at the close price of next month. We divide stocks into high and low retail ownership each month according to the tercile retail ownership in the last quarter. The sample period is from 1996-02 to 2014-12. Three types of risk factors are considered: Carhart (1997) four-factor model, Hou *et al.* (2015) q-factor model, and Fama and French (2016) five-factor model. t-statistics are reported in the parenthesis below the portfolio returns (risk adjusted alphas).

Portfolios	High Retail Ownership				Low Retail Ownership			
	ExcRet	Cahart-4	HXZ-q	FF-5	ExcRet	Cahart-4	HXZ-q	FF-5
Long	1.50%	0.81%	0.80%	0.88%	0.92%	0.23%	0.12%	0.05%
	(3.62)	(2.63)	(2.53)	(2.74)	(2.39)	(1.05)	(0.55)	(0.22)
2	0.58%	0.01%	0.12%	0.15%	0.73%	0.12%	-0.01%	-0.13%
	(1.20)	(0.02)	(0.36)	(0.43)	(1.76)	(0.46)	(-0.04)	(-0.50)
3	0.74%	0.27%	0.36%	0.49%	0.58%	-0.10%	-0.17%	-0.26%
	(1.65)	(0.84)	(1.08)	(1.46)	(1.42)	(-0.37)	(-0.63)	(-0.97)
4	0.56%	-0.01%	0.00%	0.15%	0.53%	-0.13%	-0.23%	-0.21%
	(1.58)	(-0.05)	(0.02)	(0.65)	(1.21)	(-0.44)	(-0.71)	(-0.66)
5	0.77%	0.41%	0.42%	0.46%	0.51%	-0.18%	-0.21%	-0.28%
	(1.91)	(1.53)	(1.48)	(1.64)	(1.17)	(-0.64)	(-0.71)	(-0.95)
6	0.41%	-0.01%	0.18%	0.02%	1.02%	0.27%	0.15%	0.06%
	(0.96)	(-0.02)	(0.56)	(0.05)	(2.20)	(0.96)	(0.51)	(0.21)
7	-0.17%	-0.60%	-0.52%	-0.42%	0.68%	0.03%	-0.12%	-0.17%
	(-0.40)	(-2.01)	(-1.68)	(-1.37)	(1.57)	(0.1)1	(-0.41)	(-0.57)
8	0.43%	-0.06%	-0.06%	0.10%	-0.20%	-0.88%	-0.94%	-0.97%
	(1.04)	(-0.22)	(-0.22)	(0.36)	(-0.49)	(-3.54)	(-3.72)	(-3.78)
9	1.08%	0.71%	0.81%	0.80%	0.59%	-0.05%	-0.24%	-0.33%
	(2.57)	(2.34)	(2.60)	(2.58)	(1.34)	(-0.18)	(-0.81)	(-1.12)
Short	0.49%	-0.07%	0.02%	0.08%	0.88%	0.18%	0.19%	0.04%
	(1.16)	(-0.21)	(0.05)	(0.23)	(2.01)	(0.63)	(0.65)	(0.13)
Long - Short	**1.03%**	**0.89%**	**0.79%**	**0.82%**	0.04%	0.06%	-0.06%	0.02%
	(2.40)	(2.10)	(1.78)	(1.84)	(0.13)	(0.18)	(-0.16)	(0.05)

A Mathematical Appendix

In this appendix, we explain the technical details regarding the construction of separate NNTA index under different weighting schemes. We start with the *occurrence information matrix*, $\mathcal{M}_t$, which stores the indicators of stocks' occurrence in the news at time t:

$$\mathcal{M}_t = \begin{array}{c} \\ stock_1 \\ stock_2 \\ \vdots \\ stock_N \end{array} \begin{array}{c} \begin{array}{cccc} news_1 & news_2 & \cdots & news_{K_t} \end{array} \\ \begin{bmatrix} Occr^1_{1,t} & Occr^2_{1,t} & \cdots & Occr^{K_t}_{1,t} \\ Occr^1_{2,t} & Occr^2_{2,t} & \cdots & Occr^{K_t}_{2,t} \\ \vdots & \vdots & \ddots & \vdots \\ Occr^1_{N,t} & Occr^2_{N,t} & \cdots & Occr^{K_t}_{N,t} \end{bmatrix} \end{array}, \tag{A.1}$$

where N is the total number of stocks in the sample, K_t is the total number of news of month t which may vary every month, and $Occr^k_{n,t}$ equals 1 if stock n is mentioned by news k at time t. Based on the occurrence information matrix, we then obtain the *weighted adjacency matrix*, $\mathcal{W}_t$, that measures the connectivities between the stocks and their strength:

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

where $w_{ij,t} = \sum_{k=1}^{K_t} Occr^k_{i,t}Occr^k_{j,t}$ with $i, j = 1, 2, \cdots, N$. Intuitively, $w_{ii,t}$ denotes the self news coverage of the stock i at time t, while $w_{ij,t}$ with $i \neq j$ is the connected news coverage between stock i and j at time t.

Next, we calculate the connected news coverage ratio by rescaling the each stock's connected news coverage by its self news coverage, i.e.,$w^*_{ij,t} = w_{ij,t}/w_{ii,t}$. Then, we obtain the abnormal measure by taking the first difference of $w^*_{ij,t}$, and all the elements are collected in the *adjusted weighted adjacency matrix* as below:

$$\mathcal{AW}_t = \begin{array}{c} \\ stock_1 \\ stock_2 \\ \vdots \\ stock_N \end{array} \begin{array}{c} \begin{array}{cccc} stock_1 & stock_2 & \cdots & stock_N \end{array} \\ \begin{bmatrix} 0 & aw_{12,t} & \cdots & aw_{1N,t} \\ aw_{21,t} & 0 & \cdots & aw_{2N,t} \\ \vdots & \vdots & \ddots & \vdots \\ aw_{N1,t} & aw_{N2,t} & \cdots & 0 \end{bmatrix} \end{array}, \tag{A.3}$$

where $aw_{ij,t} = w^*_{ij,t} - w^*_{ij,t-1}$.

Finally, based on the weighting schemes we discussed in the main text, we adjust the abnormal connected news coverage ratios in the above matrix with the firm sizes or the centrality scores, which give:

$$aw^s_{ij,t} = \begin{cases} Size_{i,t} \times Size_{j,t} \times aw_{ij,t}, & \text{if } s = sz, \\ Ctry_{i,t} \times Ctry_{j,t} \times aw_{ij,t}, & \text{if } s = ctr. \end{cases} \tag{A.4}$$

By aggregating the weighted abnormal measures of all the stocks in the market, we obtain two separate *News Network Triggered Attention* (NNTA) indices under different weighting schemes,

$$NNTA^s_t = \sum_{i=1}^{N} \sum_{j=1}^{N} aw^s_{ij,t}, \quad s \in \{sz, ctr\}. \tag{A.5}$$