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THREE ESSAYS ON
INFORMATION DIFFUSION AND MARKET FRICTION

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Three Essays on Information Diffusion and Market Friction

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I hereby declare that this PhD dissertation is my original work
and it has been written by me in its entirety.
I have duly acknowledged all the sources of information
which have been used in this dissertation.

This PhD dissertation has also not been submitted for any degree
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Abstract

How markets impound information into asset prices is one of the most important concerns of financial economics. Due to behavioural bias and transaction friction, information could be mispriced in the real world, thus driving market anomalies and return predictability of behavioural factors. My dissertation contributes to the literature by investigating how information can be quantified, acquired, disseminated and priced in the financial market with the existence of market frictions.

In Chapter 2, we propose an efficient method based on machine learning and textual analysis to quantify cross industry news and shed light on how news travels across different industries. The results show that cross-industry news contains valuable information about firm fundamentals that is not fully captured by firms' own news or within-industry peers' news. Stock prices do not promptly incorporate cross-industry news, generating return predictability. Moreover, underreaction to cross-industry news is more pronounced among smaller stocks that are more illiquid, more volatile, and have fewer analysts following. A long–short strategy exploiting cross-industry news yields annual alphas of over 10%.

In Chapter 3, we construct a novel measure of market wide investor attention by applying a social network analysis to aggregate the attention spillover effects among stocks that are co-mentioned by media news. Empirically, we find that the News Network Triggered Attention index (NNTA), negatively predicts market returns with a monthly in-sample (out-of-

sample) R-square of 5.97% (5.80%). In the cross-section, a long-short portfolio based on a news co-occurrence generates a significant monthly alpha of 68 basis points. We further validate the attention spillover effect by showing that news co-mentioning significantly increases Google and Bloomberg search volumes than that of unconditional news coverage. The results hence suggest that attention spillover in a news-based network can lead to significant stock market overvaluations, especially when arbitrage is limited.

Besides behavioural bias, security analysts seem to also contribute to the market friction by issuing biased recommendations. In Chapter 4, we find that the biased recommendations of analysts could be a source of market friction that impede the efficient correction of mispricing. In particular, analysts tend to make more favourable recommendations to overvalued stocks, which have particularly negative abnormal returns ex-post. While analysts whose recommendations are better aligned with anomaly signals are more skilled and elicit stronger recommendation announcement returns.

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Chapter 1

Introduction

The central role of financial markets is to channel funds within an economy. To realize this basic function, the market price is expected to accurately reflect all available information. Therefore, how the markets react to a new information has been always one of the most important concerns of financial studies. Fama (1970) elaborates in detail the dynamic process of accurately incorporating information into prices with the concept of efficient market. Under this theory, investors are assumed to process all relevant information instantaneously and the market is assumed to be complete and frictionless. In this case, any new information will be immediately incorporated in the equilibrium prices. However, complete and constant market efficiency is arguably an unattainable ideal. A large body of empirical evidences have shown that investors face sizable market frictions, such as behaviour bias and limits to arbitrage (incomplete markets and limited market participation, asymmetric information, noise traders, limited investor attention, transaction costs, short sale constraints, and legal restrictions). Therefore, information can be mispriced in the real world, thus driving market anomalies and return predictability of behavioral factors. My dissertation contributes to the literature by investigating how information can be quantified, disseminated and priced in the financial market with the existence of market frictions.

An increasing number of empirical and theoretical literatures have relaxed some of the stringent assumptions of the efficient market hypothesis and postulate that gradual diffusion of information among investors explains the observed predictability of returns (Hong and Stein, 1999). A long line of early work mainly focus on the lagged price response of assets to their own past returns. While in most recent studies, firms are intertwined through various observable and subtle economic links and these relations could easily transcend the traditional industry boundaries. Accordingly, this new channel of information flow has been widely explored in the recent literature to explain cross asset return predictability(Cohen and Frazzini (2008); Menzly and Ozbas (2010); Hong and Stein (1999); Hong, Torous and Valkanov (2007), and Rapach, Strauss, Tu and Zhou (2018); Lee, Sun, Wang and Zhang (2018)).

Nevertheless, these studies mainly focus on the customer-supplier linkage to understand inter-sectorial relationship, in Chapter 2, we provide several reasons to believe that media news may capture inter-industry relationship beyond what is captured by the customer-supplier economic linkage. First, media news, due to the crowd wisdom of journalists, reveals connections such as trade credit, banking and financing, geographical links, business alliance links, law suit and regulation changes among industries that are much more complex than customer-supplier linkage. To support this argument, we construct a cross-industry network based on media news that simultaneously mentions firms operating in two different industries. Using techniques from graph theory, we find industries in the highest quintile of weighted eigen-centrality have, on average, a price delay that is 6.58% (6.22%) lower than industries in the lowest quintile of eigen-centrality (degree centrality). Similar pattern can be also observed when measuring the pairwise inter-industry connections. Second, in contrast to the linkage extracted from traditional data sources, news-implied connections are available in high frequency and provide timely information to explain the industry-interdependence. Data on the interconnections between firms is notoriously hard to collect. Usually, data available is incomplete and lagged. For example, the 10-K reports reveal a fraction of the business links for corporations in the U.S. but they are published only once a year. The Bureau of Economic Analysis reports on input-output links across sectors but these data are only updated once every 5 years. By contrast, media news allows us to construct a timely network of firm interconnections as it covers sufficient information about the relationships between firms (Schwenkler and Zheng 2019). Last but not the least, media news contains soft information that may not be quickly absorbed in the prices, thus further contributing to the cross industry information diffusion (Tetlock, SaarTsechansky and Macskassy, 2008; Jegadeesh and Wu, 2013; Bushee, Core and Hamm, 2010). Accordingly, we propose an efficient method based on machine learning and textual analysis to quantify cross industry news (CIS) and find that it contains valuable information about firm fundamentals that are not fully captured by firms' own news or within-industry peers' news. A long-short strategy exploiting cross-industry news yields annual alphas of over 10% and it is more pronounced among smaller stocks that are more illiquid, more volatile, and have fewer analysts following.

As noted by Shiller (2003), in terms of non-risk based models, behavioral finance has become an important part of research, and investors' behavior bias profoundly contributes to the market frictions. Among various behavioral forces, financial research has comprehensively explored the role of investor attention. Merton (1987) claim that constrained investors only know a subset of the securities in the stock world. Early studies by Shiller emphasized the link between time-varying investor attention and stock market returns (e.g., Shiller (1984), Shiller (1989), and Shiller (1999)). A recent study by Peng and Xiong(2006) shows that due to limited attention, investors tend to deal with more market information rather than company-specific information, which results in a return co-movement phenomenon. Subsequent research by Peng et al. (2007) shows that both limited attention and attention shift hypothesis could explain the time-varying, co-movement of assets. From the perspective of news attention, Odean (1999) and Barber and Odean (2008) found that individual investors pay limited attention to transaction search so they were more likely to trade stocks that attracted their attention, especially for buying stocks. Fang and Peress (2009) and Fang, Peress and Zheng (2014) further studied the predictability of cross-sectional returns and mutual fund transactions and performance by using media coverage as the proxy of attention-grabbing events. There is also evidence that individual and institutional investors are subjected to limited attention. Other related works include Kahneman (1973), Shiller, Fischer and Friedman

(1984), Barberis and Shleifer (2003), Peng (2005), Gabaix, Laibson, Moloche and Weinberg (2006), Cohen and Frazzini (2008), Hirshleifer, Lim and Teoh (2009), DellaVigna and Pollet (2009), and Van Nieuwerburgh and Veldkamp (2009).

Given that investor attention has proved to be one of the most important driving forces of stock returns in recent literature, the lack of investigation on the impact of investor attention on market premium forecast is surprising. In Chapter 3, we construct the News Network Triggered Attention (NNTA) index to forecast market returns. When multiple stocks are mentioned in the same news article, investors' attention to one stock will spill over to other jointly mentioned stocks, thus increasing the attention for all the connected stocks. Based on the attention spillover effect in the news network, the response to good news may be stronger than that to bad news due to the existence of short-sale constraints (Barber and Odean(2008)), which in turn may lead to over-valuation and subsequent underperformance. Accordingly, we collect the news of S&P 500 stocks in the market on a monthly basis, and construct the adjacency matrix to aggregate the attention spillover effects that can asymmetrically affect non-shareholders' trading behavior. In line with our expectation, NNTA negatively predicts future market return, with the monthly in-sample and out-of-sample R^2 being 5.97% and 5.80% respectively. After controlling alternative attention proxies and other forecasting factors such as investor sentiment, hard information and soft information, the results are indeed robust. Particularly, our attention proxy reasonably fits the fact that non-shareholders are more short-sale constraint than shareholders. And consistent with literature, the source of the return predictability of NNTA comes from the retail investors' trading behaviour through the short-sales constraint and belief divergence. Therefore, our proxy is obviously more effective than those who do not distinguish the roles of investors in predicting the market premium. Considering that attention proxy is aggregated from the firm level, attention spillover effect should hold cross-sectionally as well. Then, we extend the research results to the predictability of cross-sectional returns, and find that the long-short portfolio based on abnormal connected news produces 0.68% monthly alpha, which is statistically significant at 1%. As Da et al. (2011) discussed, unless investors read, news reports will not attract attention. To solve this problem, we further verify the attention spillover effects by showing that, compared with unconditional news coverages, news co-mentioning significantly increases the search volume of Google and Bloomberg. Moreover, consistent with the literature, the source of the return predictability of NNTA comes from retail investors' trading behavior through short-sale constraints and belief divergence.

Although behaviour bias and limits to arbitrage contribute to the informational inefficiency, sophisticated investors or informed traders such as speculators, firm insiders, short sellers, institutional investors and security analysts are less restricted by these constraints and should be able to process relevant information and correct the market mispricing, hence contributing to a better information environment. Consistent with this argument, using short interest as a proxy for arbitrage capital, Hanson and Sunderam (2014) point out that an increase in arbitrage capital on the anomalies leads to lower strategy returns. Chen, Da, and Huang (2018) propose a new method for net arbitrage trading and find that anomaly returns come exclusively from the stocks traded by arbitrageurs. Anginer, Hoberg, and Seyhun (2015) show that the return predictability of anomalies disappears when there is disagreement between the insider trading and the anomalies. On the contrary, the recent studies on institutional investors seem to provide a different angle. Several recent papers argue that institutional investors and mutual funds in particular, through their correlated trading behavior, may contribute to the pervasiveness of these anomaly patterns. Jiang (2010) claim that institutional investors herding behavior leads to the value effect. Edelen et al. (2016) find that institutional investors tend to trade in a direction contrary to anomaly prescriptions and that their trading amplifies anomaly returns. Akbas, Armstrong, Sorescu, and Subrahmanyam. (2015) find that aggregate flows into the mutual fund sector exacerbate well-known stock return anomalies, while aggregate flows into the hedge fund sector attenuate anomalies.

In the meantime, analysts have been commonly viewed as the information intermediaries in capital markets. Their stock recommendations and earnings forecasts serve as an important information source that affect regulators, investors and other market participants' decisions. In this case, analysts activities and competition between them are expected to improve the informational efficiency. However, there is a longstanding debate in the literature concerns whether security analysts research is useful for market participants. Early studies using short-run event windows to measure market reactions usually find that analyst forecasts and recommendations elicit large announcement returns and analysts research indeed contributes to a better information environment (Elton, Gruber, and Grossman (1986) and Womack (1996), Barber et al. (2001) and Jegadeesh et al. (2004)). While recent studies have shown that analysts research is often biased for either strategical reason or behaviour bias (Lin and McNichols (1998), Dechow, Hutton, and Sloan (2000), OBrien, McNichols, and Lin (2005), Bradshaw, Richardson, and Sloan (2006); Cowen, Groysberg, and Healy 2006; Chen and Mastsumoto 2006), McNichols and OBrien (1997), La Porta (1996), Jegadeesh et al. (2004), Drake, Rees, and Swanson (2011), Hribar and McInnis (2012)).

In Chapter 4, the interaction effect between the stock market anomalies and analyst recommendations has been carefully examined. The results reveal that analysts tend to give more favourable recommendations to overvalued stocks and these stocks earn particularly negative abnormal returns in the future. Furthermore, the amplification effect is more pronounced during high-sentiment periods than during low-sentiment periods, suggesting that analysts behavioural biases, rather than misaligned incentives, could partially explain their overly optimistic recommendations for overvalued stocks. Overall, our findings indicate that analysts biased recommendations could be a potential source of market friction that impedes the efficient correction of mispricing.

Chapter 2

Media-based Inter-Industry Network and Information Transmission

Li Guo, Jun Tu

2.1 Introduction

In modern economy, firms are intertwined through various observable and subtle economic links and these relations could easily transcend the traditional industry boundaries. Previous studies show that investors, largely due to their limited attention, underreact to the value-relevant information contained in the news of economically-related firms, which then leads to cross-firm return predictability.[1] While these prior studies mainly focus on customer-supplier linkage to understand inter-sectorial relationship[2], it may not fully capture the complex interdependence among firms operate in different sectors. In this paper, we use media news to construct a comprehensive inter-industry network and examine information transmission across industries.

There are several reasons to believe that media news may capture inter-industry relationship beyond what is captured by customer-supplier relation. First, media news, due to journalists' wisdom of crowd, is a comprehensive measure of cross-firm connections including product similarity, geographic overlap, business alliance, labor market competition, and regulatory impact. Second, unlike the customer-supplier relation which is updated infrequently, media news provide timely information about the dynamics of

[1]See, for example, Cohen and Frazzini (2008); Menzly and Ozbas (2010); Hong and Stein (2007), and Rapach, Strauss, Tu and Zhou (2015); Lee, Sun, Wang and Zhang (2018).

[2]Related studies include Cohen and Frazzini (2008); Menzly and Ozbas (2010), Ahern (2013), Ahern and Harford (2014), Kelly, Lustig and Van Nieuwerburgh (2013), Herskovic, Kelly, Lustig and Van Nieuwerburgh (2016), Long Jr and Plosser (1983), Loualiche *et al.* (2014) and Oberfield (2012)

industry interdependence. Last but not the least, while prior studies mainly use realized stock returns as proxy for news, our use of media news is potentially less noisy and also contains soft information that may not be quickly impounded into prices. As a result, the media-based cross-industry network could complement the customer-supplier linkage in capturing the complexity of industry interdependence.

We construct the cross-industry network based on the number of media news simultaneously mentioning firms operating in two different industries. We then validate our media-based industry network using the price delayless measure of Hou and Moskowitz (2005). Using techniques from graph theory, we calculate the centrality of each industry by measuring the strength of connections between this industry and all other industries in the economy. We find industries in the highest quintile of eigen-centrality (degree-centrality) have, on average, an average price delayness that is 6.58% (6.22%) lower than industries in the lowest quintile of eigen-centrality (degree centrality). This result is statistically significant and economically meaningful. We observe similar pattern when measuring the pairwise inter-industry connections. A pair of industries connected by the largest number of media news, on average, has an 8.15% shorter delay in incorporating the pair industry's news, compared to pair of industries connected by very few news.

Having validate the media-based industry network, we next examine hows news diffuse across industries. Recent work suggests that media news contains soft information about firms' fundamentals, and has incremental predictive power for firms' future performance.[3] The literature, however, almost exclusively focus on the soft information contained in firms' own news. In this paper, we deviate from prior studies in examining the information contained in cross-industry news.

Specifically, we conduct textual analysis using the Thomson Reuters News Archive and construct news tones for each of the Fama-French 30 industry categories, where news

[3]For example, Tetlock, SaarTsechansky and Macskassy (2008) found that negative words predict future earnings, and Bushee, Core and Hamm (2010) showed that the media serves as an information intermediary which incrementally contributes to firms' information environment.

tone is measured as the proportion of negative words following Tetlock *et al.* (2008). We test the informativeness of cross-industry news by examining its predictability for firms' future unexpected earnings. If cross-industry news is incrementally useful, it should predict firms' fundamentals. Indeed, our analysis reveals the strong predictability of cross-industry news tone for firms' earnings news, even after controlling other predictor of firm fundamentals and firms' own news. The result also reveals the complexity of the cross-industry network in the real economy, as the coefficients in front of the cross-industry news tones exhibit substantial heterogeneity across industries.

Next, we link the cross-industry news to cross-industry return predictability. However, we do not test return predictability directly at the industry level. Instead, we estimate the value implication of cross-industry news for each firm and examine its return predictability at stock level. There are some reasons for doing this. First, even for firms within the same industry, they may react differently towards cross-industry news depending on their competitive positions within the industry. If this is the case, our approach would fully explore firms' heterogeneous exposure to the cross-industry information. Second, due to limited number of industries, industry-level test may lack the power to detect the informativeness of cross-industry news. Our stock-level test circumvent this power issue since we have on average 2,234 firms in each cross section, generating wide spread in terms of cross-industry news signal.

Return predictability test shows that stock prices incorporate the information embedded in the cross-industry news with a significant delay. We obtain consistent results using both Fama-MacBeth regression and portfolio sorting. For example, a weekly-rebalanced, long-short portfolio that long stocks with positive CIS and short those with negative CIS generates Carhart (1997) four-factor alpha of more than 10% annually. The profitability of trading on cross-industry news survives after accounting for reasonable estimate of transaction costs. We further explore the horizon over which cross-indutry news diffuse into stock prices, and find news travel slowly in our case. The long-short portfolio based on cross-industry news still generates a sizeable alpha even 10 weeks after the news is announced to public. On the contrary, we find market prices impound firm-specific news relatively quickly, as the return to a long-short portfolio based on firms' own news fully dissipate after 4 weeks. In Fama-MacBeth regressions with firms' own news and news of within-industry peers as controls, we find cross-industry news continues to be a significant predictor of future returns, suggesting that cross-industry news contain novel information not captured by these alternative information sources.

We conduct several subsample tests based on firms' information environments, arbitrage frictions, and aggregate uncertainty. Our proxies for firms' information environments include firm size, analyst coverage and forecast dispersion. The results show that the return predictability of cross-industry news is much more pronounced among stocks with poor public information environments, such as small stocks with thin analyst coverage. In addition, cross-industry news seem to diffuse more slowly during highly uncertain periods, as proxied by higher VIX and more dispersed news signal.

The paper contributes to several strands of literature. First, our work relates to the empirical studies on gradual information diffusion among economically linked firms and industries. Cohen and Frazzini (2008) and Menzly and Ozbas (2010) document return predictability from customer firms/sectors to supplier firms/sectors. Hong and Stein (2007) show that the returns of the leading industry lead the market returns. Lee *et al.* (2018) show that returns of technology-linked firms have strong predictive power for focal firm returns. Parsons, Sabbatucci and Titman (2018) document lead-lag effects in stock returns between co-headquartered firms operating in different sectors. Our study is similar in spirit, but examines information diffusion along the inter-industry network extracted from media news. As we have conjectured, our media-based industry network has the advantage of being a more comprehensive measure of cross-firm connections and is also dynamic.

Second, this paper contributes to the growing literature on quantifying soft information in news and examine its value implications for firms' fundamentals and stock prices. Tetlock (2007) analyzes the content of a commentary section in the Wall Street Journal, and finds that pessimistic words predict lower stock returns the next day. Davis, Piger and Sedor (2006), Tetlock *et al.* (2008), and Demers and Vega (2011) extract the tone from firm-specific news and show its informativeness for firms' future earnings and stock returns. Our study builds upon this literature and shows that tones of cross-industry news contain valuable information about firm fundamentals beyond what is captured by firms' own news.

Third, this paper also enhances our understanding of the role of media as an information intermediary. Fang and Peress (2009) show firms with lower media coverage have higher expected returns, as predicted by Merton (1987) when investors have incomplete information and market is segmented. Peress (2014) uses newspaper strikes as an exogenous shock, and show that media affect the stock market by improving the speed of information diffusion among investors. Engelberg and Parsons (2011) document direct evidence of local media coverage affecting local investors' trading activities. Bushee *et al.* (2010) find that media coverage reduces information asymmetry around earnings announcements through broad dissemination of information. Our paper differs from these studies by showing media news help facilitate the information transimision across industries and firms.

The rest of the paper is organized as follows. Section 2 describes the data used in this paper, and explains how the Cross-Industry News Signal (CIS) is constructed. Section 3 constructs and validates the media-based inter-industry network. Section 4 presents results on the information diffusion of cross-industry news. Section 5 explores the channels through which cross-industry news diffuse into stock prices. The last section concludes.

2.2 Data and Methodology

2.2.1 Data and Variables

The data used in this paper is collected from five major datasets. Media news is from Thomson Reuters. Analysts' annual earnings forecasts and other related information are obtained from the I/B/E/S. The institutional fund flow data is collected from the EPRF database. The data for firms' fundamentals and stock market variables are obtained from the Compustat and CRSP databases, respectively.

We construct the news sample using firm-specific news articles for all U.S. public firms from January 1996 to December 2014. We require the news articles to be novel news, which means that it is the first release or record by Thomson Reuters. We classify news items into Fama-French 30 industry categories according to the firms' RIC mentioned in each news article.[4] In total, we retrieve 11.63 million news stories from the Reuters News Archive database.

To construct the media-based inter-industry network, we first convert news data every year into the matrix $\mathcal{M}_t$ below:

$$\mathcal{M}_t = \begin{array}{c} \\ \scriptstyle Industry_1 \\ \scriptstyle Industry_2 \\ \vdots \\ \scriptstyle Industry_N \end{array} \begin{array}{c} \begin{array}{cccc} \scriptstyle news_1 & \scriptstyle news_2 & \scriptstyle \cdots & \scriptstyle news_{K_t} \end{array} \\ \begin{bmatrix} Occr_{1,t}^{1} & Occr_{1,t}^{2} & \cdots & Occr_{1,t}^{K_t} \\ Occr_{2,t}^{1} & Occr_{2,t}^{2} & \cdots & Occr_{2,t}^{K_t} \\ \vdots & \vdots & \ddots & \vdots \\ Occr_{N,t}^{1} & Occr_{N,t}^{2} & \cdots & Occr_{N,t}^{K_t} \end{bmatrix} \end{array}, \tag{2.2.1}$$

where N is the total number of industries in the sample, K_t is the total number of news each year, and $Occr_{n,t}^{k}$ equals 1 if a stock in industry n is mentioned by a news article,

[4]The RIC is made up primarily of the security's ticker symbol, optionally followed by a period and exchange code based on the name of the stock exchange using that ticker. For instance, IBM.N is a valid RIC, referring to IBM being traded on the New York Stock Exchange. By extracting ticker symbol from RIC, we are able to match it with CRSP permno.

k. Based on $\mathcal{M}_t$, we then obtain the *weighted adjacency matrix*, $\mathcal{W}_t$, that measures the strength of connectivities between two industries:

$$\mathcal{W}_t = \mathcal{M}_t\mathcal{M}_t^\top = \begin{array}{c} \\ industry_1 \\ industry_2 \\ \vdots \\ industry_N \end{array} \begin{array}{c} \begin{array}{cccc} industry_1 & industry_2 & \cdots & industry_N \end{array} \\ \begin{bmatrix} w_{11,t} & w_{12,t} & \cdots & w_{1N,t} \\ w_{21,t} & w_{22,t} & \cdots & w_{2N,t} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1,t} & w_{N2,t} & \cdots & w_{NN,t} \end{bmatrix} \end{array}, \tag{2.2.2}$$

where $w_{ij,t} = \sum_{k=1}^{K_t} Occr_{i,t}^k Occr_{j,t}^k$ with $i, j = 1, 2, \cdots, N$. Intuitively, when $i = j$, $w_{ii,t}$ counts the number of news mentioning the industry i at time t, and when $i \neq j$, $w_{ij,t}$, it counts the number of news co-mentioning industry i and j at time t. We then calculate the Eigen-centrality for the above weighted adjacency matrix after setting the diagonal element to 0. Different from the adjacency matrix, the Eigen-centrality for the weighted adjacency matrix considers the strength of connections between nodes. Specifically, Eigen-centrality is defined as follows:

$$\mathcal{W}_t\mathbf{x}_t = \lambda_{\max}\mathbf{x}_t, \text{ for each } t = 1, 2, \cdots, T, \tag{2.2.3}$$

where $\mathbf{x}_t = (Ctry_{1,t}, Ctry_{2,t}, \cdots, Ctry_{N,t})'$ and $Ctry_{i,t}$ is the eigenvector centrality score of industry i at time t.[5] We also construct the degree-centrality measure by counting the number of news connecting industry i and all other industries, namely:

$$Degree - centrality_{i,t} = \frac{\sum_{j\neq i} w_{ij,t}}{\sum_{i=1}^{i=N}\sum_{j\neq i} w_{ij,t}}.$$

We conduct textual analysis to quantify the information content of each news article

[5]According to Segarra and Ribeiro (2016), eigen-centrality shows stable property for the weighted adjacency matrix.

using the word list of Loughran and McDonald (2011). We use a variation of the approach in Hu and Liu (2004) to account for sentiment negation. If the word distance between a negation word (not, never, no, neither, nor, none, nt) and the sentiment word is not larger than five, the positive or negative polarity of the word is changed to the opposite of its original polarity. Following Tetlock *et al.* (2008), we measure the tone of each news article using the negative word ratio according to the following equation:

$$\text{Tone} = \frac{\text{\# of negative words}}{\text{Total \# of words in the news article}}.$$

We then compute the firm-specific news tone by averaging the tone for all news articles related to the firm i at time t:

$$\text{Firm News}_{i,t} = \frac{\sum_{d=1}^{D} \text{Tone}_{i,d}}{\text{D}}.$$

where D is the total number of firm-specific news at time t. We define the news tone for firm i's industry peers as the average news tone of peer firms within the same industry as firm i:

$$\text{Peer News}_{i,t} = \frac{\sum_{k=1}^{K} \text{Firm News}_{k,t}}{\text{K}},$$

where i $\neq$ k and K is the total number of firms in industry excluding firm i. Similarly, we define the cross-industry news of firm i as the average firm-specific news tone of a cross-industry $\mathbf{J}$, namely:

$$\text{Cross-Industry News}_{i,\mathbf{J},t} = \frac{\sum_{j=1}^{J} \text{Firm News}_{j,t}}{J},$$

where $\mathbf{J} \in \{1, 2..., N-1\}$, N is the total number of industries, and J is the total number of firms in industry $\mathbf{J}$. To control for the effect of media coverage (Fang and Peress (2009)), we also calculate the number of firm-specific news, the number of industry peer news and the number of cross-industry news as additional controls.

We use the firm's standardized unexpected earnings (SUE) as a proxy for the firm fundamentals. Following Bernard and Thomas (1989), SUE is defined as:

$$\mathrm{UE}_t = \mathrm{E}_t - \mathrm{E}_{t-4}$$

$$\mathrm{SUE}_t = \frac{\mathrm{UE_t} - \overline{\mathrm{UE}}_\mathrm{t}}{\mathrm{Std}(\mathrm{UE}_t)},$$

where E_t is the firm's earnings in quarter t. $\overline{\mathrm{UE}}$ and Std(UE) are the mean and volatility of the unexpected earnings calculated using firm's previous 20 quarters of unexpected earnings, respectively. We also include control variables including firm size, book-to-market ratio (B/M), turnover, three measures of recent stock performance, and analyst forecast dispersion. Firm size (log(market capitalization)) and B/M are calculated at the end of the preceding calendar year, following Fama and French (1993). The turnover is the natural log of number of shares traded divided by shares outstanding (Log(Share Turnover)) at the end of the preceding calendar year. We calculate analyst dispersion as the standard deviation of analysts' earnings forecasts 3 to 30 days prior to the earnings announcement scaled by earnings volatility.

Following Tetlock *et al.* (2008), we calculate past returns based on a simple event study methodology. We chose the analysts' forecast announcement day or earnings announcement day as the event day in accordance with the dependent variable. Specifically, we calculate the expected return using the Fama-French three-factor model with an estimation window of [-252,-31] trading days before the event day t. We also calculate the abnormal return on day $t-2$ before the event day CAR_{t-2}, and the cumulative abnormal return in the [-30,-3] trading day window before the event day, denoted as $\mathrm{CAR}_{t-30,t-3}$.

Following Druz *et al.* (2015), we include some firm characteristics as control variables.

Market return is defined as the percent value-weighted market return for the period starting 5 days after an earnings announcement for the quarter t-1 and ending 5 days before the earnings announcement for the quarter t. Momentum is defined as the firm's buy-and-hold return over the previous 6 months. Illiquidity is defined as the absolute value of the stock return scaled by the dollar trading volume. Leverage is defined as the long-term debt scaled by the sum of the long-term debt and equity market capitalization. Institutional Ownership is defined as the number of shares held by 13F institutions scaled by shares outstanding. Return volatility is the standard deviation of the monthly return over the previous 48 months. In some specifications, we also include firm fixed effects and year fixed effects.

Panel C of Table 2.1 presents the summary statistics for the variables related to media news. For an average firm in our sample, there are 57,507 cross-industry news, 1,237 industry peer news, and 28 firm-specific news within 90 days before the earnings announcement. The # of Cross-Industry News is much larger than the number of firm-specific news, suggesting that more information is potentially revealed by cross-industry news. The mean industry-level news tone is 0.045, ranging from 0.038 to 0.052. As expected, the volatility of industry-level news tone is much smaller than firm-specific news tone. Following Tetlock *et al.* (2008), we standardize all news tones to make it comparable across industries.

< Insert Table 2.1 here >

2.2.2 Cross-Industry News Signal

To examine the information content of cross-industry news, one needs to measure the overall impact of cross-industry news for each individual firm. This is challenging due to the complex inter-industry relationship, and the same industry's news may have differential value implication for different firms. In this paper, we use a machine learning approach to extract the information from multiple cross-industry news, which we denote as the cross-industry news signal (CIS).

The approach consists of three steps. First, we calculate the news tone of each industry J over the most recent week $t-1$, denoted as Cross-Industry News$_{i,\mathbf{J},t-1}$. Next, we predict stock i's week-t return using the news tone of firm i's cross industries over the week $t-1$. The predictive regression is estimated as follows:

$$\mathrm{r}_{i,t} = \alpha_i + \sum_{\mathbf{J}=1}^{N-1} b_{i,\mathbf{J},t}\text{Cross-Industry News}_{\mathrm{i},\mathbf{J},\mathrm{t}-1} + \epsilon_{i,t}, \text{for t = 1,..., T,} \tag{2.2.4}$$

where $r_{i,t}$ is the week-t return of stock i in excess of the risk-free return, and N is the total number of industries. We require at least 260 weekly observations for each firm, and set the initial estimation window at 208 weeks (4 years of observation).

Moreover, to improve out-of-sample prediction and avoid model overfitting, we use the adaptive LASSO method following Zou (2006). The adaptive lasso includes parameter weights in the LASSO penalty term to achieve the oracle properties for appropriate weights. The adaptive LASSO estimates are defined as:

$$\hat{b}_i^* = \text{argmin}\|r_{i,t} - \alpha_i - \sum_{\mathbf{J}=1}^{N-1} b_{i,\mathbf{J}}\text{Cross-Industry News}_{\mathrm{i},\mathbf{J},\mathrm{t}-1}\|^2 + \lambda_i \sum_{\mathbf{J}=1}^{N-1} \hat{w}_i |b_{i,\mathbf{J}}|,$$

where Cross-Industry News$_{i,\mathbf{J},t-1}$ is the standardized news tone of cross-industry $\mathbf{J}$, $\hat{b}_i^* = (\hat{b}_{i,1}^*, ..., \hat{b}_{i,N-1}^*)'$ is the N-1 vector of adaptive LASSO estimates, λ_i is a nonnegative regularization parameter, and $\hat{w}_{i,\mathbf{J}}$ is the weight assigned to $|b_{i,\mathbf{J}}|$ in the penalty term. The adaptive LASSO uses the L1-norm penalty to prevent overfitting, and enables the selection of the most informative predictors.

Using the estimated $\hat{b}_i^*$, we then predict the out-of-sample return in week $t+1$ using the cross-industry news available at time t and denote it as CIS:

$$\text{CIS}_{i,t} = \alpha_i + \sum_{\mathbf{J}=1}^{N-1} E_t[b_{i,\mathbf{J},t+1}]\text{Cross-Industry News}_{\text{i},\mathbf{J},\text{t}},$$

where $E_t[b_{i,\mathbf{J},t+1}]$ is the estimated coefficient from equation 2.2.4 and is defined as $E_t[b_{i,\mathbf{J},t+1}] = b_{i,\mathbf{J},t}$. The cross-industry news signal is a real-time predictor of stock returns and does not suffer from look-forward bias.[6]

2.3 Media-based Inter-industry Network

2.3.1 Properties of the Media-based Inter-industry Network

In this section, we first show that our media-based inter-industry network reveals complex and dynamic inter-industry relationship, beyond what is captured by the customer-supplier linkages. Figure 2.1 illustrates the time-varying inter-industry network for the Fama-French 30 industries based on Thomson Reuters News data from 1996 to 2014. We define two industries as connected if a piece of news article simultaneously mentions stocks in the two industries. The thickness of an edge reflects the degree of inter-industry connections, as determined by the number of news connecting an industry pair. The node size denotes the eigenvector centrality of an industry. The figure shows two stylized facts. First, our media-based inter-industry network varies significantly over time, suggesting a dynamic industry interdependence. Moreover, we observe that the inter-industry connections become stronger in the recent years. Second, unlike customer-supplier relation, Manufacturing-related industries are usually not the central industries in our media-based industry network. Instead, the more central industries (represented by the larger node size) seem to be Business Equipment, Personal and Business Services, and Finance in-

[6]In the empirical analysis below, we only use stocks with negative CIS due to the uninformativeness of positive CIS.

dustry. Overall, the analysis suggests that our media-based inter-industry network is dynamic and distinct from the traditional customer-supplier network, and is potentially a more comprehensive measure of inter-industry relationship.

< **Insert Figure 2.1 here** >

2.3.2 Media-based Inter-industry Network and Price Delayness

To verify that our media-based industry network indeed captures the network position of industries, we first link industry-level centrality based on the media network with the price delayness measure of Hou and Moskowitz (2005). The idea is that more central industries should more quickly incorporate economy-wide shocks. Panel A of Table 2.1 reports the summary statistics of cross industry media connection, including eigenvector centrality, degree centrality, the frequency that an industry is assigned into a low (high) eigenvector centrality and low (high) degree centrality and the delayness measure. Consistent with Figure 2.1, Financials, Business Equipment, Services and Retails are the most important nodes in the media network, while Coal, Oil and Mines tend to be the periphery groups. Moreover, the industries with the highest network centrality tend to have a lower delayness measure.

In Table 2.2, we sort all industries into five quintiles based on the eigen-centrality (degree-centrality) and reports the average delayness measure for each group over 1996 to 2014. Column 1 of Table 2.2 shows the average delayness for quintiles sorted on eigen-centrality. The industries with the lowest eigen-centrality has an average price delayness of 7.90%, compared to 1.32% for industries in the highest quintile. The differences in price delayness between the highest and lowest quintiles of industries is -6.58% and highly significant. We observe similar pattern between industries' network centrality and price delayness using the degree-centrality measure in Column 2 of Table 2.2.

< **Insert Table 2.2 here** >

In Table 2.3, we report the cross-industry information delayness for five groups sorted on the number of news mentioning the given industry pair. Our approach to construct cross-industry delayness measure is similar to Hou and Moskowitz (2005). For an industry pair A and B, the delayness of industry B's news on industry A's return, $Delay_{B\to A}$, is the fraction of industry A's returns explained by industry B's lagged returns. More specifically, the measure is one minus the ratio of the R^2 from regression (4.1) by restricting $\delta_j^{-n} = 0, n \in [1, 4]$, over the R^2 from regression (4.1) without restrictions.

$$\mathrm{r}_{A,t} = \alpha_j + \beta_A r_{B,t} + \sum_{n=1}^{4} \delta_A^{-n} r_{B,t-n} + \epsilon_{A,t}, \qquad (4.1)$$

where $r_{A,t}$ is the daily return of industry A and $r_{B,t}$ is the daily return of industry B. The pairwise information delayness between industry A and B is calculated as the average of $Delay_{A\to B}$ and $Delay_{B\to A}$. We then sort all industry pairs into five quintiles according to the # of news mentioning the paired industries and report the average pairwise delayness measure for each quintile. Consistent with our measure capturing cross-industry relationship, we find industry pairs that are more closely connected through media have much lower cross-industry price delayness. For example, the average delayness for industry pairs with the lowest media connection is 13.21%, more than twice the average delayness of the industry pairs with the strongest media-based connection. Overall, our validation test based on price delayness measure strongly support the notion that media is an important information intermediary that contribute to cross-industry information diffusion.

< **Insert Table 2.3 here** >

2.4 Cross-Industry News and Information Transmission

2.4.1 Cross-Industry News and Firm Fundamentals

In this section, we examine whether cross-industry news contain value-relevant information about firm fundamentals. We perform the following regression analysis:

$$\text{SUE}_{it} = \alpha_i + \sum_{\mathbf{J}=1}^{N-1} \beta_{\mathbf{J}} \text{Cross Industry News}_{i,\mathbf{J},t-90,t-3} + \gamma^{`}\text{X} + \epsilon_{it},$$

The dependent variable, SUE, is firms' standardized unexpected earnings following Bernard and Thomas (1989). Cross-Industry $\text{News}_{i,\mathbf{J},t-90,t-3}$ is the news tone of industries J over the period (t-90, t-3) relative to the earnings announcement day t. The control variables include firm-specific news tone, news tones of within-industry peer firms, # of firm-specific news, # of news of within-industry peer firms, # of cross-industry news. We also include those controls suggested by Tetlock *et al.* (2008), including firms' lagged earnings (proxied by last quarter's SUE, lagSUE), Size, B/M, Turnover, three measures of recent stock returns ($\text{AR}_{t-252,t-31}$, $\text{CAR}_{t-30,t-3}$ and AR_{t-2}), analysts' earnings forecast revisions (Forecast Revision), and analyst forecast dispersion (Analyst Dispersion). Besides, we further control other variables documented in prior literatures (Jegadeesh, Kim, Krische and Lee (2004) and Druz, Wagner and Zeckhauser (2015), among others), including a dummy variable indicating news coverage ($I_{newscoverage}$), Consensus Forecast, Management Forecast, Earnings Surprise, Return Volatility, Market Return, Institutional Ownership, Leverage, Momentum, Illiquidity and Overconfidence.

< Insert Table 2.4 here >

Table 2.4 presents the panel regression results, with standard errors clustered at firm level. In Panel A, we only include the news tone of one cross industry in the regression. The first three columns show the estimated coefficients, T-value and adjusted R^2 for the univariate regression. The middle three columns report the corresponding results that follow the specification of Tetlock *et al.* (2008). In the last three columns, we added all control variables. The results are consistent across different specifications. We find most cross-industry news negatively predict individual firm's earnings surprise. Only the news of the Coal industry positively predicted SUE. This is intuitive since the Coal industry serves as the most important raw inputs to other industries, thus a negative shock to the Coal industry causes a reduction of the input cost and positively affects the earnings of other downstream industries. In Panel B, we run the regression by including the news of all the cross-industries into one regression. The results change a lot due to the interactions of cross-industry news information. Indeed, some cross industry news become insignificant or even change their prediction signs. A number of industries remain strong predictors of individual firms' earnings, such as Food, Beer, Smoke, Books, Hlth, ElcEq, Autos, Mines, Paper and Trans.

On top of that, the loading on those industry news tones exhibits substantially positive and negative predictions on SUE, suggesting complex industry interdependencies that have bullish implications for some industries and bearish implications for others. This again emphasize the complexity of network effect in the real word. In this case, media news provides an new angle to understand the information diffusion across industries.

2.4.2 Cross-Industry News and Stock Returns

Having established that cross-industry news can predict firms' fundamentals, we examine if cross-industry news also provides novel information not fully reflected in stock prices. To test this, we examine the return predictability of CIS at stock level by running Fama-MacBeth regression. The advantage of Fama-MacBeth methodology is that one can control for a large set of firm characteristics that commonly associated with stock returns, including Lagged Return, Size, B/M, Leverage, Turnover, Return Volatility, Firm News, Industry News, # of Firm News, # of Industry news and # of Cross-Industry News.

Table 2.5 reports the time-series averages of the coefficients of the independent variables, and the t-statistics are Newey-West adjusted. The first three columns report the results using the whole sample period from 2000 to 2014 (year 1996 to 1999 is used as initial estimation window). The middle three columns report results for 2000 to 2007, and the last three columns show results for 2008 to 2014. Overall, CIS exerts a strong cross-sectional return predictability, and the results are robust across different specifications and sub-periods. The economic magnitude is also quite large. For the whole sample period, a one-standard-deviation increase in CIS increases the stock returns by 2.25%.

< Insert Table 2.5 here >

The significant coefficient in front of CIS in Fama-Macbeth regression suggests that a long-short strategy based on CIS should earn positive abnormal returns. At the end of each week, we sort all stocks with negative CIS into deciles and form an equal-weight long-short portfolio by shorting the stocks with most negative CIS and longing the stocks with the least negative CIS. We then hold the portfolio for one week and rebalance the portfolio at the end of each week. Figure 2.2 plots the cumulative return of the CIS long-short portfolio and the cumulative returns of the portfolio with all stocks included. The CIS long-short portfolio performs extremely well compared with the equal-weighted portfolio, suggesting the usefulness of the cross-industry news in predicting future price movements.

< Insert Figure 2.2 here >

Table 2.6 shows the weekly alphas of the long-short strategy based on CIS. Column (1),

(4) and (7) report the CAPM adjusted alpha, column (2), (5) and (8) for the Fama-French three factor adjusted alpha, and column (3), (6) and (9) for the Carhart (1997) four-factor adjusted alpha. Standard errors are computed using the White (1980) heteroskedasticity-consistent covariance matrix. Consistent with the results from Fama-MacBeth regression, the CIS-based long-short strategy generates highly significant risk-adjusted returns of 20 bps per week, or around 10% annualized returns. In addition, the returns to CIS strategy have low exposures to common factors and are stable across sub-periods.

< Insert Table 2.6 here >

The above analysis suggests that cross-industry news contains valuable information about firms' future fundamentals. However, market seems to underreact to the information embedded in cross-industry news, leading to predictable returns. To further examine how cross-industry news slowly diffuse into stock price, we form long-short portfolios by skipping a period following the CIS signal. Specifically, we form the long-short portfolio at the end of each week based on the CIS signals from 2 to 10 weeks ago and hold the portfolio for 1 week. As a benchmark, we also report the returns to the long-short strategy based on firms' own news. Table 2.7 shows that cross-industry news diffuse more slowly into stock prices compared with firms' own news. The alphas of CIS-based strategy remains significant with 10.9% annualized return even 10 weeks after the signal. In sharp contrast, the long-short strategy based on firms' own news is no longer profitable 6 weeks after the signal. The result suggests that news travels slowly across industries.

< Insert Table 2.7 here >

2.4.3 Is Cross-industry News Explained by Alternative Information?

In this section, we examine the alternative explanation that cross-industry news may be explained by other sources of value-relevant information, including firms' own news, news from within-industry peers, and return-based cross-industry news. To investigate this possibility, we add the returns of three additional long-short portfolios in the time series regression, and the result is reported in Table 2.8. Column (1), (4) and (7) reports the alphas of CIS-based strategy after adding the portfolio returns based on the news of within-industry peer. Column (2), (5) and (8) reports the alphas after adding portfolio returns based on firms' own news. Columns (3), (6) and (9) reports the alphas after including portfolio returns based on cross-industry returns.

Indeed, the alphas to the CIS-based strategy reduce by around 1/3 after accounting for these alternative information sources, but remains positive and significant at 1% level. The result suggests that cross-industry news are partially overlapped with but not fully captured by these alternative sources of information, especially firms' own news and cross-industry returns.[7]

< Insert Table 2.8 here >

2.4.4 Impact of Economic Uncertainty

It is reasonable to expect that in more uncertain times, it takes longer time for investors to understand the implication of cross-industry news. To test this, we divide the whole sample into low and high uncertainty period based on the median value of economic uncertainty. Our proxies for economic uncertainty include VIX, economic policy uncer-

[7] In untabulated analysis, we show that cross-industry return strategy can be fully explained by the CIS-based strategy, suggesting that cross-industry news contain soft information not fully captured by cross-industry returns.

tainty (Baker, Bloom and Davis (2016)), and a measure of market-wide news dispersion (Dzieliski and Hasseltoft (2015)). Market-wide news dispersion is defined as the cross-sectional standard deviation of news tone across firms. We then examine the profitability of the CIS strategy over the high and low uncertainty periods separately.

Table 2.9 reports the returns and alphas to the CIS-based strategy. The results are broadly consistent with our conjecture that the return predictability of CIS is indeed more pronounced in more uncertain market environment. For example, the annualized alpha of CIS strategy in high VIX periods is 4-5% higher than that in low VIX periods. We observe similar pattern using market-wide news dispersion, but not for economic policy uncertainty.

< **Insert Table 2.9 here** >

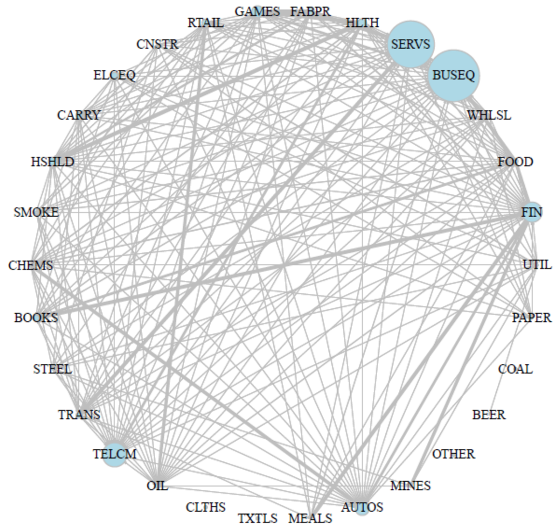
2.4.5 Cross-Sectional Heterogeneity in Information Environment and Arbitrage Frictions

Cross-industry news should be more valuable to firms with an opaque public information environment and limited firm-specific information. To test this, we use firm size as measure of a firm's information environment. We then examine the profitability of CIS strategy among firms with good and poor information environment, and plot the cumulative returns of the long-short portfolio in Figure 2.3. Consistent with our expectations, the CIS strategy performs much better among small firms with low analyst coverage, suggesting that cross-industry news travel slowly among such firms. Results are indeed robust using alternative proxies for information environment, such as analyst coverage and analyst forecast dispersion.

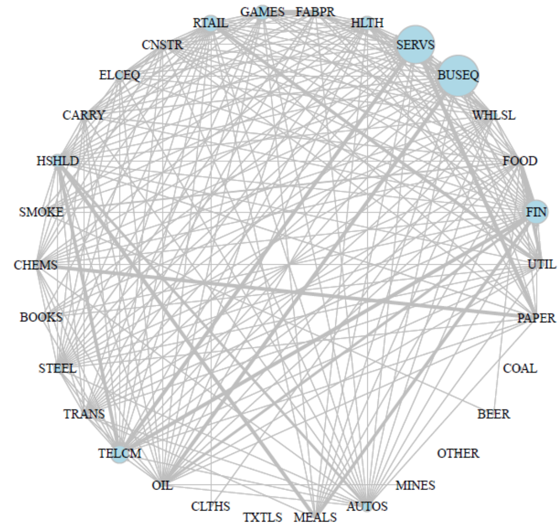
< **Insert Figure 2.3 here** >

2.5 Conclusion

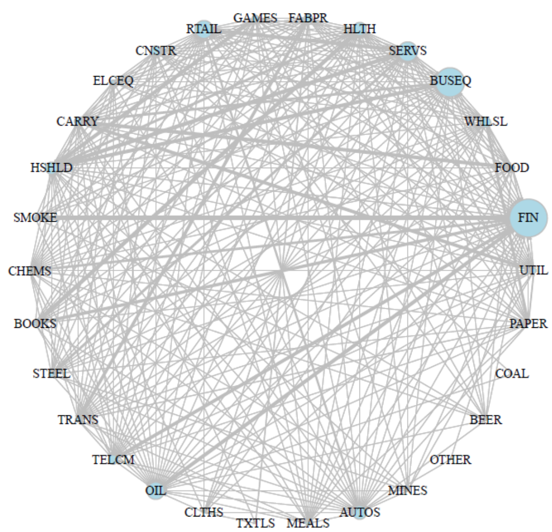
In this paper, we construct a dynamic inter-industry network using a comprehensive sample of media news to examine how news travels across industries. Our analyses show that cross-industry news contains valuable information about firm fundamentals that is not fully captured by firms' own news or within-industry peers' news. Stock prices do not promptly incorporate cross-industry news, generating return predictability. Underraction to cross-industry news is more pronounced among smaller stocks that are more illiquid, more volatile, and have fewer analysts following. A longshort strategy exploiting cross-industry news yields annual alphas of over 10%.



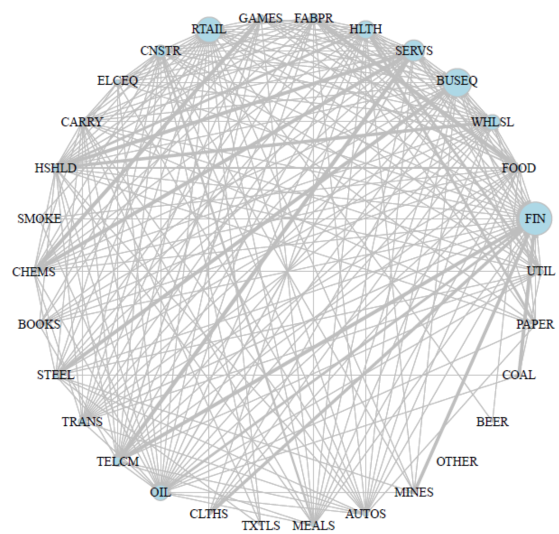
(a) Year: 1996



(b) Year: 2002



(c) Year: 2008



(d) Year: 2014

Figure 2.1: **Media-based Inter-Industry Network.** This figure plots the media-based inter-industry network for Fama-French 30 industries in selective years. Two industries are connected if any news article simutaneously mentions stocks in these two industries. The thickness of an edge reflects the degree of connections between two industries, as measured by the number of news connecting two industries. The node size denotes the eigenvector centrality of an industry.

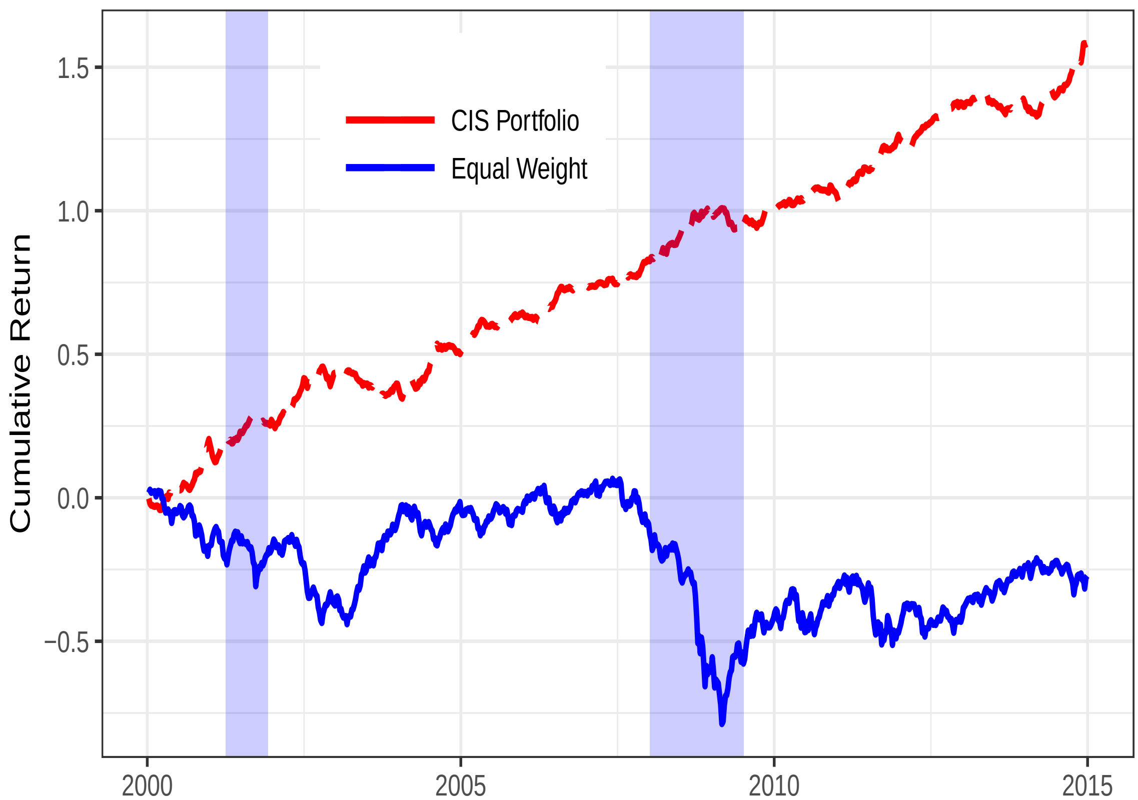


Figure 2.2: **Cumulative Returns of Long-Short Portfolio based on Cross-Industry News Signal (CIS).** This figure plots the cumulative log returns of the long-short CIS portfolio (red line) and the portfolio holding all stocks with CIS available (blue line). At the end of each week, we sort all stocks with negative CIS into deciles and form an equal-weighted long-short portfolio by shorting the stocks with the most negative CIS and longing the stocks with the least negative CIS. We then hold the portfolio for 1 week and rebalance at the end of each week. The sample period runs from January 2000 to December 2014.

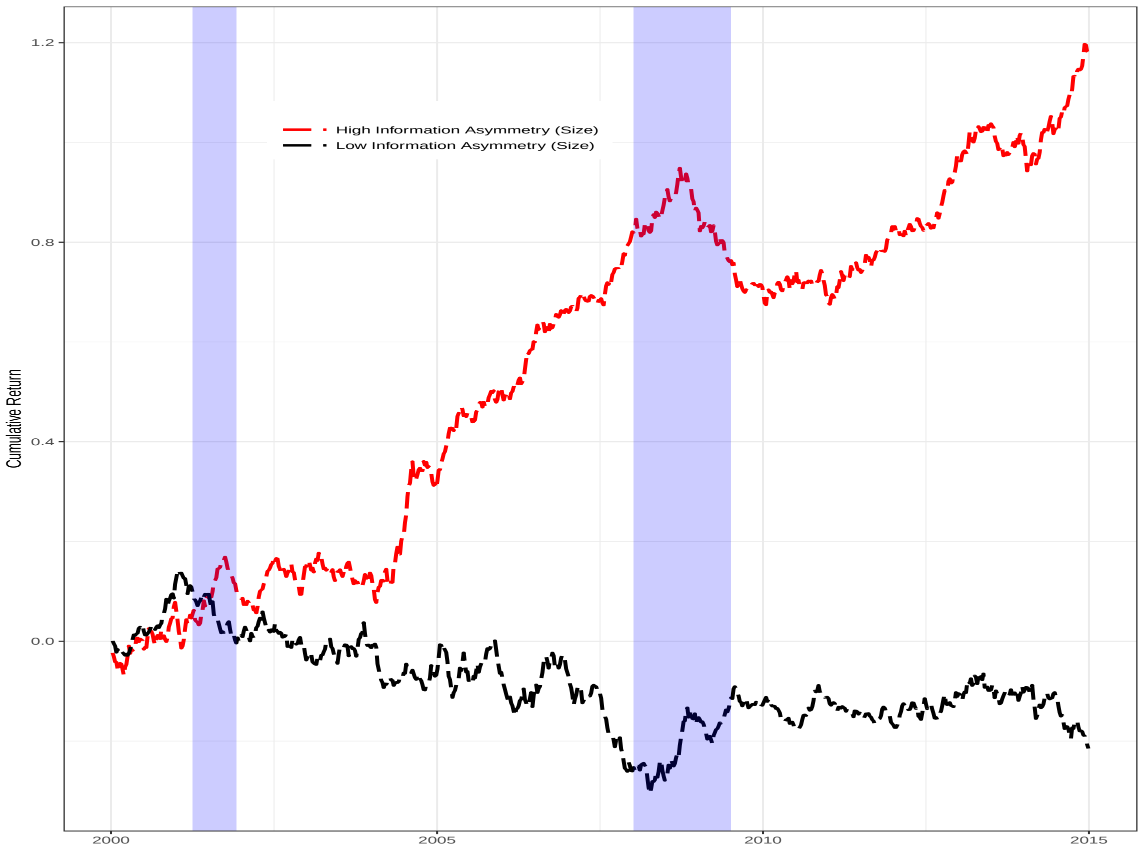


Figure 2.3: **CIS-based Long-Short Portfolio Performance in Subsamples** This figure shows the cumulative log returns of the long-short CIS portfolio in subsamples with different information environments and arbitrage costs. The information environment measures include firm size, analyst coverage, and analyst forecast dispersion, and the arbitrage costs measures are liquidity and return volatility. At the end of each week, we sort all stocks with negative CIS into deciles and form an equal-weighted long-short portfolio by shorting the stocks with the most negative CIS and longing the stocks with the least negative CIS. We then hold the portfolio for 1 week and rebalance at the end of each week. The sample period runs from January 2000 to December 2014.

Table 2.1: **Summary Statistics**

This table reports the summary statistics for the main variables used in the paper. All variables are defined in section 2. Panel A reports the network centrality for Fama-French 30 industries and the price delayness measure of Hou and Moskowitz (2005). Panel B presents weekly industry returns, firm characteristics and Cross-Industry News Signal (CIS). Panel C reports the average cross-industry news tone for Fama-French 30 industries.

Panel A: Cross Industry Media Connection

	EigenCtr	DegreeCtr	Delay	Freq. in Low EigenCtr	Freq. in High EigenCtr	Freq. in Low DegreeCtr	Freq in High DegreeCtr
Util	1.55%	1.97%	11.20%	0	0	0	0
Fin	11.31%	13.13%	0.75%	0	19	0	19
Food	1.78%	2.23%	8.24%	0	0	0	0
Whlsl	3.43%	3.49%	1.56%	0	4	0	5
BusEq	15.05%	14.59%	0.85%	0	19	0	19
Servs	13.07%	10.36%	0.54%	0	19	0	19
Hlth	5.27%	4.86%	1.73%	0	12	0	11
FabPr	2.66%	2.69%	0.88%	0	0	0	1
Games	3.95%	3.40%	3.52%	0	4	0	1
Rtail	6.63%	6.93%	1.17%	0	15	0	15
Cnstr	2.63%	2.44%	0.95%	0	1	0	0
ElcEq	2.20%	1.81%	0.59%	0	0	0	0
Carry	2.54%	2.70%	2.46%	0	0	0	0
Hshld	4.22%	4.47%	4.50%	0	5	0	8
Smoke	0.67%	0.91%	14.24%	12	0	12	0
Chems	1.25%	1.70%	3.15%	0	0	0	0
Books	1.71%	1.48%	2.34%	1	1	1	0
Steel	1.73%	2.00%	1.76%	0	0	0	0
Trans	2.03%	2.22%	1.26%	0	0	0	0
Telcm	5.60%	4.45%	1.23%	0	7	0	7
Oil	3.67%	4.66%	7.12%	0	6	0	8
Clths	0.61%	0.64%	1.77%	11	0	12	0
Txtls	0.08%	0.10%	3.74%	19	0	19	0
Meals	1.37%	1.32%	2.85%	2	0	1	0
Autos	3.25%	3.23%	2.22%	0	2	0	1
Mines	0.57%	0.68%	20.58%	11	0	12	0
Other	0.06%	0.07%	1.74%	19	0	19	0
Beer	0.14%	0.20%	9.70%	19	0	19	0
Coal	0.13%	0.17%	13.54%	18	0	18	0
Paper	0.86%	1.08%	1.85%	2	0		

Panel B: Cross Sectional Return Predictability

	Mean	SD	5%	25%	Median	75%	95%
Return (%)	-0.51	7.26	-12.41	-3.23	-0.00	2.44	10.40
CIS (%)	-0.43	0.74	-1.56	-0.49	-0.21	-0.08	-0.01
Peer News	0.041	0.017	0.00	0.037	0.043	0.051	0.63
Firm News	0.012	0.023	0.00	0.00	0.001	0.012	0.68
# of Cross News	7,436.69	5,180.39	0.00	3,468	7,977	10,890	15,698
# of Peer News	814.44	1,051.30	0.00	138	473	1,063	3,000
# of Firm News	2.42	11.02	0.00	0.00	0.00	1.00	12.00
Size	3.56	3.34	0.00	0.00	3.84	6.18	9.25
B/M	1.05	33.64	0.00	0.00	0.90	1.27	2.95
Turnover	7.38	6.04	0.00	0.00	11.04	12.58	13.80
Leverage	0.14	0.23	0.00	0.00	0.00	0.20	0.67
Volatility*100	0.75	8.54	0.00	0.01	0.06	0.34	2.56

Table 2.1 (continued)

Panel C: Earnings Annoucement	Mean	SD	5%	25%	Median	75%	95%
Cross Industry News Tone							
Food	0.044	0.006	0.037	0.041	0.043	0.048	0.056
Beer	0.041	0.007	0.032	0.036	0.040	0.045	0.055
Smoke	0.052	0.006	0.044	0.048	0.051	0.056	0.064
Games	0.044	0.006	0.037	0.040	0.043	0.048	0.056
Books	0.040	0.009	0.029	0.035	0.039	0.044	0.057
Hshld	0.043	0.006	0.035	0.039	0.041	0.046	0.056
Clths	0.038	0.008	0.028	0.033	0.038	0.043	0.052
Hlth	0.049	0.005	0.041	0.046	0.049	0.052	0.057
Chems	0.044	0.007	0.035	0.039	0.042	0.047	0.058
Txtls	0.042	0.011	0.028	0.034	0.041	0.049	0.061
Cnstr	0.043	0.007	0.034	0.037	0.042	0.049	0.056
Steel	0.046	0.006	0.038	0.042	0.045	0.049	0.059
FabPr	0.042	0.008	0.032	0.036	0.040	0.048	0.058
ElcEq	0.042	0.008	0.031	0.037	0.040	0.046	0.058
Autos	0.049	0.008	0.038	0.042	0.047	0.053	0.065
Carry	0.041	0.006	0.031	0.036	0.040	0.044	0.051
Mines	0.049	0.008	0.036	0.042	0.049	0.055	0.062
Coal	0.038	0.011	0.023	0.031	0.038	0.044	0.058
Oil	0.050	0.006	0.041	0.046	0.050	0.053	0.059
Util	0.040	0.006	0.032	0.037	0.039	0.043	0.054
Telcm	0.042	0.006	0.034	0.037	0.041	0.046	0.055
Servs	0.043	0.006	0.036	0.039	0.041	0.046	0.056
BusEq	0.043	0.008	0.035	0.038	0.040	0.046	0.061
Paper	0.043	0.008	0.033	0.038	0.041	0.047	0.058
Trans	0.045	0.007	0.036	0.039	0.043	0.049	0.058
Whlsl	0.041	0.006	0.034	0.037	0.040	0.045	0.052
Rtail	0.047	0.006	0.038	0.043	0.045	0.050	0.058
Meals	0.043	0.007	0.033	0.038	0.042	0.048	0.056
Fin	0.046	0.006	0.037	0.041	0.044	0.050	0.057
SUE	0.22	1.48	-1.84	-0.53	0.12	0.85	2.60
Other Variables							
Firm Tone	0.040	0.021	0.008	0.024	0.039	0.054	0.077
Industsry Ttone	0.045	0.009	0.032	0.039	0.044	0.050	0.060
# of Firm News	28.46	57.53	1.00	4.00	11.00	29.00	105.00
# of Industry News	1,237.61	1,582.90	70	277	636	1,446	5,270
# of Cross Industry News	57,506.56	26,226.19	17,900	30,621	64,594	78,568	96,313
Forecast Dispersion	0.04	0.06	0.00	0.01	0.02	0.04	0.13
Forecast Revision	-0.00	0.00	-0.01	-0.00	0.00	0.00	0.00
Size	7.70	2.49	0.00	6.78	7.99	9.22	11.00
B/M	1.75	1.25	0.00	1.08	1.40	2.05	4.01
Turnover	13.56	3.41	0.00	13.81	14.34	14.83	15.54
$AR_{t-252,t-31}$	-0.03	0.17	-0.33	-0.11	-0.02	0.06	0.20
$AR_{t-30,t-3}$	-0.27	10.26	-15.72	-4.36	0.17	4.48	14.41
AR_{t-2}	0.05	2.09	-3.10	-0.88	0.02	0.96	3.28
Consensus Forecast	0.46	0.67	-0.10	0.16	0.35	0.63	1.37
Management Forecast	0.25	0.43	0.00	0.00	0.00	0.00	1.00
Volatility	0.11	0.05	0.06	0.08	0.10	0.14	0.21
Market Return	0.01	0.05	-0.09	-0.02	0.01	0.04	0.08
Institutional Ownership	0.69	0.20	0.30	0.57	0.71	0.83	0.97
Leverage	0.20	0.19	0.00	0.03	0.14	0.31	0.58
Momentum	-0.00	0.30	-0.54	-0.12	0.03	0.16	0.41

Table 2.2: **Media-Based Industry Centrality and Price Delayness**

In this table, we sort all Fama-French 30 industries into five quintiles based on network centrality measure and report the average price delayness measure of Hou and Moskowitz (2005) for each group from 1996 to 2014. Column 1 (2) shows the eigenvector (degree) centrality, constructed based on media news. Statistical significance of the difference between the highest and lowest centrality quintiles is reported by Newey-West adjusted t-statistics.

	Eigen-centrality	Degree-centrality
Low Centrality of Industry in Media Network	7.90%	7.62%
2	5.44%	4.01%
3	2.24%	4.51%
4	2.60%	2.90%
High Centrality of Industry in Media Network	1.32%	1.40%
High - Low	-6.58%	-6.22%
T-stats	-3.96	-4.17

Table 2.3: **Pairwise Industry Connection and Cross-Industry Information Delayness**

This table reports the cross-industry information delayness for five groups sorted on pairwise industry connection. Our measure of pairwise industry connection is the number of news mentioning an industry pair simultaneously. Similar to the delay measure of Hou and Moskowitz (2005), for an industry pair A and B, the delayness of industry B's news on industry A's return, $Delay_{B \to A}$, is the fraction of industry A's returns explained by industry B's lagged returns. More specifically, the measure is one minus the ratio of the R^2 from regression (2.3.1) by restricting $\delta_j^{-n} = 0, n \in [1, 4]$, over the R^2 from regression (2.3.1) without restrictions. The pairwise information delayness between industry A and B is the average of $Delay_{A \to B}$ and $Delay_{B \to A}$. We then sort all industry pairs into five quintiles according to the # of news mentioning the industry pair simultaneously and report the average delayness of each quintile. We test the statistical significance of the difference between the highest and lowest quintiles of Pairwise Industry Connection and report the Newey-West adjusted t-statistics.

	Average Delay $_{A \leftrightarrow B}$	$Delay_{A \to B}$	$Delay_{B \to A}$
Low # of Connected News between A and B	13.21%	13.40%	13.01%
2	9.97%	10.30%	9.65%
3	6.78%	6.70%	6.85%
4	6.26%	5.89%	6.64%
High # of Connected News between A and B	5.06%	4.85%	5.27%
High - Low	-8.15%	-8.56%	-7.75%
T-stats	-5.14	-5.00	-5.17

Table 2.4: **Cross-Industry News and Earnings Surprise**

This table reports the predictability of cross-industry news for earnings surprise (SUE). The regression is run as follows:

$$\text{SUE}_{it} = \alpha_i + \sum_{\mathbf{J}=1}^{N-1} \beta_{\mathbf{J}} \text{Cross Industry News}_{i,\mathbf{J},t-90,t-3} + \gamma^{`}\text{X} + \epsilon_{it},$$

The dependent variable, SUE, is the standardized unexpected earnings following Bernard and Thomas (1989). Cross Industry $\text{News}_{i,\mathbf{j},t-90,t-3}$ is the news tone of Industry J measured over the period (t-90, t-3) relative to the earnings announcement day t. X denotes other explanatory variables. We only include the news tone of one cross industry in Panel A, and all cross-industry news in Panel B for the regression. For each panel, we have 3 specifications with different control variables. The first three columns show the estimated coefficients, T-value and adjusted R^2 for the univariate regression. The middle three columns report the corresponding results that follow the specification of Tetlock *et al.* (2008). In the last three columns, we added all control variables. Standard errors are clustered at firm level.

Panel A: One Industry	SUE								
Empirical Design:	Univariate			Tetlock 2008			All Controls		
	Coef	T-value	R^2 (%)	Coef	T-value	R^2 (%)	Coef	T-value	R^2 (%)
Food	-0.08	-9.68	0.30	-0.05	-5.66	17.41	-0.02	-1.77	16.72
Beer	-0.10	-12.76	0.52	-0.06	-7.46	17.55	-0.04	-3.93	16.89
Smoke	-0.04	-4.60	0.07	-0.02	-2.24	17.31	-0.00	-0.16	16.72
Games	-0.14	-16.54	0.88	-0.08	-10.36	17.60	-0.05	-4.97	16.79
Books	-0.13	-16.31	0.84	-0.08	-10.71	17.57	-0.06	-6.49	16.85
Hshld	-0.18	-21.80	1.52	-0.11	-13.56	17.78	-0.09	-8.12	16.96
Clths	-0.10	-12.25	0.48	-0.04	-5.93	17.23	-0.02	-2.47	16.57
Hlth	-0.05	-5.73	0.11	-0.03	-4.03	18.13	0.00	0.30	17.55
Chems	-0.12	-14.70	0.71	-0.07	-8.49	17.31	-0.04	-3.89	16.61
Txtls	-0.12	-14.96	0.71	-0.07	-8.85	17.56	-0.05	-4.56	16.83
Cnstr	-0.15	-18.23	1.09	-0.09	-11.52	17.16	-0.06	-5.16	16.34
Steel	-0.12	-14.72	0.70	-0.06	-8.52	17.37	-0.03	-3.42	16.66
FabPr	-0.15	-17.94	1.06	-0.08	-10.26	17.29	-0.06	-5.45	16.46
ElcEq	-0.15	-17.86	1.02	-0.09	-11.04	17.67	-0.08	-7.12	16.91
Autos	-0.18	-21.69	1.50	-0.12	-14.87	17.74	-0.11	-10.40	16.98
Carry	-0.12	-14.30	0.65	-0.06	-7.37	17.36	-0.03	-3.11	16.64
Mines	-0.08	-10.10	0.33	-0.05	-6.65	17.55	-0.03	-3.78	16.90
Coal	0.06	7.17	0.19	0.03	4.15	15.68	0.04	3.87	15.89
Oil	-0.05	-6.05	0.12	-0.03	-4.05	17.74	0.01	0.68	17.20
Util	-0.04	-5.03	0.09	-0.02	-2.14	18.63	0.03	2.68	18.14
Telcm	-0.12	-14.11	0.64	-0.07	-8.69	17.77	-0.03	-2.54	16.99
Servs	-0.12	-14.68	0.73	-0.07	-9.00	17.11	-0.04	-3.70	16.37
BusEq	-0.13	-14.25	0.71	-0.07	-8.77	17.01	-0.06	-4.95	16.22
Paper	-0.13	-15.99	0.82	-0.07	-9.22	17.61	-0.04	-3.37	16.82
Trans	-0.18	-22.09	1.60	-0.11	-13.92	17.47	-0.09	-8.45	16.55
Whlsl	-0.13	-15.90	0.82	-0.07	-8.95	17.22	-0.05	-4.41	16.51
Rtail	-0.15	-17.74	1.07	-0.09	-11.04	17.00	-0.07	-6.65	16.14
Meals	-0.11	-12.90	0.54	-0.06	-7.58	17.35	-0.04	-3.36	16.69
Fin	-0.08	-9.33	0.34	-0.04	-4.86	17.51	0.00	0.22	17.04
Other	-0.09	-10.47	0.35	-0.05	-6.48	17.45	-0.04	-3.89	16.82
Year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.4 (continued)

Panel B: All Industries	SUE					
Empirical Design:	No Other Controls		Tetlock 2008		All Controls	
	Coef	T-value	Coef	T-value	Coef	T-value
Food	0.06	2.44	0.04	1.79	0.06	2.23
Beer	-0.05	-4.83	-0.03	-2.61	-0.03	-2.53
Smoke	-0.06	-3.15	-0.06	-3.51	-0.06	-2.66
Games	-0.08	-3.56	-0.04	-1.95	-0.05	-1.86
Books	-0.03	-1.94	-0.03	-2.05	-0.03	-2.05
Hshld	-0.03	-1.29	-0.04	-1.61	-0.03	-1.22
Clths	0.03	2.10	0.03	1.95	0.02	1.08
Hlth	0.18	6.50	0.10	3.93	0.11	3.70
Chems	-0.01	-0.30	-0.00	-0.15	-0.00	-0.21
Txtls	-0.04	-2.94	-0.01	-0.95	-0.01	-0.64
Cnstr	-0.04	-2.30	-0.03	-1.98	-0.01	-0.48
Steel	-0.04	-2.01	-0.01	-0.35	0.00	0.02
FabPr	0.01	0.28	0.02	1.26	0.03	1.68
ElcEq	-0.08	-4.25	-0.06	-3.53	-0.07	-3.56
Autos	-0.16	-8.44	-0.12	-7.35	-0.13	-6.83
Carry	0.04	1.79	0.04	2.15	0.04	1.79
Mines	-0.04	-2.75	-0.03	-2.16	-0.03	-2.25
Coal	0.05	4.59	0.01	0.93	0.01	0.93
Oil	0.09	4.44	0.02	1.32	0.01	0.71
Util	0.10	4.35	0.06	2.72	0.05	1.81
Telcm	-0.01	-0.34	0.01	0.48	0.03	1.14
Servs	0.07	2.94	0.04	1.80	0.04	1.39
BusEq	0.06	2.64	0.05	2.24	0.04	1.75
Paper	0.03	1.59	0.02	1.37	0.06	2.48
Trans	-0.13	-5.35	-0.09	-3.82	-0.08	-3.12
Whlsl	0.00	0.07	0.01	0.30	-0.02	-0.63
Rtail	-0.00	-0.11	0.00	0.15	0.02	0.71
Meals	0.06	3.40	0.04	2.51	0.03	1.44
Fin	0.05	1.74	0.03	1.05	0.04	1.23
Other	-0.02	-1.69	-0.02	-1.51	-0.01	-1.23
Year effect	Yes		Yes		Yes	
Firm effect	Yes		Yes		Yes	
N	32,917		32,917		28,206	
adj. R^2 (%)	2.59		18.25		17.47	

Table 2.5: **Fama-MacBeth regressions of stock returns on CIS**

This table reports the Fama-MacBeth regression of stock returns on cross-industry news signals (CIS). CIS is the out-of-sample forecasted return based on cross-industry-news tones. Peer News is average news tone of peer firms within the same industry. Firm News is the firm-specific news tone. We only include stocks with negative CIS in the regression. The sample period is from Jan 2000 to Dec 2014. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	2000 - 2014			2000 - 2008			2009 - 2014		
CIS	0.137***	0.130***	0.095***	0.126***	0.118***	0.079***	0.153***	0.148***	0.118***
	(7.15)	(6.48)	(5.09)	(5.21)	(4.51)	(3.32)	(4.90)	(4.74)	(3.98)
Lagged Return	-0.036***	-0.036***	-0.042***	-0.039***	-0.039***	-0.045***	-0.032***	-0.032***	-0.038***
	(-21.08)	(-22.12)	(-23.60)	(-17.62)	(-18.46)	(-19.27)	(-11.81)	(-12.43)	(-13.73)
Peer News		-0.001	-0.002		-0.001	-0.001		-0.001	-0.002
		(-0.60)	(-1.53)		(-0.56)	(-1.14)		(-0.28)	(-1.02)
Firm News		-0.001**	-0.002***		-0.000	-0.001***		-0.001***	-0.002***
		(-2.04)	(-5.02)		(-0.68)	(-2.72)		(-2.63)	(-5.09)
# of Peer News		0.000	0.000		0.000	-0.000		-0.000	0.000
		(0.01)	(0.24)		(0.06)	(-0.54)		(-0.07)	(1.11)
# of Firm News		0.001***	0.000		0.000*	-0.000**		0.001***	0.001***
		(5.17)	(0.76)		(1.66)	(-2.25)		(7.29)	(6.05)
Size			0.001***			0.001***			0.001***
			(8.39)			(6.67)			(5.13)
B/M			0.000***			0.000***			0.000***
			(8.19)			(6.10)			(5.52)
Turnover			-0.000***			-0.000***			-0.000***
			(-4.83)			(-3.84)			(-3.00)
Leverage			-0.003***			-0.003***			-0.002***
			(-5.90)			(-4.58)			(-3.78)
Volatility			-0.013***			-0.009*			-0.020***
			(-3.41)			(-1.73)			(-3.44)
Intercept	-0.000	-0.000	-0.001**	-0.001	-0.001	-0.001***	0.001	0.001	-0.000
	(-0.04)	(-0.14)	(-2.41)	(-0.94)	(-1.25)	(-2.95)	(0.99)	(0.82)	(-0.64)
N	1,401,162	1,401,162	1,401,162	855,092	855,092	855,092	546,070	546,070	546,070
Average R^2 (%)	1.17	2.43	4.00	1.20	2.54	4.06	1.14	2.28	3.91

Table 2.6: **Portfolio Alphas Sorted by Cross-Industry News Signal**

This table reports the weekly alpha of the long-short portfolio constructed on cross-industry news signal (CIS). At the end of each week, we sort all stocks with negative CIS into deciles and form an equal-weight long-short portfolio by shorting the stocks with most negative CIS and longing the stocks with the least negative CIS. We then hold the portfolio for one week and rebalance the portfolio at the end of each week. Column (1), (4) and (7) report the CAPM adjusted alpha, column (2), (5) and (8) for the Fama-French three factor adjusted alpha, and column (3), (6) and (9) for the Carhart (1997) four-factor adjusted alpha. Standard errors are computed using the White (1980) heteroskedasticity-consistent covariance matrix. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

	2000 - 2014			2000 - 2008			2009 - 2014		
Alpha (%)	0.21***	0.22***	0.21***	0.21***	0.22***	0.21***	0.21***	0.21***	0.22***
	(5.17)	(5.31)	(5.22)	(3.44)	(3.61)	(3.37)	(4.47)	(4.53)	(4.75)
Market Risk	-0.04**	-0.03	-0.03*	-0.05**	-0.03	-0.04*	-0.02	-0.01	-0.02
	(-2.49)	(-1.65)	(-1.71)	(-2.21)	(-1.53)	(-1.83)	(-0.99)	(-0.61)	(-0.74)
SMB		-0.11***	-0.13***		-0.12***	-0.15***		-0.08*	-0.09**
		(-3.49)	(-4.12)		(-2.91)	(-3.56)		(-1.83)	(-2.06)
HML		0.03	0.05*		0.01	0.03		0.03	0.07*
		(0.99)	(1.94)		(0.35)	(0.66)		(0.79)	(1.76)
UMD			0.08***			0.09***			0.06***
			(4.76)			(3.99)			(2.70)
N	772	772	772	462	462	462	310	310	310
adj. R^2	0.007	0.025	0.052	0.008	0.026	0.057	-0.000	0.011	0.031

Table 2.7: **Persistence of CIS-based Strategy**

This table shows the persistence of the CIS-based strategy. At the end of each week, we form a long-short portfolio based on cross-industry news or firm-specific news observed 2 to 10 weeks ago, and hold the portfolio for 1 week, and rebalance weekly. Reported is the (annualized) raw returns and Fama-French three-factor alphas of the long-short portfolio.

Week	Cross Industry News				Firm Specific News			
after News	Raw Return (%)	T_{Raw}	α (%)	T_α	Raw Return (%)	T_{Raw}	α (%)	T_α
2	11.49	5.65	13.16	6.63	2.96	1.70	3.12	1.85
3	9.40	4.59	11.28	5.60	2.99	1.63	3.19	1.94
4	10.77	5.31	12.25	6.18	3.82	2.18	3.87	2.30
5	13.01	5.81	14.84	7.11	4.58	2.67	5.13	3.11
6	10.14	4.97	12.43	6.28	1.91	1.09	2.25	1.32
7	10.48	4.96	12.69	6.08	1.43	0.84	1.86	1.14
8	11.97	5.46	13.65	6.33	1.18	1.49	1.38	1.68
9	13.77	6.63	15.79	7.79	3.82	2.28	3.97	2.44
10	9.86	4.48	10.85	4.99	1.69	1.05	2.05	1.31

Table 2.8: **Performance of CIS-based Strategy after Controlling for Alternative Information**

This table reports the weekly alpha of the long-short portfolio constructed on cross-industry news signal (CIS). At the end of each week, we sort all stocks with negative CIS into deciles and form an equal-weight long-short portfolio by shorting the stocks with most negative CIS and longing the stocks with the least negative CIS. We then hold the portfolio for one week and rebalance the portfolio at the end of each week. Column (1), (4) and (7) reports the alphas of CIS-based strategy after adding the portfolio returns based on the news of within-industry peer. Column (2), (5) and (8) reports the alphas after adding portfolio returns based on firms' own news. Columns (3), (6) and (9) reports the alphas after adding portfolio returns based on cross-industry returns. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

	2000 - 2014			2000 - 2008			2009 - 2014		
Alpha (%)	0.20***	0.15***	0.14***	0.20***	0.16***	0.15**	0.20***	0.14***	0.13***
	(4.95)	(3.79)	(3.45)	(3.23)	(2.64)	(2.46)	(4.42)	(3.00)	(2.79)
Market Risk	-0.02	-0.03*	-0.03*	-0.04	-0.04*	-0.04	-0.02	-0.02	-0.03
	(-1.55)	(-1.79)	(-1.88)	(-1.63)	(-1.69)	(-1.62)	(-0.71)	(-0.80)	(-1.42)
SMB	-0.12***	-0.11***	-0.13***	-0.14***	-0.12***	-0.16***	-0.09**	-0.10**	-0.09**
	(-4.05)	(-3.76)	(-4.40)	(-3.42)	(-3.06)	(-3.89)	(-2.18)	(-2.36)	(-2.10)
HML	0.04	0.06**	0.04	0.02	0.04	0.01	0.06	0.07*	0.07*
	(1.61)	(2.20)	(1.60)	(0.53)	(0.99)	(0.30)	(1.44)	(1.77)	(1.87)
UMD	0.06***	0.02	0.01	0.07***	0.03	0.03	0.04*	-0.01	-0.01
	(3.60)	(0.88)	(0.81)	(3.14)	(1.13)	(1.39)	(1.81)	(-0.23)	(-0.63)
Peer News	0.10***	0.07***	0.06**	0.09**	0.07*	0.05	0.10***	0.06*	0.06*
	(3.51)	(2.61)	(2.15)	(2.26)	(1.86)	(1.39)	(3.09)	(1.92)	(1.74)
Firm News		0.49***	0.44***		0.47***	0.40***		0.52***	0.50***
		(5.89)	(5.37)		(3.89)	(3.38)		(5.30)	(5.04)
Cross-Industry Return			0.26***			0.30***			0.19***
			(5.92)			(5.03)			(2.94)
N	772	772	772	462	462	462	310	310	310
adj. R^2	0.065	0.105	0.143	0.065	0.093	0.139	0.057	0.134	0.156

Table 2.9: **Economic Uncertainty and Profitability of CIS-based Strategy**

This table reports the raw returns and risk-adjusted returns of CIS-based portfolio over periods of high and low economic uncertainty. Our proxies for economic uncertainty include VIX, Economic Policy Uncertainty (EPU), and a measure of market-wide news dispersion. News dispersion is defined as the cross-sectional standard deviation of news tone across firms. A period is indicated as high (low) uncertainty if the economic uncertainty index in the previous week is above (below) the median value of the whole sample. The sample period is between Jan 2000 and Dec 2014. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Average	Annulized Risk Adjusted Return			
	Return	CAPM	FF3	FF3M	All Control
Panel A: VIX					
Low	0.07**	0.08**	0.08**	0.09**	0.06*
	2.54	2.26	2.38	2.50	1.87
High	0.15***	0.15***	0.15***	0.15***	0.11***
	4.53	3.52	3.65	4.07	3.23
Panel B: EPU					
Low	0.11***	0.12***	0.12***	0.12***	0.08***
	3.52	3.27	3.31	3.29	2.69
High	0.11***	0.11***	0.11***	0.12***	0.09***
	3.66	2.95	3.21	3.48	2.73
Panel C: News Dispersion					
Low	0.06**	0.07*	0.08**	0.08**	0.06*
	2.11	1.88	2.12	2.18	1.72
High	0.16***	0.16***	0.16***	0.15***	0.12***
	4.87	4.06	4.09	4.40	3.36

Chapter 3

News Co-Occurrence, Attention Spillover and Return Predictability

Li Guo, Lin Peng, Yubo Tao, Jun Tu

3.1 Introduction

Among several studies regarding stock market return predictability, most are about information-based predictors constructed using hard information (e.g., fundamental economic variables in Goyal and Welch (2008)); however, soft information is increasingly being consulted (e.g., news tones in Tetlock (2007)). However, without investor attention, information by itself cannot influence stock prices. Given that investor attention has been documented as one of the most important driving forces of stock returns in recent literature, the lack of investigation on the impact of investor attention on market premium forecasting is surprising. In this study, we construct a novel attention-based predictor, that is, the *news network triggered attention* (NNTA) index, for forecasting the market equity premium.

There is evidence suggesting that attention is a scarce resource for investors, especially for individual investors.[8] Therefore, it is likely that investor recognition of a security is limited (Merton (1987)), and investors 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 attention to one stock spills over to the co-mentioned stocks, thereby increasing attention toward all the mentioned

[8] Related work includes 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 (2008), Hirshleifer, Lim and Teoh (2009), DellaVigna and Pollet (2009), and Van Nieuwerburgh and Veldkamp (2009).

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, would result in overvaluation and subsequent underperformance.

In this study, by aggregating the news about all the stocks in the market on a monthly basis, we formulate the NNTA index using the adjacency matrix in the network analysis to gauge the amount of attention that a news co-occurrence-triggered attention spillover generates for non-shareholder type of investors. We assume that the higher the NNTA index, the larger would be the overvaluation of the aggregate stock market. Consistent with this assumption, 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. Additionally, 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 in Fang and Peress (2009), the Google search index[9], the 52-week highest price indicator in George and Hwang (2004), the analyst coverage and trading volume aggregated from individual S&P500 stocks using value weights, and news tones based on the 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 recession and expansion periods. We find that NNTA obtains larger and positive R^2s in both recession and expansion periods when compared with the alternative predictors. We further verify the investor attention channel by predicting cross-sectional portfolios and find that a more frequent news co-occurrence produces lower returns. The long-short portfolio based on

[9]We calculate the frequency of the search queries in Google using keywords "S&P500," "SP500," "S&P 500," or "SP 500," over the sampled period January 2004–December 2014.

abnormally connected news coverage generates a 0.68% monthly return, with statistical significance at the 1% level. The conventional risk factors, such as the four-factor, q-factor, and five-factor models by Carhart (1997), Hou *et al.* (2015), and Fama and French (2016), respectively, fail 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 a higher correlation of Google and Bloomberg search volumes. According to Da *et al.* (2011), correlated search activities directly support the conjecture that the NNTA constructed from a news co-occurrence measures investor attention. Since investor attention needs a heterogeneous belief or a short-sales constraint to generate an asymmetric buying pressure (Hong and Stein, 2007), we check the return predictability performance of the NNTA index under different scenarios of investor disagreement and short-sales constraint. Expectedly, the NNTA index shows a 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 by short-sales. These results are consistent with the intuition that stock mispricing is more profound when investor disagreement is high, and a short-sales constraint is more binding.

Our study sheds new light on a different aspect of investor attention. Peng and Xiong (2006) 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 by Peng *et al.* (2007) showed that the time-varying, asset co-movement can be explained under both limited attention and attention shift assumptions. In terms of news attention, Odean (1999) and Barber and Odean (2008) found that individual investors are more likely to trade stocks that capture their attention due to limited attention to their trade searches, 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 by using media coverage as the proxy of attention-grabbing events; they also found evidence that both individual and institutional investors are subject to limited attention. Unlike these studies, we identify an efficient proxy for investor attention through the media network formation. This proxy addresses the fact that non-shareholders' trading behavior is more subject to short-sales constraint when compared to that of shareholders. Therefore, our proxy is more powerful in predicting the market premium than those proxies that do not distinguish between 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 examined how the news tones between the lines predicted stock prices. Tetlock (2007) presented that the linguistic tone, especially, negative tones, can predict excess market returns. Tetlock *et al.* (2008) explored the cross-sectional return predictability by processing firm-specific news. Similarly, Wang *et al.* (2016) documented a sector-specific reaction based on their distilled sentiment measure. Jegadeesh and Wu (2013) further improved the results in Tetlock (2007) with a term-weighting scheme, based on ordinary least squares (OLS) and Naïve Bayes; they also found 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 items possess valuable information for predicting market premium.

Finally, we contribute to the literature that applies network analysis to financial studies. Cohen and Frazzini (2008) and Menzly and Ozbas (2010) found that economic links among certain individual firms and industries contribute to cross-firm and cross-industry return predictability. They interpreted 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) investigated the predictability of industry returns based on a wide range of industrial interdependencies. Different from the above literature, to the best of our knowledge, this is the first study 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 3.2, we show how to compose a comprehensive measure of the media-network-based attention index. Subsequently, we conduct some empirical tests and present our results in section 3.3. In section 3.4, we provide economic explanations to our NNTA. We conclude in section 3.5.

3.2 Data and Methodology

In this section, we introduce the data sources and explain the intuition behind the news network triggered attention index[10]. Subsequently, for conducting a comparative analysis, we introduce the alternative predictors and their corresponding data sources.

3.2.1 News network triggered attention

The data we use for constructing a media network comprise firm-specific news from the Thomson Reuters News Analytics and Archive dataset spanning from January 1996 to December 2014. The data contain various types of news categories, such as reviews, stories, analysis, and reports, about markets, industries, and corporations. For all the mentioned firms in each piece of news, tt 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). These three probabilities sum up to 1 and are being computed from a neural-network-based sentiment engine. In the subsequent analysis, we will use Neg^{NN} and Opt^{NN} ($Pos^{NN} - Neg^{NN}$), in addition to soft information predictors.

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

The news network triggered attention measure is constructed in three steps. First, we classify the news into two categories: *connected news* that mentions more than one stock, and *self-news* that only refer to one stock. Empiricists measure investor attention indirectly by counting the total number of mentions (news coverage) (Barber and Odean, 2008) or appearances in headlines (Yu, 2015), without distinguishing the subtle difference in these two types of news categories. 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 relevant investors but may also trigger those investors who care only about the one stock mentioned to pay attention to other stocks co-mentioned. Therefore, connected news can substantially enlarge the investor base when compared 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 news coverage between them. Subsequently, we rescale the connected news coverage by its self-news coverage to measure connected news' contribution to the overall investor base. Finally, we follow Da *et al.* (2011) to construct the abnormal attention measure by taking the first difference of the rescaled connected news coverage, which may also help with detrending the potentially non-stationary time series.

Until now, 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 easily capture investor attention. Therefore, we propose to adjust abnormal connected news coverage by the importance of stocks. In this study, we measure the importance of the stocks in two dimensions. One dimension is the firm's own characteristic, that is, *firm size*, which determines how much investor attention a firm can attract by itself. The other dimension is the overall importance of the connected firms, that is, *centrality*, which evaluates how much investor attention the firm can attract by connecting with other firms. Particularly, 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), various types of centrality measures are applied to network analysis (e.g., degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality), and we decided to use eigenvector centrality in our study. Specifically, we first define the adjacency matrix $\mathcal{A}_t$,

$$\mathcal{A}_t = \begin{array}{c} \\ stock_1 \\ stock_2 \\ \vdots \\ stock_N \end{array} \begin{array}{c} \begin{array}{cccc} stock_1 & stock_2 & \cdots & stock_N \end{array} \\ \begin{bmatrix} a_{11,t} & a_{12,t} & \cdots & a_{1N,t} \\ a_{21,t} & a_{22,t} & \cdots & a_{2N,t} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1,t} & a_{N2,t} & \cdots & a_{NN,t} \end{bmatrix} \end{array}. \tag{3.2.1}$$

where $a_{ij,t} = 1$ if there exists news that co-mentions stocks i and j at time t, and 0 otherwise. Subsequently, we calculate the eigenvector, $\mathbf{x}_t$, which corresponds to the largest eigenvalue[11] ($\lambda_{\max}$) of the adjacency matrix. We define the values of $\mathbf{x}_t$ as our centrality score, that is,

$$\mathcal{A}_t\mathbf{x}_t = \lambda_{\max}\mathbf{x}_t, \text{ for each } t = 1, 2, \cdots, T, \tag{3.2.2}$$

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 degree centrality that awards nodes according to the number of degrees, eigenvector centrality does not consider all vertices to be equivalent: some are more relevant than the others, and, reasonably, endorsements from important nodes have more significance. Hence, the eigenvector centrality indicates that a node is important if it connects to other important nodes. Take a simple network in Figure 3.1 as an example; each vertex in the network represents a firm, and the edges indicate the media connections induced by a news co-occurrence. Degree centrality suggests that firm 1 and 3, firm 2 and 6, or firm

[11] In this way, the corresponding eigenvector captures most of the 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).

4 and 5 are equally important because 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 consider firm 6 to be more important than firm 2 in terms of spreading the news because 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 $[0.5641, 0.2960, 0.5454, 0.1268, 0.2337, and 0.4753]$. Clearly, the eigenvector centrality scores fit the situation better in describing the propagation of news.

[Insert Figure 3.1 here.]

Evidently, a firm's size and its 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 formulate a composite news network triggered attention index, NNTA, as the simple average of the two standardized attention measures, as in equation (3.2.3). Since both measures are likely to contain information about investors' attention as well as idiosyncratic non-attention noise, the composite NNTA measure will help in capturing the common investor attention component in the connected news and diversifying the idiosyncratic noise.

$$NNTA_t = 0.5NNTA_t^{sz} + 0.5NNTA_t^{ctr}. \tag{3.2.3}$$

In Figure 3.2, we plot the composite NNTA index and the other two individual NNTA indices. Generally, the size-based index shows a similar pattern as that of the 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 that it would be beneficial to combine these two indices. By construction, NNTA correlates with NNTA^{sz} and NNTA^{ctr} at a similar level, 0.72 and 0.78, respectively.

[Insert Figure 3.2 here.]

3.2.2 Alternative predictors

To ensure that NNTA captures a different aspect of investor attention, we would control some of the 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 conduct a market-wide news coverage using the articles from Dow Jones and Wall Street Journal, which were searched based on Factiva keywords "S&P500," "SP500," "S&P 500," or "SP 500," and obtain firm-specific news coverage from the Thomson Reuters News Archive. Additionally, we take the first difference of these predictors to obtain the abnormal media coverages, labeled as ΔTRN, ΔDJI, and ΔWSJ.

Other than the news coverage, we also construct various attention measures based on the literature, such as the Google search volume (*Google Search*) of keywords "S&P500," "SP500," "S&P 500," and "SP 500," following Da *et al.* (2011); the 52-week highest price indicator (Prc^{High}), following George and Hwang (2004); the level of and change in the average number of analysts, aggregated from individual S&P500 stocks using value weights (*Analyst* and $\Delta Analyst$); the residual of analyst coverage regressing on the NASDAQ index and firm size (*Analyst_r*), following Hong *et al.* (2000); the value-weighted trading volume of each stock (*TrdVol*); and the abnormal trading volume ($\Delta TrdVol$), following 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; for example, a 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 $Opt = \frac{\#\ of\ Pos\ Words_{i,t} - \#\ of\ Neg\ Words_{i,t}}{Total\ \#\ of\ Words_{i,t}}$, wherein positive words and negative words follow the Loughran and McDonald (2011) dictionary. The second set of factors are those that may affect investors' beliefs, namely, the sentiment (Baker and Wurgler, 2006; Huang *et al.*, 2014) and uncertainty indices, including the volatility index (VIX), the economic uncertainty index (UNC) in Bali *et al.* (2014), the treasury implied volatility (TIV) in Choi *et al.* (2017), the economic policy uncertainty (EPU) in Baker *et al.* (2016), the financial uncertainty (FU), and the economic 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 the following factors presented 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 Comovement Index* (ECI) for controlling fundamental correlations. First, we run the regression

$$ROA_i = a_i + b_i \times ROA_m + \epsilon_i, \tag{3.2.4}$$

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

$$Earnings\ Comovement\ Index = \frac{\sum_i R_i^2(ROA) \times SST_i(ROA)}{\sum_i SST_i(ROA)}, \tag{3.2.5}$$

where $R_i^2(ROA)$ and $SST_i(ROA)$ are R^2 and the sum of squared total variations, derived from the regression (3.2.4) for firm i. A higher ECI indicates that the earnings frequently move together. The variables used in this study are summarized in Table 3.1.

[Insert Table 3.1 here.]

From the summary statistics in Table 3.1, 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 can also 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.

3.3 Predicting Stock Market Returns with News Co-occurrence

In this section, we provide several empirical results. Section 3.3.1 examines the time series return predictability of the NNTA index on the aggregate market level. Section 3.3.2 compares the in-sample return predictability of the NNTA index with alternative predictors. Section 3.3.3 analyzes the out-of-sample predictability. Finally, Section 3.3.4 assesses the cross-sectional predictability of the NNTA index.

3.3.1 Forecasting the market

Consider the standard predictive regression model,

$$R^m_{t+1} = \alpha + \beta X_t + \epsilon_{t+1}, \tag{3.3.1}$$

where R^m_{t+1} is the excess market return, that is, the monthly return on the S&P500 index in excess of the risk-free rate, and X_t is the NNTA index or another 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, the earnings comovement index, and the equal-weighted short interest ratio. Specifically, we test the null hypothesis $\mathcal{H}_0 : \beta = 0$, which means that NNTA has no predictability for stock returns, against the alternative $\mathcal{H}_1 : \beta \neq 0$. Under the null hypothesis, (3.3.1) reduces to the constant expected return model, $R^m_{t+1} = \alpha + \epsilon_{t+1}$.

[Insert Table 3.2 here.]

Table 3.2 reports the results of the in-sample predictive regressions. Economically, the OLS coefficient suggests that a one-standard-deviation increase in NNTA is associated with an approximately 1.09% decrease in the 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 by multiplying the change in the rate of return by 12, then the annualized level of 13.08% will be large to a certain extent. In this case, it may be interpreted that 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 the soft/hard information predictors. This implies that if this level of predictability can be sustained out-of-sample, then it will be of substantial economic significance (Kandel and Stambaugh (1996)). Campbell and Thompson (2008) showed that, given the large unpredictable component inherent in the monthly market returns, a monthly out-of-sample R^2 of 0.5% can generate a significant economic value. Additionally, our findings in section 3.3.3 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 to ensure 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}),

$$R^2_c = 1 - \frac{\sum_{t=1}^{T} 1_{\{t \in \mathbb{T}_c\}} \cdot \epsilon_t^2}{\sum_{t=1}^{T} 1_{\{t \in \mathbb{T}_c\}} \cdot (R^m_t - \bar{R}^m)^2}, \quad c \in \{up, down\}, \tag{3.3.2}$$

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 based on an expansion (recession) period set by the National Bureau of Economic Research (NBER), that is, $\mathbb{T}_{up}$ ($\mathbb{T}_{down}$), and zero otherwise; ϵ_t is the fitted residual, based on the in-sample estimates of the predictive regression model in (3.3.1); $\bar{R}^m$ is the full-sample mean of R^m_t; and T is the number of observations for the full sample. It must be noted 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 3.2 report the R^2_{up} and R^2_{down} statistics. It is shown that NNTA gains return predictability over the recession periods twice as large than those over the expansion periods. Additionally, NNTA has significant higher return predictability than all the other predictors over the expansion periods, and it only underperforms the abnormal Wall Street Journal (WSJ) news coverage over the recession periods. This confirms that our news-network-based attention proxy possesses a stable predictive power of market premium under all economic environments.

3.3.2 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 the 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,

$$R_{t+1}^{m} = \alpha + \beta X_t + \phi Z_t + \epsilon_{t+1}, \tag{3.3.3}$$

where X_t is one of the NNTA indices, and Z_t is one of the alternative predictors described in section 3.2.2; our main focus is on the coefficient β and on testing $\mathcal{H}_0 : \beta = 0$ against $\mathcal{H}_1 : \beta \neq 0$.

[Insert Table 3.3 here.]

Table 3.3 shows that the estimates of β in (3.3.3) are negative and stable in magnitude, which is in line with the results of the predictive regression (3.3.1) reported in Table 3.2. Importantly, β remains statistically significant when augmented by other predictors. These results illustrate that NNTA contains a sizeable complementary forecasting information, beyond what is contained in the media coverage, alternative attention proxies, and other mainstream return predictors. Since controlling other predictors does not undermine NNTA's impact, (β retains almost the same magnitude as that reported in Table 3.2), and we claim that the information content of the news-network based predictors do not overlap with existing attention proxies.

3.3.3 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, argued that the out-of-sample tests seem more relevant for assessing the genuine return predictability in real time and avoiding the over-fitting issue and are much less affected by the finite sample bias, such as the Stambaugh bias (Busetti and Marcucci (2013)). Therefore, it is essential to show the out-of-sample predictive performance of NNTA indices.

For out-of-sample forecasts at time t, we only use the information available up to t to forecast stock returns at $t+1$. Following Goyal and Welch (2008), Kelly and Pruitt (2013), and many others, we conduct the out-of-sample analysis by estimating the predictive regression (3.3.4), recursively based on our news network triggered attention index,

$$\hat{R}^m_{t+1} = \hat{\alpha}_t + \hat{\beta}_t X_{1:t;t}, \tag{3.3.4}$$

where $X_{1:t;t}$ is the recursively estimated composite NNTA index or individual NNTA indices, and $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates from regressing $\{R^m_{r+1}\}_{r=1}^{t-1}$ with model (3.3.1) recursively. We also carry out the 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 3.4.

To assess the out-of-sample performance, we apply the widely used Campbell and Thompson (2008) R^2_{OS} statistics based on the unconstrained and truncated forecasts that impose a non-negative equity premium constraint. The unconstrained R^2_{OS} statistic measures the proportional reduction in the mean squared forecast error (MSFE) for the predictive regression forecast, relative to the historical average benchmark. Goyal and Welch (2008) showed 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; this will ensure that the future expected return can be estimated at time $t = r + 1, r + 2, ..., T$. Subsequently, we compute the following $s = T - r$ out-of-sample forecasts: $\{\hat{R}^m_{t+1}\}_{t=r}^{T-1}$. Specifically, we use the first 1/3 data from January 1996 to June 2002 as the initial estimation period to ensure that the forecast evaluation period spans from July 2002 to December 2014.

$$\hat{R}^2_{OS} = 1 - \frac{\sum_{t=r}^{T-1}(R^m_{t+1} - \hat{R}^m_{t+1})^2}{\sum_{t=r}^{T-1}(R^m_{t+1} - \bar{R}^m_{t+1})^2}, \tag{3.3.5}$$

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

$$R^m_{t+1} = \frac{1}{t}\sum_{s=1}^{t} R^m_s. \tag{3.3.6}$$

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

The statistical significance of the out-of-sample R^2s that 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) showed 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. Thus, we expect the benchmark model's MSFE to be smaller than the predictive regression model's MSFE under the null hypothesis. The MSFE-adjusted statistic accounts for the negative expected difference between the historical average MSFE and the predictive regression MSFE under the null hypothesis to ensure that it can reject the null hypothesis even if the R^2_{OS} statistic is negative.

[Insert Table 3.4 here.]

Panel A of Table 3.4 shows that the NNTA index generates a positive and significant R^2_{OS} statistics (5.80%) and delivers a lower MSFE than that of the historical average. Hence, it can be concluded that NNTA has a strong out-of-sample predictability for market returns, which confirms our conjectures in the previous in-sample results (Table 3.2). When compared to NNTA, all the other predictors show much weaker out-of-sample predictability for excess market 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. Apparently, our NNTA index is a more powerful predictor of market returns, among other attention proxies and news-related predictors. The last two columns of Table 3.4 show that the predictability of the NNTA index is significantly strong and stable over both expansion and recession periods.

In summary, the out-of-sample analysis shows that, consistent with our previous in-sample results (Tables 3.2 and 3.3), the NNTA index is a powerful and reliable predictor of the excess market returns, and it consistently outperforms the other state-of-the-art return predictors, in the out-of-sample sense.

3.3.4 Forecasting the cross-sectional portfolio

The news co-occurrence generates excessive investor attention from an enlarged investor base. Due to the short-sales constraint, bullish investors will buy the connected stocks, while bearish investors (especially the non-shareholders or retail investors) will find it hard to short-sell the stocks (Barber and Odean, 2008). Consequently, an increased news co-occurrence would increase the buying pressure rather than the selling pressure through the prices of connected stocks, thereby leading to a surge in 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 the purchase of stocks with low abnormal connected news coverage and sale of those with high abnormal connected news coverage. Particularly, we construct 10 value-weighted portfolios by sorting the stocks into deciles, according to their total abnormal connected news coverage ratio, that is, $\sum_j aw_{ij,t}$. Considering that a significant number of stocks do not have any connected news, we label those stocks as the lowest attention portfolio. The rest of the stocks are divided into nine groups. All portfolios are rebalanced monthly at the subsequent month's closing price. The performances of cross-sectional portfolios are shown in the second column of Table 3.5. Expectedly, the portfolio with the lowest abnormally 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 the highest abnormally connected news coverage ratio.

[Insert Table 3.5 here.]

In the last three columns of Table 3.5, we also test if the cross-sectional portfolio returns can be explained by the existing factor models. We apply the four-factor, q-factor, and five-factor models by Carhart (1997), Hou *et al.* (2015), and Fama and French (2016), respectively, to dissect the risk-adjusted alphas. The results show that our portfolio remains at a consistently significant alpha of 0.47% per month. This provides strong evidence that a connected news item indeed captures a different aspect of the excess market returns, which is hardly explained by conventional risk factors.

3.4 Economic Explanations

In this section, we explore the source of predictability of NNTA through different channels. First, we test if a higher news co-occurrence leads to an increase in correlated search activities, which is an important proxy for investor attention (Da *et al.*, 2011). Subsequently, we explore why connected news is powerful in predicting negative returns by relating it to the investor base. Next, we examine the performance of NNTA under different levels of belief divergence and the short-sales constraint. Finally, we confirm that the excessive buying pressure is triggered by the retail investors whose investment decisions are more subject to belief divergence and the short-sales constraint.

3.4.1 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;" that is, if a stock's name is mentioned in the news media, then the investors would have paid attention to the mentioned stock. However, a news coverage does not capture attention unless investors 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 that news co-occurrences can induce the correlated search or even stronger, co-search activities, then it will provide clear evidence that NNTA indeed reflects investor attention.

Considering the connected news coverage between stocks is quite sparse, we classify stock pairs into five groups based on the range of connected news coverage to ensure sufficient observations in each group. Specifically, we assign stock pairs with no connected news, 1 to 5 connected news, 6 to 10 connected news, 11 to 15 connected news, and the rest of the pairs to groups 1, 2, 3, 4, and 5, respectively. Table 3.6 summarizes the number of observations in each group from January 2005 to December 2014. Given that 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 3.3.

[Insert Table 3.6 here.]

[Insert Figure 3.3 here.]

As shown in Figure 3.3, the average correlations of Google and Bloomberg search volumes increase with the news co-occurrences significantly. Particularly, the average correlation coefficients in group 5 that has the maximum number of 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 a news co-occurrence is associated with more correlated search behaviors.

3.4.2 Connected news and investor base

Merton (1987) proposed 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 this regard, a stock potentially enjoys a larger investor base when it witnesses an increase in news coverage than other stocks. Barber and Odean (2008) asserted that an increase in news coverage will attract the attention of more investors, and individual investors will be more likely to buy rather than sell those stocks that catch their attention. Therefore, an enlarged investor base will aggravate the excessive buying pressure triggered by an increase in news coverage and increase negative future returns.

To illustrate that highly connected news items help to enlarge the investor base, we first proxy the investor base with an abnormal Google search volume[12] (ASV):

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

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

$$ASV_{it} = \alpha + \beta Connected\ News_{it} + \theta' Z_{it} + \varepsilon_{it}, \tag{3.4.1}$$

where Z_{it} is a set of controls for other attention proxies. Particularly, we follow Da *et al.* (2011) by controlling for the total number of news items, firm size, stock turnover, absolute abnormal return, the total number of news items on other stocks, the total number of analysts, and advertisement expenditures. The 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 3.7.

[Insert Table 3.7 here.]

Evidently, the significant positive coefficient of *Connected News* in Table 3.7 strongly supports our hypothesis on the positive correlation between the connected news and investor base. The result is quite robust across the regression with various controls.

3.4.3 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

[12]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.

short-selling is not allowed. Similarly, Hong and Stein (2007) argued that heterogeneous belief and short-sales constraint are the two key ingredients that explain overpricing of stocks. Aligned with this argument, we would expect NNTA to have stronger return predictability when investor beliefs are highly divergent, and the short-sales constraint is tighter.

A high belief divergence indicates highly dispersed 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) as a proxy for 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, such as 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 the institutional investor ownership to proxy for the tightness of the short-sales constraint. This construction follows Asquith *et al.* (2005) who double sorted the stock returns on institutional investor ownerships and the short interest ratio.[13]

Specifically, we sort returns on the market environment indicator, that is, market uncertainty, investor sentiment, or short-interest ratio, and divide the sample into High/Low groups according to its median. Concerning both subsamples, the in-sample return predictability results are summarized in Table 3.8.

[Insert Table 3.8 here.]

[13] Asquith *et al.* (2005) defined *short-sales constrained stocks* as those in the highest decile of the short interest ratio as well as those in the lowest tertile of the institutional ownership. However, if we use a similar method to divide the sample according to the median of short interest ratios and institutional ownership, then the number of observations will be small for both the subsample periods, weakening the statistical inference. Therefore, we modify the short-sales constraint with a new proxy (the short interest ratio divided by the institutional ownership) to retain enough subsample observations to derive Table 3.8.

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 the proxy for both the market indicators/short-sales constraint—NNTA—and their interaction terms as below

$$R^m_{t+1} = \alpha + \beta NNTA_t + \phi Z_t + \gamma NNTA_t \times Z_t + \epsilon_{t+1}, \tag{3.4.2}$$

where Z_t is the proxy for the market environment indicator/short-sales constraint. For investor sentiment and market uncertainty proxies, we rank them from 1 to 10 to indicate the level of strength. For the short-sales 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 the aggregated institutional ownership is in the highest (lowest) tercile, and it equals 2 for the rest sample periods. The results are reported in Table 3.9.

[Insert Table 3.9 here.]

The significantly negative coefficients of the interaction terms in Table 3.9 strongly support that the tight short-sales constraint and high belief divergence exaggerate the over-valuation caused by a news co-occurrence. It is also serves as 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 an overvaluation of the correlated stocks.

3.4.4 Connected news and retail investors

Considering that 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 recheck the cross-sectional portfolio results in each subsample. The results are summarized in Table 3.10.

[Insert Table 3.10 here.]

Expectedly, only the stocks with a higher level of retail investor ownership generate a significant risk-adjusted alpha in cross-sectional portfolio. To show that excessive buying pressure is triggered by the retail investors, we check the retail order imbalance of each stock during the good news and bad news periods. Particularly, in the event of good news, the retail order imbalance increases in the case of stocks with more connected news, thereby leading to an excessive buying pressure. Conversely, in the event of bad news, due to the short-sales constraint, the retail investors fail to generate an excessive selling pressure for stocks with more connected news, provided that to the stocks capture retail investors' attention. In Figure 3.4, we conduct this test and define 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 3.4 here.]

Combining these results with those in Table 3.8, we verify that the return predictability of the NNTA index is, particularly, triggered by the retail investors' attention, which is more short-sales constrained and divergent in beliefs.

3.5 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 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 for abnormal investor attention with the news co-occurrence. In general, we find that NNTA consistently provides negative return forecasts for the time-series and cross-sectional portfolios. Using a sample of S&P500 stocks from 1996 to 2014, first, we document that NNTA can provide a significant in-sample and out-of-sample return predictability. Subsequently, we justify the investor attention interpretation of the NNTA index by showing that the abnormally connected news coverage ratio can significantly predict the correlated Google/Bloomberg search and Edgar co-search activities. Finally, we source the return predictability of NNTA from the retail investors' trading behaviors through the short-sales constraint and belief divergence.

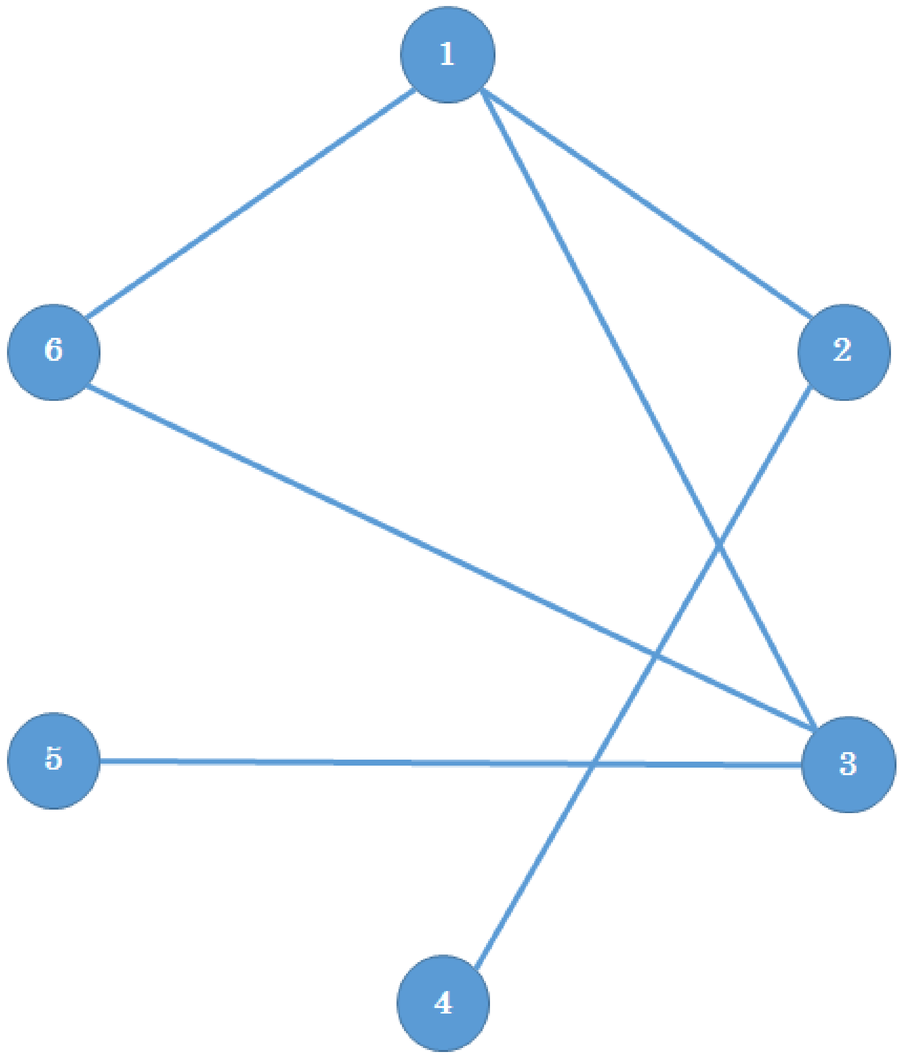


Figure 3.1: This figure is a simple network example to illustrate how eigenvector centrality differs from degree centrality. Each node in the network represents a stock and each edge denotes the existence of connected news between two stocks.

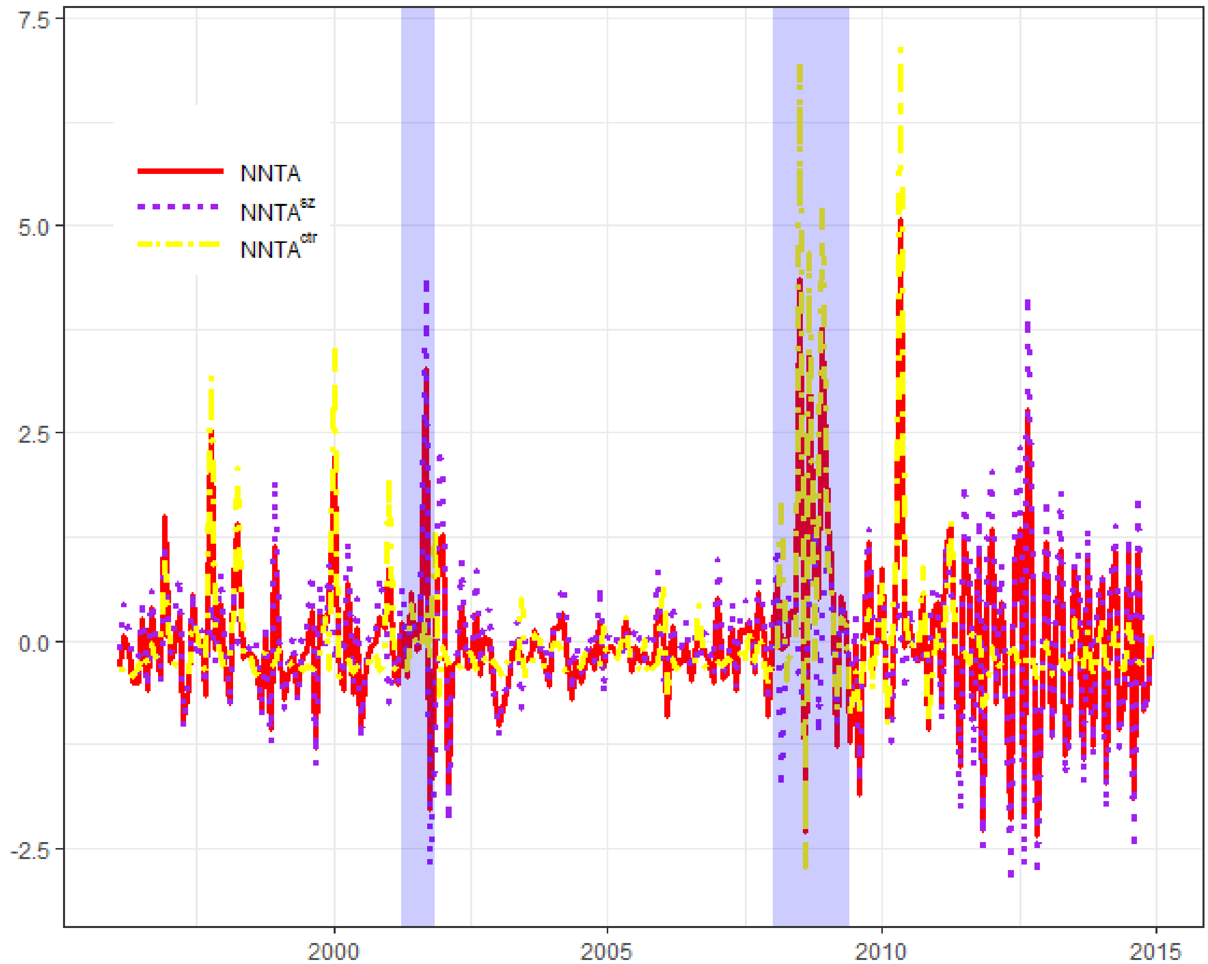


Figure 3.2: This figure plots the composite news network triggered attention index, size-based news network triggered attention index, and the centrality-based news network triggered attention index. The red line depicts the composite news network triggered attention index, the dotted dashed yellow line 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.

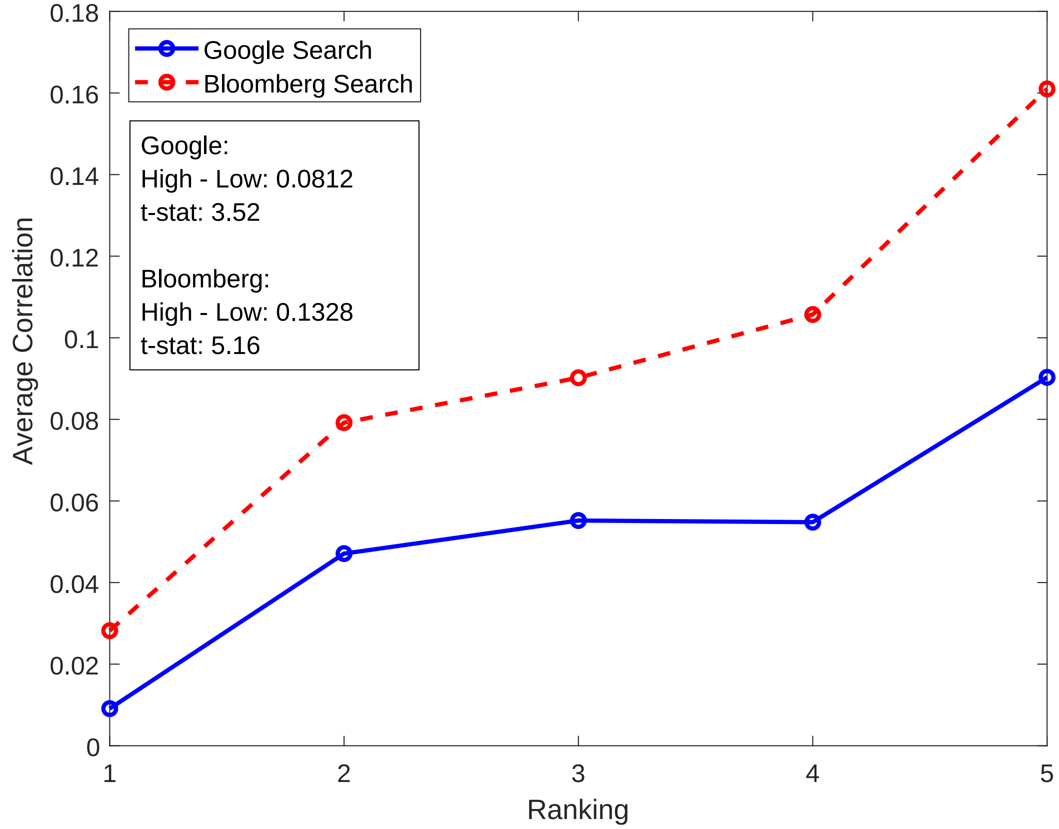


Figure 3.3: This figure plots the average correlation coefficient of Google and Bloomberg search volumes within 5 groups of stock pairs. Stock pairs in the first (last) group have no (more than 15) connected news. The middle three groups require the number of connected news between pair stocks within 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.

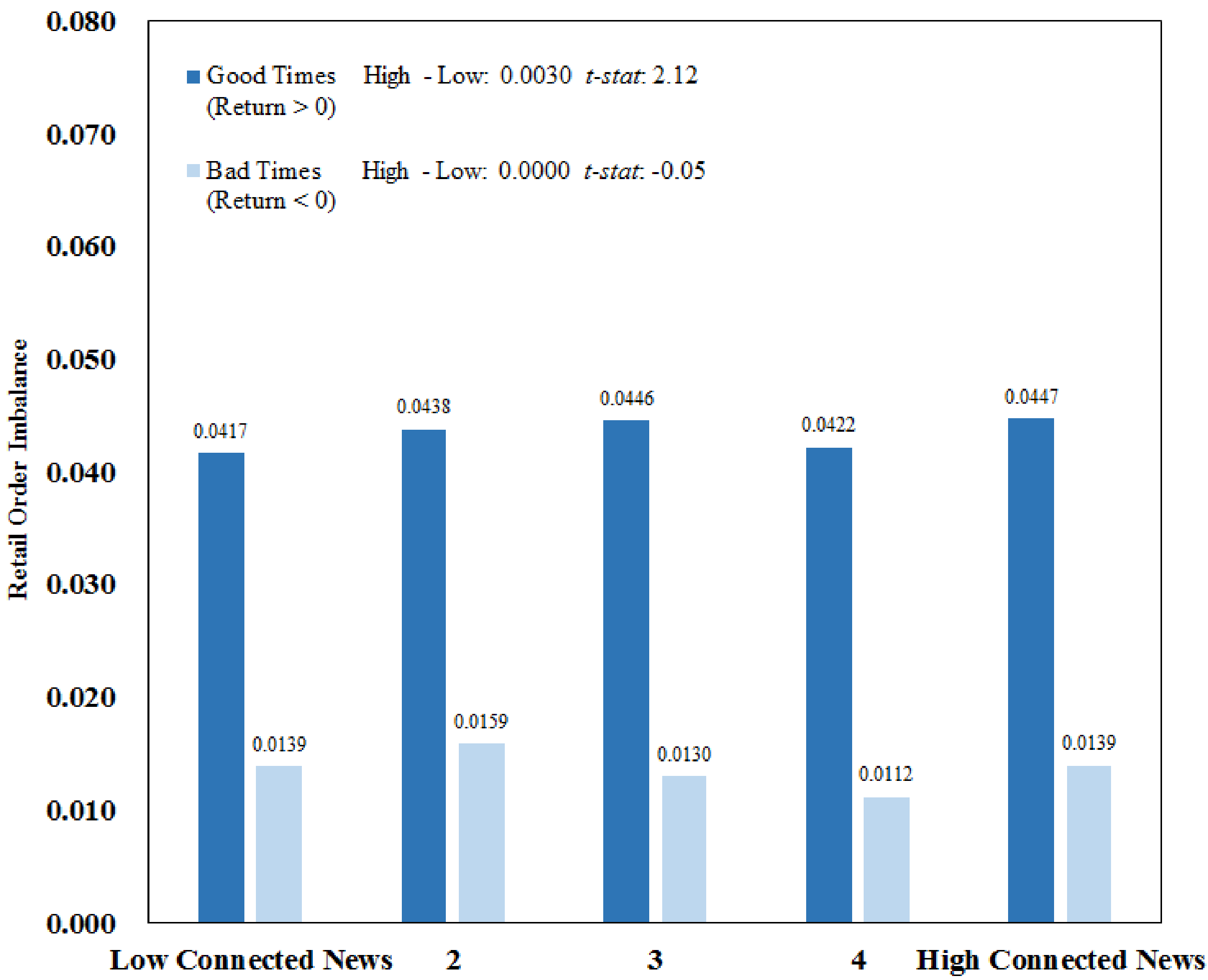


Figure 3.4: This figure shows the average retail order imbalance for each group of stocks under good/bad news period. The stocks are sorted into quintiles according to the number of connected news. The good (bad) news period is characterized by the return performance on the news event day, i.e., $r_{it} > 0$ ($r_{it} < 0$). 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 3.1: 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 ΔTRN); Level and change of Dow Jones News/Wall Street Journal related to S&P 500 index (DJI/WSJ and $\Delta DJI/\Delta WSJ$); 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 a 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 $\Delta TrdVol$); Negative and optimistic news tones based on Thomson Reuters News Analytics (Neg^{NN} and Opt^{NN}), and Loughran and McDonald (2011) dictionary with value weights (*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 comovement index (ECI), Rapach *et al.* (2016) equal-weighted short interest ratio (EWSI), and 14 economic variables from Amit Goyal's 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
ΔTRN	0.005	1.042	0.038	4.300	-3.155	4.273	-0.345
ΔDJI	0.133	6.569	-0.498	11.452	-36.000	29.577	0.066
ΔWSJ	0.045	1.472	1.185	8.970	-4.386	7.896	-0.217

Table 3.1 (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 3.2: 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
$\Delta\,TRN$	-0.259	-0.870	0.337	0.058	2.332
$\Delta\,DJI$	0.035	0.118	0.006	0.269	4.363
$\Delta\,WSJ$	-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 3.3: 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
$\Delta\,TRN$	-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
$\Delta\,WSJ$	-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 3.3 (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 3.4: 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
Δ*TRN*	-2.248	-0.373	0.646	-0.805	-4.885
Δ*DJI*	-1.051	-0.939	0.826	-1.048	-1.057
Δ*WSJ*	-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
Δ*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
Δ*TrdVol*	-0.655	-0.098	0.539	0.022	-1.892

Table 3.4 (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 3.5: 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 3.6: 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 3.7: 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)
ΔAbn ReturnΔ					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 3.8: 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 constraint. 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 3.9: 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 3.10: 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)

Chapter 4

Security Analysts and Capital Market Anomalies

Li Guo, Frank Weikai Li, and K.C. John Wei

4.1 Introduction

A longstanding debate in the finance and accounting literature concerns whether security analysts' research helps to improve stock market efficiency. Early studies that examine market reactions to analyst earnings forecast revisions or recommendation changes tend to support the notion that analysts are skilled information processors (Womack, 1996; Barber, Lehavy, McNichols, and Trueman, 2001). That is, analysts' information-production role helps to improve price efficiency. However, recent studies question the usefulness of analyst research outputs, arguing that analysts' incentives to gain investment banking business, generate trading commissions, and curry favor with management for access to private information may compromise their integrity and objectivity.[1] More generally, Bradshaw, Richardson, and Sloan (2006) find that a firm's level of external financing is a more important driver of analyst optimism than existing investment banking ties. This suggests that even unaffiliated analysts may upwardly bias their forecasts or recommendations in anticipation of future business.

In addition to conflicts of interest arising from investment banking/brokerage affiliations, analysts' recommendations or forecasts may be inefficient due to behavioral biases (La Porta, 1996). Several recent studies explicitly model analysts' biased expectations and examine their effect on stock mispricing. Bouchaud, Krueger, Landier, and Thesmar (2018) find that analysts' expectations are sticky in the short run and that they underreact to persistence in firms' profitability.

[1] See, for instance, Lin and McNichols (1998), Chen and Matsumoto (2006), and Cowen, Groysberg, and Healy (2006).

Bordalo, Gennaioli, La Porta, and Shleifer (2018) find that analysts are extrapolative in their long-term growth forecasts and overreact to past earnings growth.

In this paper, we address this important question by examining whether analysts exploit well-documented stock return anomalies when making recommendations. Over the last several decades, researchers have discovered numerous cross-sectional stock return anomalies. Irrespective of the sources of return predictability, these anomalies represent publicly available information, of which skilled agents, such as analysts, should be able to take advantage. If analysts are truly sophisticated, informed, and unbiased, they should exploit such well-known sources of return predictability when making recommendations.[2]

We propose two competing views of analyst research that offer opposite predictions to our research question. The *sophisticated analyst hypothesis* predicts that analysts should on average tilt their recommendations to be consistent with anomaly prescriptions. In contrast, the *biased analyst hypothesis* suggests that analyst recommendations are unrelated or even contradictory to anomaly prescriptions. Most importantly, the two competing hypotheses have different asset pricing implications when analyst recommendations disagree with anomaly prescriptions. The sophisticated analyst hypothesis predicts that when analyst recommendations contradict anomaly prescriptions, anomaly stocks should not be associated with future abnormal returns. In sharp contrast, the biased analyst hypothesis predicts that anomaly returns can be amplified when analysts disagree with anomaly prescriptions, especially if certain groups of investors naïvely or

[2] We focus on analyst recommendations because they directly reflect analysts' view of the relative over- or under-valuation of a stock, while analysts' forecasts of firm earnings do not directly correspond to their perception of relative misevaluation.

strategically follow analyst recommendations.[3] In other words, biased analyst recommendations are a potential source of market friction that may contribute to stock mispricing.

Following Stambaugh, Yu, and Yuan (2012), we construct 11 prominent asset pricing anomalies using a sample of available analyst recommendation data from the Institutional Brokers' Estimate System (I/B/E/S). We first show that during our sample period of 1993-2014, all long-short portfolios based on these 11 anomalies generate significant Fama and French (1993) three-factor alphas, ranging from 0.35% to 1.09% per month. Following Stambaugh and Yuan (2017), we also create two composite mispricing scores, MGMT and PERF, which generate monthly three-factor alphas of 0.86% and 0.99%, respectively.[4] This strong return predictability suggests that anomaly signals are part of the information set that analysts can use when making stock recommendations.

To examine whether analysts incorporate anomaly signals into their recommendation decisions, we analyze the level and change of analyst recommendations during the window of anomaly portfolio formation.[5] The results strongly reject the sophisticated analyst hypothesis. First, not only do analysts fail to tilt their recommendations to take advantage of anomalies, but also their recommendations are often contradictory to anomaly predictions. This tendency is particularly strong for anomalies related to equity issuance and investment. For example, for MGMT, the mean recommendation value is 4.07 for stocks in the short leg and 3.52 for stocks in the long leg with a difference of -0.55, which is highly significant. In contrast, analyst

[3] Mikhail, Walther, and Willis (2007) and Malmendier and Shanthikumar (2007) find that small investors naïvely follow analyst recommendations without accounting for analysts' biased incentives. Brown, Wei, and Wermers (2014) show that mutual funds tend to herd into stocks with consensus sell-side analyst upgrades and herd out of stocks with consensus downgrades; they further show that herding by career-concerned fund managers is price destabilizing.
[4] MGMT mainly consists of anomalies related to managerial actions, and PERF mainly consists of anomalies related to firm performance.
[5] We measure the change in recommendations by taking the difference between the current consensus recommendation and its value one year ago.

recommendations seem to be more consistent with prescriptions of the anomalies associated with firm performance (PERF), such as gross profitability and return on assets, although the relation is weak and not monotonic. The results are similar for recommendation changes, which is particularly puzzling. This finding suggests that analysts actively revise opinions on anomaly stocks, but their views tend to be in the wrong direction of anomaly predictions. Thus, neither analyst inattention nor stale recommendation stories can fully explain our findings.

The difference in analyst behavior across the two categories of anomalies is consistent with evidence in the literature that analysts tend to issue overly optimistic growth forecasts or recommendations for firms characterized by high growth, large capital spending, and equity financing needs. Such firms are more likely to be potential investment banking clients of the brokerage firms employing the analysts. Analysts are also likely to issue more favorable recommendations for better-performing firms with high profitability or past winners.

Most importantly, analyst recommendation behavior itself is not sufficient to distinguish the two competing hypotheses. Analysts may have superior (private) information such that even when their recommendations contradict anomaly prescriptions, the information value of their recommendations may offset that of the anomalies. We therefore examine anomaly returns when analyst recommendations confirm or contradict anomaly signals. The results reveal the same message. When analyst recommendations and anomaly prescriptions are contradictory, anomaly returns are amplified, especially for anomalies in the PERF category.

The abnormal returns in inconsistent cases are larger than those in consistent cases for all 11 anomalies, and significantly so for seven anomalies. For example, the long-short portfolio based on PERF generates a monthly three-factor alpha of 1.57% for the inconsistent case, whereas it is only 0.90% for the consistent case. The result is more pronounced in the short leg of anomalies with the most favorable recommendations, which earns a particularly large negative return. This is in line with the idea that short selling overvalued stocks is costlier than correcting underpriced stocks (Nagel, 2005; Stambaugh, Yu, and Yuan, 2015), especially when betting against analyst consensus. The amplification effect of biased analyst recommendations on anomalies is not driven by other firm characteristics. The results of the Fama and MacBeth (1973) regressions after controlling for standard return predictors are in line with portfolio sorting results.

The amplification effect of biased recommendations on anomaly returns suggests that some investors who follow analyst opinions or think like analysts might trade in the same direction of recommendations over the portfolio formation period. If this is the case, investors' excess demand will lead to further mispricing. Anomaly returns are thus amplified as prices subsequently revert to fundamental values. Using changes in stock ownership by mutual funds as a proxy for investors' demand, we find strong evidence supporting this underlying channel. For both the long and short legs of anomaly portfolios, stocks with favorable consensus recommendations experience significantly larger mutual fund net buys over the portfolio formation window compared with stocks with unfavorable recommendations. Moreover, the effect of favorable recommendations on mutual fund demand is more pronounced for stocks in the short leg of the anomalies, consistent with our portfolio return patterns.

The above findings may mask significant heterogeneity across individual analysts who differ in their skill in generating and/or incentives to generate informative recommendations. To shed light on this issue, for each analyst at the end of each year, we calculate the correlation between stocks' anomaly rankings and recommendation values, using all recommendations issued by the analyst over the past three years. Consistent with the idea that this correlation metric captures an analyst's skill or unbiasedness, we find that analysts with a higher correlation metric elicit stronger market reactions when announcing recommendation changes.

We consider several potential explanations for analysts' tendency to recommend contrary to anomaly prescriptions. First, analysts may simply be unaware of the return predictability of these anomalies before their discovery by academics (McLean and Pontiff, 2016). However, we find that analysts' tendency to recommend overvalued stocks more favorably is still significant for six anomalies in the post-publication period, suggesting that analysts' unawareness of expected return information in the anomalies is unlikely to fully explain our findings. Second, analysts may be reluctant to incorporate anomaly signals into their recommendations because their institutional clients can face severe constraints when trading these stocks. Using firm size and bid-ask spread as proxies for trading frictions, we find very similar results for big or highly liquid stocks, suggesting that limits-to-arbitrage concerns on the part of analysts are unlikely to explain our findings.

Analyst recommendations can be biased due to misaligned incentives or behavioral bias. Based on the Baker-Wurgler (2006) sentiment index, we find that analyst recommendations are more biased toward overvalued stocks and that the amplification effect of biased recommendations on anomaly returns is more pronounced during the high-sentiment period than during the low-sentiment period. This evidence suggests that the behavioral bias of analysts may partially explain their overly optimistic (pessimistic) recommendations for overvalued (undervalued) stocks.

Using analyst data from Zacks Investment Research over an earlier sample period, Barber et al. (2001) and Jegadeesh, Kim, Krische, and Lee (2004) document the investment value of both the level and change of analyst consensus recommendations. To reconcile their evidence with our finding that analyst consensus recommendations are on average inefficient, we reexamine the unconditional return predictability of analyst consensus recommendations. Using I/B/E/S data over the sample period from 1993 to 2014, we do not find any return predictability for the level of analyst consensus recommendations. While we do find some return predictability for the change of consensus recommendations over the full sample period, it is concentrated only in the 1993-2000 period. Overall, we conclude that the seeming contradiction between our results and those of prior studies is mainly attributable to the different sample periods studied.

In a recent concurrent working paper, Engelberg, McLean, and Pontiff (2018b) similarly document that analysts' price forecasts and recommendations often contradict anomaly predictions. Our paper differs from theirs by further showing that anomaly returns are significantly amplified when analyst opinions contradict anomaly signals. We thus provide stronger evidence that analysts' biased recommendations may contribute to the persistence of anomalies. Moreover, we develop a simple method to identify skilled analysts ex ante.

4.2 Data and Summary Statistics

Analyst consensus recommendation data come from the I/B/E/S summary file, while the individual analyst recommendations are from the I/B/E/S detailed history file. The I/B/E/S detailed recommendation data begin in December 1992, and consensus recommendations start from 1993. Recommendation value (Rec) is coded as a number from 5 (strong buy) to 1 (strong sell). We also construct the change of consensus recommendations (ΔRec), as Jegadeesh et al. (2004) find that recommendation changes are more informative than recommendation levels. The recommendation change is calculated as the current consensus recommendation minus its value for the same firm one year ago. We merge the analyst data with Center for Research in Security Prices data after eliminating firms with share codes other than 10 or 11 and firms with stock prices below one dollar.

Following Stambaugh and Yuan (2017), we construct anomaly variables at the end of each month *t*. For the anomaly variables requiring annual financial statements from Compustat, we require at least a four-month gap between the portfolio formation month and the end of the fiscal year. For the quarterly reported earnings, we use the most recent data in which the earnings announcement date (RDQ in Compustat) precedes month *t*. For the quarterly balance sheet items, we use the data from the prior quarter.

We construct anomaly portfolios as follows. We sort all of the stocks into quintile portfolios based on each of the anomaly characteristics at the end of each month, and we define the long and short legs as the extreme quintiles. When constructing the composite mispricing scores, we require a stock to have a non-missing value at the end of month *t* - 1 for at least three of the anomalies to be included in that composite mispricing measure. For an anomaly to be included in the composite mispricing measure at the end of month *t* - 1, we also require at least 30 stocks to have non-missing values for that anomaly.

For each individual analyst, we also calculate the rank correlation between stocks' recommendation values and composite mispricing scores, $Corr_{MGMT}$ and $Corr_{PERF}$, using all recommendations issued by an analyst over the last three years. Specifically, in each month, we sort stocks into quintiles based on the two composite mispricing scores, where the highest (lowest) quintile represents the most undervalued (overvalued) stocks. Then, for each individual analyst *i* at the end of each year *t*, we calculate the rank correlation between stocks' anomaly rankings and recommendation values, using all recommendations issued by this analyst over the last three years as follows:[6]

[6] We only keep the latest recommendation of an analyst for each stock in a month. We include those analysts who issue at least three recommendations over the last three years in our sample.

$$Corr_{i,type,t} = \frac{\sum_{n=1}^{N}\left(Rec_{i,n,t} - \overline{Rec}_{i,t}\right)\left(Rank_n^{type} - \overline{Rank}^{type}\right)}{\sqrt{\sum_{n=1}^{N}\left(Rec_{i,n,t} - \overline{Rec}_{i,t}\right)^2 \sum_{n=1}^{N}\left(Rank_n^{type} - \overline{Rank}^{type}\right)^2}}, \tag{1}$$

where $type$ stands for the anomaly type, MGMT or PERF. $Rec_{i,n,t}$ is the value of the n^{th} recommendation issued by analyst *i* within the last three years before the end of year *t*, ranging from 1 (least favorable) to 5 (most favorable). *N* is the total number of recommendations issued by analyst *i* over the three-year period. $\overline{Rec}_{i,t}$ is the mean value of all recommendations issued by analyst *i* within the three years before the end of year *t*. $Rank_n^{type}$ is a quintile ranking variable (with a higher value indicating more underpricing) for the stock associated with the n^{th} recommendation, based on the composite mispricing score (MGMT or PERF) measured in the same month as when the n^{th} recommendation is issued.

We also construct variables proposed in the literature that are associated with the informativeness of analyst research, including analyst, recommendation, broker, and firm characteristics. Following Green et al. (2014), we use $|\Delta Rec_{individual}|$ to measure the magnitude of individual analysts' recommendation changes. Kecskés, Michaely, and Womack (2016) find that stock recommendations accompanied by earnings forecast revisions lead to larger price reactions. We thus add a dummy variable, $Concurrent\ Rec$, that equals one if the analyst issues a forecast revision and a recommendation change for the same stock in the three trading days surrounding the forecast revision date and the recommendation change is in the same direction as the forecast revision. Ivkovic and Jegadeesh (2004) find that recommendations before (after) an earnings announcement lead to greater (weaker) price reaction. To control for these effects, we create a $Pre\text{-}earnings$ ($Post\text{-}earnings$) dummy variable that equals one if the recommendation is issued within two weeks prior to (after) the earnings announcement date and zero otherwise. $Away\ from\ consensus$ is a dummy variable that equals one if the absolute deviation of the recommendation change from the consensus is larger than the absolute deviation of the prior recommendation from the consensus. This is motivated by Gleason and Lee (2003) and Jegadeesh and Kim (2010), who find that analyst earnings forecast revisions or recommendation changes that move away from the consensus (i.e., bold forecasts) generate larger price impacts.

Regarding analyst characteristics, Stickel (1991) documents that recommendation changes made by all-star analysts have greater price impacts. Hence, we add a dummy variable $AllStar$ that equals one if the analyst is ranked as an All-American (first, second, third, or runner-up teams) in *Institutional Investor* magazine and zero otherwise. Loh and Mian (2006) show that analysts with more accurate earnings forecasts issue recommendations that are more profitable. We therefore control for *Accuracy*, which is the difference between the absolute forecast error of analyst *i* on firm j's earnings and the average absolute forecast error across all analysts on firm j, scaled by the average absolute forecast error across all analysts' forecasts on firm j's earnings. We then multiply this value by -1 and average across all stocks covered by an analyst in a given year, so that a higher value indicates that the analyst is on average more accurate. Mikhail, Walther, and Willis (1997) emphasize the importance of analyst experience for forecast accuracy. We thus construct two experience measures: $Ln(FirmExp + 1)$ ($Ln(TotalExp + 1)$) is the natural logarithm of one plus the number of days since the analyst first issued an earnings forecast for this firm (any firm). $Ln(BrokerSize)$ is the natural logarithm of the total number of analysts working for the brokerage company in a given year. This is to control for differences in the level of resources available to analysts employed by brokerage firms of different sizes (Clement 1999). $Average\ Size$ is the average $Ln(Size)$ of stocks followed by an analyst in a given year. $Coverage$ is the total number of firms followed by an analyst in a given year.

Finally, we include several firm characteristics related to recommendation announcement returns. $Ln(Size)$ is the natural logarithm of firm market capitalization. $Volatility$ is the standard deviation of daily returns over the 63 trading days prior to the recommendation change. $MOM_{(-21,-1)}$ is the cumulative stock returns over the 21 trading days prior to the recommendation change. $MOM_{(-252,-22)}$ is the cumulative stock returns over the 252 trading days prior to the recommendation change, excluding the 21 trading days prior to the recommendation change.

Table 1 presents the summary statistics for the sample, including the number of observations and the mean, median, standard deviation, and the 25th and 75th percentiles of the main variables used in the analysis. In general, these summary statistics are consistent with the literature. The mean value of Rec is 3.85 and the median is 3.89, suggesting an overall optimism in analyst consensus recommendations (otherwise, both values should be close to 3). The mean of ΔRec is positive (0.04) in our sample, suggesting that analysts are more likely to upgrade than to downgrade a firm. Finally, $Corr_{MGMT}$ is on average negative, while $Corr_{PERF}$ is positive, suggesting that analysts may use the information in different types of anomalies differently.

[Insert Table 1 here]

4.3 Empirical Results

4.3.1 Informativeness of anomaly signals

In this section, we construct the 11 prominent asset-pricing anomalies and examine the unconditional anomaly returns using the sample overlapped with analyst consensus recommendation data from the I/B/E/S. We also construct two composite mispricing factors (MGMT and PERF) that combine the information of two clusters of anomalies.

Table 2 reports the monthly raw returns and the Fama and French (1993) three-factor alphas of long-short portfolios sorted by 11 anomalies and two composite mispricing factors. The *t*-

statistics reported in parentheses are based on Newey-West standard errors with the optimal lag length.[7] Panel A (Panel B) reports the raw returns of the MGMT (PERF) anomalies, and Panel C (Panel D) reports the corresponding Fama and French (1993) three-factor alphas. Overall, long-short portfolios based on the 11 anomalies all generate significant Fama and French (1993) three-factor alphas ranging from 0.35% to 1.09% per month. The result suggests that anomalies contain valuable information about future expected returns, of which sophisticated information intermediaries, such as analysts, should take advantage. In addition, for most anomalies, the short leg generates much stronger abnormal returns than the long leg, consistent with evidence in the literature that short selling overvalued stocks is more prohibitive and costly than taking long positions on undervalued stocks (Nagel, 2005; Stambaugh et al, 2012).

[Insert Table 2 here]

4.3.2 Analyst recommendations around the anomalies

In this section, we examine whether analysts use anomaly information when making recommendations. We first sort all of the stocks into quintile portfolios based on their anomaly characteristics, and we then test the difference in the mean values of analyst consensus recommendations between the long and short legs of the portfolios. We analyze both the level and change of recommendations across the anomaly-sorted quintile portfolios. As recommendations might be persistent over time, we calculate the *t*-statistics for the differences in recommendations between the long and short legs of the anomalies based on Newey-West standard errors with the optimal lag length.[8]

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[7] In the remainder of the paper, all *t*-statistics with stock returns as the dependent variable are based on the Newey-West standard errors with the optimal lag length.

[8] As a robustness check, we also calculate the *t*-statistics based on standard errors double clustered by stock and month (Petersen, 2009). Specifically, we run a panel regression, where the dependent variable is the level or change of consensus recommendations for each stock-month, and the independent variables are dummies indicating the quintile portfolio category to which each stock belongs (except for the short-leg portfolio, which is omitted). Using this

Table 3 reports the results. In Panel A (Cluster 1), stocks in the short leg of the anomalies receive more favorable recommendations than those in the long leg of the anomalies. For example, the average recommendation value is 3.52 for the long leg of MGMT and 4.07 for its short leg. The difference of -0.55 is highly significant at the 1% level (*t*-stat = -13.47). We find similar results across all individual anomalies in the MGMT category. Indeed, the level (and change) of recommendations monotonically increases from the long leg to the short leg for almost all of the anomalies in the MGMT category. However, the anomalies in the PERF category display a different story. Analysts on average seem to issue recommendations in line with these anomalies' predictions. The mean recommendation level is 3.89 for the long leg of PERF and 3.71 for its short leg. The difference of 0.18 (*t*-stat = 5.62) is statistically significant but economically small compared with the difference of recommendations across portfolios sorted by MGMT anomalies.

[Insert Table 3 here]

The results are similar when we examine the change of recommendations. For anomalies in the MGMT category, analysts are more likely to upgrade stocks in the short leg and downgrade firms in the long leg of the portfolios. For example, analysts downgrade recommendations by 0.06 for the long leg of MGMT and upgrade recommendations by 0.02 for the short leg. The difference (-0.08) in the change of recommendations between long- and short-leg stocks is again highly significant (*t*-stat = -9.48), although small. The result for the change of recommendations is particularly puzzling because it suggests that while analysts actively issue opinions on anomaly stocks, their opinions tend to be in the opposite direction to the anomaly predictions. Thus, analyst inattention and stale recommendation stories cannot fully explain our finding.

regression approach, we then report the estimated coefficient and corresponding *t*-statistic for the dummy variable indicating the long-leg portfolio. The results remain largely unchanged, and most *t*-statistics are still highly significant.

Overall, our results suggest that analysts tend to issue more favorable recommendations to stocks with high investment growth and large external financing needs but also to those with higher profitability and better recent stock performance. As firms with high investment rates and financing activities have lower expected returns, the result suggests that analysts on average do not fully use the expected return information contained in anomalies when making stock recommendations.

4.3.3 Anomaly returns conditional on analyst recommendations

The inconsistency between analyst recommendations and anomaly ranking presented in the previous section is not sufficient to conclude that analyst recommendations are biased. Given that analysts may have superior private information beyond that contained in anomaly characteristics, the information content of their recommendations may offset the information in the anomalies. To distinguish the two competing views of analyst research, we must examine ex post anomaly returns conditional on whether analyst recommendations confirm or contradict the anomaly signals.

To test this, we conduct independent double sorts of all stocks based on the anomaly signals and the level of recommendations. At the end of each June, we sort all stocks into three groups based on the level of consensus recommendations and independently into quintiles based on anomaly characteristics. Up (Middle, Down) refers to stocks in the top (middle, bottom) tercile based on analyst consensus recommendation values. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. We then take the intersection of the two extreme quintiles of each anomaly with three terciles of recommendations. We then calculate the Fama and French (1993) three-factor alphas for each of the six portfolios. We further construct two types of long-short portfolios: one for which analyst recommendations are congruent with the anomaly prescriptions (Long/Up – Short/Down) and another for which recommendations are contradictory to the anomaly predictions (Long/Down – Short/Up). We also test the difference in the long-short portfolio returns between the consistent and inconsistent groups.

The Fama-French alphas and their corresponding *t*-statistics are reported in Table 4. The long-short portfolio alphas are larger for inconsistent portfolios than for consistent portfolios for all 11 anomalies, and seven of them are statistically significant. The result is particularly strong for anomalies in the PERF category. For example, the long-short portfolio based on PERF generates a monthly three-factor alpha of 1.57% for the inconsistent case, while it is only 0.90% for the consistent case. The difference in alphas between the inconsistent and consistent groups is 0.67%, with a *t*-statistic of 2.96. The results from individual anomalies in the PERF group are similar, with the differences in alphas between the inconsistent and consistent groups ranging from 0.43% to 0.65%, all of which are statistically significant. This suggests that although analysts tend to issue recommendations that are on average weakly consistent with performance-related anomalies, the stocks on which they make "mistakes" according to anomaly signals generate particularly large abnormal returns, especially on the short leg. The results suggest that analysts' biased recommendations might amplify performance-related anomalies.

[Insert Table 4 here]

For MGMT-related anomalies, we know from Table 3 that analyst recommendations on average tend to be contradictory to the prescriptions of anomalies. However, compared to PERF-related anomalies, although the differences in alphas between the inconsistent and consistent groups are all positive, they are much smaller and mostly insignificant, except in two cases: 0.54% (*t*-stat = 2.34) for Accrual and 0.51% (*t*-stat = 2.41) for IA. However, if we focus on the short-leg portfolios, the amplification effect of biased recommendations on anomaly returns is also evident for those anomalies in the MGMT category. For example, the difference in the alphas of the short-leg portfolios between the inconsistent and consistent groups is -0.39% (-0.83% – (-0.44%)), with a *t*-statistic of -2.09 (not shown), for MGMT.[9] For comparison, the corresponding difference in alphas of the short-leg portfolios is -0.59% (= -1.09% – (-0.50%)), with a *t*-statistic of -2.92 (not shown), for PERF.

The preceding results suggest that a much smaller and largely insignificant return spread between inconsistent and consistent groups for MGMT-related anomalies must come from the offsetting effect in the long leg. This is indeed the case for MGMT, where the consistent group actually outperforms the inconsistent group by 0.23% (= 0.40% – 0.17%). For PERF, the long-leg result is more in line with our hypothesis, in that the consistent group slightly underperforms the inconsistent group. The above observations are also evident for most individual anomalies.[10,11]

Another approach complementary to portfolio sorts is to run Fama-MacBeth regressions of future stock returns (in percentage) on anomaly characteristics interacted with analyst recommendations. The regression approach allows us to control for other firm characteristics commonly associated with cross-sectional stock returns. Firm size ($Ln(Size)$) is the natural logarithm of market capitalization at the end of June in each year. Book-to-market ratio ($Ln(BM)$) is the natural logarithm of the most recent fiscal year-end reported book value divided by the market capitalization at the end of the prior calendar year. The short-term reversal measure (Rev) is the prior month's return. Idiosyncratic volatility ($IVOL$) is the standard deviation of the residuals from the regression of daily stock excess returns on the Fama and French (1993) three-factor

[9] Moreover, the differences in the alphas of short-leg portfolios between the inconsistent and consistent groups are all positive (ranging from 0.18% to 0.57%) and significant for four out of the six MGMT-related individual anomalies.

[10] We also notice that for some anomalies, there is a moderate hump-shaped relation between recommendation values and stock returns for the short leg of anomalies. We therefore conduct a formal test and find only one case (Distress) in which the *t*-statistic for the difference in alphas between Down and Middle recommendations in the short-leg portfolios is greater than 2.

[11] We also examine the earnings announcement returns of the consistent and inconsistent portfolios double sorted by analyst recommendations and anomalies. The results of the untabulated analysis are broadly consistent with, although weaker than, the results reported in Table 4.

returns over the previous month (Ang, Hodrick, Xing, and Zhang, 2006). $Turnover$ is the monthly trading volume over shares outstanding, averaged over the past 12 months. Analyst forecast dispersion ($Disp$) is the standard deviation of annual earnings-per-share forecasts scaled by the absolute value of the average outstanding forecast. $MaxReturn$ is a stock's maximum daily return the previous month (Bali, Cakici, and Whitelaw, 2011).

In addition, to preserve as many stock-month observations as possible, we replace the missing value of a control variable with its cross-sectional monthly median value, and we include a dummy variable $Missing$ that equals one if there is at least one missing value for any of the control variables and zero otherwise.[12] To facilitate the interpretation of regression coefficients, at the end of each June, we rank stocks into five groups based on anomalies and create three dummy variables, $Long$, $Short$, and Mid, which represent the long leg, the short leg, and the remaining three middle quintile portfolios, respectively. We also sort the stocks into three groups of equal size based on analyst consensus recommendations, with the most favorable (unfavorable) recommendation denoted as $RecUp$ ($RecDown$) and the middle group as $RecMid$. We run the Fama-MacBeth regression as follows:

$$\begin{aligned} Ret_{i,t+1} = {} & \alpha + \beta_1 Long \times RecUp + \beta_2 Long \times RecMid + \beta_3 Long \times RecDown \\ & + \beta_4 Short \times RecUp + \beta_5 Short \times RecMid + \beta_6 Short \times RecDown + \\ & \beta_7 Missing + \sum \beta_k X_{k,i,t} + \epsilon_{i,t+1}. \end{aligned} \tag{2}$$

$X_{k,i,t}$ represents a set of control variables, $Ln(Size)$, Rev, $Ln(BM)$, $IVOL$, $Turnover$, $Disp$, and $MaxReturn$. Panel A of Table 5 reports the results for the MGMT-related anomalies and Panel B for PERF-related anomalies. Overall, the results using the Fama-MacBeth regression are similar

[12] Our sample will be reduced by 20-30% if we do not fill in the missing values of control variables. However, our untabulated analysis shows that our main conclusion still holds using a smaller sample by excluding $Dispersion$ (which is insignificant in any model specification), which is the main driver for the reduction of stock-month observations.

to those of our portfolio sorts. The amplification effect of analyst recommendations on anomaly returns is most pronounced in the short leg. By comparing the coefficients of two interaction terms, $Short \times RecUp$ and $Short \times RecDown$, we find that the short-leg stocks experience the most negative future returns when those stocks are recommended the most favorably by analysts for all cases. For example, column (1) of Panel A shows that the estimated coefficient is -0.81 (t-stat = -6.19) for $Short \times RecUp$ and -0.58 (t-stat = -3.68) for $Short \times RecDown$ for MGMT. The result suggests that stocks in the short leg of MGMT with the most favorable recommendations underperform those with the most unfavorable recommendations by 0.23% per month after controlling for other return predictors. Similarly, column (1) of Panel B shows that stocks in the short leg of PERF generate a 1.04% (t-stat = -4.67) lower return when they have the most favorable recommendations, while it is 0.55% (t-stat = -3.53) for stocks with the most unfavorable recommendations, with an underperformance of 0.49% for the former.[13]

[Insert Table 5 here]

4.3.4 Corroborating evidence from the change of mutual fund ownership

The amplification effect of biased analyst recommendations on anomaly returns suggests that some investors who follow analyst opinions or think like analysts trade in the same direction as recommendations over the portfolio formation window. Investors' excess demand leads to further mispricing. Anomaly returns are thus amplified as prices subsequently revert to

[13] The Fama-MacBeth regression results also show a moderate hump-shaped relation between recommendation values and stock returns for the short leg of anomalies for some cases, as in portfolio sorts. A potential explanation might be that for overvalued stocks, unfavorable recommendations are more likely to reflect analysts' true opinion of the stocks and be less associated with their behavioral bias. In other words, the most unfavorable recommendations could be more informative than the middle-category recommendations (Asquith, Mikhail, and Au, 2004). As a result, two forces affect the overvalued stocks with the most unfavorable recommendations. First, investors are more likely to sell (or less likely to buy) stocks with unfavorable recommendations, facilitating the correction of overvaluation. Second, due to the incremental valuable information contained in unfavorable analyst recommendations, these stocks could be of lower quality and more overpriced compared to similarly overvalued stocks but with middle-category recommendations. We conduct a formal test and find only two cases (CEI and Distress) in which the t-statistics for the difference in the estimated coefficients between $Short \times RecMid$ and $Short \times RecDown$ are greater than 2.

fundamental value.[14] To verify the channel, we use the change of mutual fund stock ownership[15] over the portfolio formation window (July of year *t*-1 to June of year *t*) to measure investors' demand on a stock.[16] We calculate the average mutual fund net buys over the portfolio formation window for the portfolios double sorted by analyst recommendations and anomaly signals, similar to Table 4. For both the long and short legs of anomaly portfolios, we also report the differences in mutual fund net buys between stocks with the most favorable and most unfavorable recommendations.

Table 6 reports the results. It clearly shows that analyst consensus recommendations are positively correlated with changes in mutual fund demand. For both the long and short legs of anomaly portfolios, stocks with the most favorable recommendations have significantly larger mutual fund net buys over the portfolio formation window compared with stocks with the most unfavorable recommendations. For MGMT, the short-leg portfolio with the most favorable analyst recommendations has mutual fund net buys of 3.86% over the portfolio formation window, while the same short-leg portfolio with the most unfavorable recommendations has mutual fund net buys of only 0.91%. The difference in mutual fund net buys between the two groups is 2.95% (*t*-stat = 7.16). As a benchmark, Table 1 shows that the unconditional mean and standard deviation of mutual fund net buys are 1.47% and 5.63%, respectively. We observe similar patterns for PERF and all 11 individual anomalies. Moreover, the effect of analyst recommendations on mutual fund net buys is more pronounced for the stocks in the short leg of the anomaly, in line with the pattern in portfolio return results (also mainly coming from the short leg).

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[14] We thank the referee for suggesting this potential channel underlying the amplification effect of biased analyst recommendations on anomaly returns.

[15] Mutual fund ownership of a stock is defined as the sum of shares held by mutual funds from Thomson Reuters Mutual Fund holdings database (S12) each quarter scaled by total shares outstanding.

[16] We focus on mutual fund trading for two reasons. First, in the U.S., mutual funds are important stock market players and their collective trading activities are large enough to have a price impact (Lou, 2012). Second, previous studies (Brown, Wei, and Wermers, 2013) show that mutual funds tend to herd with analysts' consensus recommendations.

[Insert Table 6 here]

In sum, the mutual fund trading result suggests either that analyst recommendations lead to coordinated trading activities of mutual fund managers or that fund managers think like analysts. Mutual fund managers' excess buying demand for overvalued stocks with favorable consensus recommendations pushes up stock prices further during the portfolio formation window, leading to lower subsequent returns. We conduct several robustness checks by using benchmark-adjusted mutual fund trading and the trading by all 13F institutions to measure investor demand. First, we use the average mutual fund net buys in the Fama-French 30 industries and the 5×5 size and book-to-market double-sorted portfolios as the benchmarks to adjust stock-level mutual fund net buys. Our results remain very similar. Second, our results remain largely unchanged when we use institutional net buys from all 13F institutions to measure investor demand. These results are not reported for brevity, but they are available upon request.

4.3.5 Identifying skilled analysts based on the correlation between recommendations and anomalies

The results so far suggest that on average, analysts do not efficiently use the expected return information contained in anomalies when making recommendations, which prove to be inefficient ex post. This bias for analysts as a whole, however, may mask great heterogeneity among individual analysts who differ significantly in their skills and/or incentives to generate informative recommendations. We use the correlation measure based on Equation (1) as a proxy for analyst skill. We then study which analysts tend to issue recommendations that are more consistent with anomaly predictions. Specifically, we run the following panel regression:

$$\begin{aligned} Corr_{s,i,t} = {} & \alpha + \beta_1 AllStar + \beta_2 Away\ from\ consensus + \beta_3 Accuracy + \\ & \beta_4 Ln(FirmExp + 1) + \beta_5 Ln(TotalExp + 1) + \beta_6 Ln(BrokerSize) + \\ & \beta_7 Coverage + \beta_8 Average\ Size + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where $s \in \{MGMT, PERF\}$ and $Corr_{s,i,t}$ is the rank correlation between stocks' recommendation values and the composite mispricing score MGMT (or PERF), using all recommendations issued by analyst *i* over the last three years up to year *t*. All other variables are defined as before. We also control for analyst and year fixed effects in some specifications, and standard errors are double clustered by analyst and year.

Table 7 presents the regression results. Across different specifications, forecast accuracy is positively related to our correlation measures. Meanwhile, $Corr_{PERF}$ is also positively related to $AllStar$ and $Ln(BrokerSize)$, suggesting that star analysts and analysts working for larger brokerage firms are more likely to use performance-related anomaly information. However, for $Corr_{MGMT}$, we find the opposite results. Moreover, $Corr_{MGMT}$ is also positively associated with $Average\ Size$ and negatively associated with total experience. The finding of negative associations of brokerage firm size, all star status, and working experience with $Corr_{MGMT}$ suggests that analysts' biased recommendations for MGMT-related anomalies may be attributable to strategic reasons.

[Insert Table 7 here]

4.3.6 Market reactions to skilled analysts' recommendations

If anomaly signals are incrementally useful for identifying skilled or unbiased analysts, we expect the recommendations made by these analysts to elicit stronger market reactions. To test this, we run a panel regression of recommendation announcement returns on our correlation measures, controlling for recommendation, analyst, broker, and firm characteristics. Specifically, we run the following panel regression:

$$
\begin{aligned}
CAR[0,+1] = {} & \alpha + \beta_1 Corr_s + \beta_2 |\Delta Rec_{individual}| + \beta_3 All\ Star + \beta_4 Concurrent\ Rec + \\
& \beta_5 Pre\text{-}earnings + \beta_6 Post\text{-}Earnings + \beta_7 Away\ from\ consensus + \\
& \beta_8 Accuracy + \beta_9 Ln(Firm\ Exp + 1) + \beta_{10} Ln(Total\ Exp + 1) + \\
& \beta_{11} Ln(BrokerSize) + \beta_{12} Coverage + \sum \beta_k X_{k,i,t} + \epsilon_{i,t},
\end{aligned}
\tag{4}
$$

where $CAR[0,+1]$ is the two-day cumulative abnormal returns (in percentage) around analyst recommendation announcements. $X_{k,i,t}$ represents a set of firm characteristics, including $Ln(Size)$, $Volatility$, $MOM_{(-21,-1)}$, and $MOM_{(-252,-22)}$. Other variables are defined as before.

Panel A of Table 8 reports the results for upgrade recommendation changes and Panel B for downgrade recommendation changes. The coefficient on $Corr_{PERF}$ is significantly positive for upgrade recommendation changes and significantly negative for downgrade recommendation changes. The coefficient on $Corr_{MGMT}$ is insignificant for upgrade and marginally significant for downgrade recommendation changes. The results suggest that the market perceives analysts who are better at using performance-related anomaly signals ($Corr_{PERF}$) as more skilled in general, and these analysts therefore elicit stronger market reactions.

The economic significance of our correlation metric is non-trivial. For example, the coefficient on $Corr_{PERF}$ reported in the last column of Panel A suggests that an analyst whose stock recommendations are perfectly aligned with PERF anomaly rankings ($Corr_{PERF}$ = 1) generates a two-day announcement return 0.4% higher than that of an analyst whose recommendations are unrelated to PERF anomaly signals ($Corr_{PERF}$ = 0). The result is even stronger for downgrade recommendation changes; Panel B shows that market reactions to downgrade recommendation changes of skilled analysts are 0.5% to 0.7% more negative than they are to those of unskilled analysts. The incremental effect of our analyst skill measure survives after controlling for firm and analyst fixed effects in the panel regressions. A significant coefficient on $Corr_{PERF}$ after controlling for analyst fixed effects means that an analyst's recommendation becomes more informative when she becomes more skilled at using performance-related anomaly information for her recommendations.

[Insert Table 8 here]

4.4 Additional Tests and Explanations

4.4.1 Results in the post-publication period

A potential explanation for the contradiction between analyst recommendations and anomaly signals is that analysts are simply unaware of the information contained in anomalies before their discovery by academics. If this is true, analyst recommendations should become more aligned with anomaly predictions upon the publications of these anomaly studies (McLean and Pontiff, 2016). To examine this alternative, we redo the test by focusing on the post-publication period. Panel A of Table 9 shows the Fama-French three-factor alphas of the 11 anomalies in the post-publication period. Consistent with McLean and Pontiff (2016), anomalies are generally weaker in the post-publication period. The post-publication attenuation of anomaly returns is more pronounced for PERF-related anomalies than for MGMT-related anomalies. Of the 11 anomalies, only seven still generate positive alphas with *t*-statistics greater than 1.65, whereas three (all from PERF) actually generate negative alphas, with GP earning a significantly negative alpha of -0.44% (*t*-stat = -2.06).

[Insert Table 9 here]

Panel B of Table 9 reports the mean recommendation levels and changes for quintile portfolios sorted by each anomaly during the post-publication period. The results show that for all MGMT-related anomalies, analysts still assign more favorable recommendation values to stocks in the short leg than to stocks in the long leg of anomalies. Most MGMT-related anomalies still generate significant alphas in the post-publication period, suggesting that our findings are unlikely to be fully explained by analysts' unawareness of the return predictability of the anomalies.

4.4.2 Effect of firm size

The limits-to-arbitrage argument is often cited to explain why well-documented anomalies are not arbitraged away. According to this explanation, competition between sophisticated investors would quickly eliminate any return predictability arising from anomalies without impediments to arbitrage. This explanation is difficult to reconcile with our evidence, because analysts do not take positions and do not face trading frictions. Rather, our results suggest that analysts' biased recommendations may be a source of friction that impedes the efficient correction of mispricing. Still, analysts may need to cater to institutional investors who indeed face non-trivial trading frictions. Our findings may be concentrated among small and illiquid stocks, where analysts do not have strong incentives to efficiently use the information in anomalies simply because their institutional clients cannot trade on such stocks at a low cost.

To examine this explanation, we redo our main tests for small and big firms separately. If the limits-to-arbitrage explanation plays a role, we should find that analyst recommendations are more consistent with anomaly rankings among big stocks. We define small (big) stocks as those with market capitalization below (above) the 30% size cutoff using the NYSE size breakpoints. Panel A of Table 10 reports analyst recommendations across quintile portfolios sorted by anomalies for small and big firms separately. The general pattern is quite similar across small and big firms. For example, on average, analysts assign a recommendation value to the short leg of MGMT that is 0.54 higher than that assigned to the long leg among small stocks. For big stocks, this number is 0.53 and still highly significant. In other words, analysts tend to issue more favorable recommendations to stocks classified as overvalued, even among big firms where trading frictions are less severe.

[Insert Table 10 here]

Panel B of Table 10 shows that the degree to which biased analyst recommendations amplify anomaly returns does not differ significantly across small and big stocks. Take PERF as an example. The difference in the monthly alphas between consistent and inconsistent long-short portfolios is 0.74% (*t*-stat = 2.96) for small stocks and 0.60% (*t*-stat = 2.21) for big stocks. Overall, our results do not seem to support the alternative explanation that analysts are reluctant to use anomaly signals when making recommendations simply because of limits-to-arbitrage concerns.

4.4.3 Effect of investor sentiment

Stambaugh et al. (2012) find that anomalies are more pronounced following high sentiment periods, suggesting that investors' over-optimism during high-sentiment periods drives anomaly returns. Hribar and McInnis (2012) find that analyst forecasts are more optimistic for hard-to-value stocks during high-sentiment periods. This suggests that analyst recommendations could be more biased and the amplification effect of analysts' biased recommendations on anomaly returns should be more pronounced during high- rather than low-sentiment periods. To test this conjecture, we use the Baker-Wurgler (2006) sentiment index as a proxy for the aggregate investor sentiment in the stock market. We define a month as a high-sentiment period if the Baker-Wurgler sentiment index over the previous month is above the median of the whole sample, and as a low-sentiment period otherwise.

Panel A of Table 11 reports the averages of analyst recommendation values across the quintiles of anomaly-sorted portfolios in low- and high-sentiment periods separately. Consistent with the *biased analyst hypothesis*, analyst recommendations are more contradictory to anomaly predictions during high-sentiment periods. Following low-sentiment periods, the difference in recommendation values between the short and long legs of MGMT is 0.48. Following high-sentiment periods, the corresponding difference increases to 0.59. Given the evidence that anomalies have stronger return predictability in high-sentiment periods (Stambaugh et al., 2012), analysts should follow anomalies more closely at such times if they are sophisticated and unbiased. However, we find exactly the opposite results, suggesting that over-optimism shared with other investors during high-sentiment periods causes analyst recommendations to be more contradictory to anomaly signals.

Panel B of Table 11 shows not only that analyst recommendations are more biased during high-sentiment periods but also that their biased recommendations amplify anomaly returns more strongly at such times. Take PERF as an example. The difference in the long-short portfolio alphas between the consistent and inconsistent groups is an insignificant 0.12% (*t*-stat = 0.40) during low-sentiment periods, while it is 0.99% (*t*-stat = 3.19) during high-sentiment periods. Overall, the subsample results based on the sentiment index suggest that behavioral bias on the part of analysts is partially responsible for analysts' inefficient use of anomaly information.

[Insert Table 11 here]

4.5 Conclusion

In this paper, we examine the interaction effect between analyst recommendations and stock market anomalies. Our results reveal that analysts tend to give more favorable recommendations to stocks classified as overvalued (the short leg of an anomaly). Most importantly, both portfolio analysis and the Fama-MacBeth regression demonstrate that these overvalued stocks with the most favorable analyst recommendations earn particularly negative abnormal returns in the future. Further analysis shows that the amplification effect of biased analyst recommendations on anomalies is not driven by limits-to-arbitrage concerns or analysts catering to institutional investors' preferences. In contrast, we find that the amplification effect is more pronounced during high-sentiment periods than during low-sentiment periods, suggesting that analysts' behavioral biases, rather than misaligned incentives, could partially explain their overly optimistic recommendations for overvalued stocks. Overall, our findings indicate that analysts' biased recommendations could be a potential source of market friction that impedes the efficient correction of mispricing.

We make several contributions to the literature. First, our work sheds light on the persistence of stock return anomalies by showing that analysts' biased recommendations might be a potential force contributing to mispricing in the financial market. Second, our results add to the understanding of analysts' role as informational intermediaries, revealing that they do not fully use the valuable information contained in anomaly signals and often contradict anomaly prescriptions when making recommendations. Finally, we develop a simple method to identify skilled analysts based on the correlation between their stock recommendations and anomaly signals. We show its usefulness beyond the existing analyst skill and experience measures.

Table 4.1: Summary statistics

This table reports the summary statistics for the sample, including the number of observations and the mean, median, standard deviation, and the 25th and 75th percentiles of the main variables used in the analysis. Rec (ΔRec) is the level (change) of analyst consensus recommendations, with recommendation coded as a number from 5 (strong buy) to 1 (strong sell). $Corr_{\text{MGMT}}$ ($Corr_{\text{PERF}}$) is the rank correlation between stocks' recommendation values and composite mispricing score MGMT (PERF), using all recommendations issued by each analyst over past three years. $|\Delta Rec_{individual}|$ is the absolute value of the change of individual analyst's recommendations. $AllStar$ is a dummy variable that equals one if the analyst is ranked as an All-American (first, second, third, or runner-up teams) in the Institutional Investor magazine and zero otherwise. $Concurrent\ Rec$ is a dummy variable that equals one if the analyst issues a forecast revision and also issues a recommendation change for the same stock in the three trading days surrounding the forecast revision date and the recommendation change is in the same direction as the forecast revision. $Pre\text{-}earnings$ ($Post\text{-}earnings$) is a dummy variable that equals one if the recommendation change is issued within two weeks prior to (after) an earnings announcement. $Away\ from\ consensus$ is a dummy variable that equals one if the absolute deviation of the recommendation change from the consensus is larger than the absolute deviation of the prior recommendation from the consensus. If a firm has fewer than 3 outstanding recommendations, this value is set to zero. $Accuracy$ is the difference between the absolute forecast error of analyst *i* on firm j's earnings and the average absolute forecast error across all analysts on firm j, scaled by the average absolute forecast error across all analysts' forecasts on firm j's earnings. We then multiply this value by -1 and average across all stocks covered by an analyst in a given year, so that a higher value indicates that the analyst is on average more accurate. $Ln(FirmExp + 1)$ is the natural logarithm of one plus the number of days since the analyst first issued an earnings forecast on this firm. $Ln(TotalExp + 1)$ is the natural logarithm of one plus the number of days since the analyst first issued an earnings forecast for any firm. $Ln(BrokerSize)$ is the natural logarithm of the total number of analysts working at the brokerage firm. $Coverage$ is the total number of firms followed by an analyst in a given year. $Ln(Size)$ is the natural logarithm of firm market capitalization. $Average\ Size$ is defined as the average $Ln(Size)$ of stocks followed by an analyst in a given year. $Volatility$ is the standard deviation of daily returns over the 63 trading days prior to the recommendation change. $MOM_{(-21,-1)}$ is the cumulative stock returns over the 21 trading days prior to the recommendation change. $MOM_{(-252,-22)}$ is the cumulative stock returns over the 252 trading days prior to the recommendation change, excluding the 21 trading days prior to the recommendation changes. *Mutual Fund Net buys* is the change of stock ownership by mutual funds over the anomaly formation window (July of year *t* – 1 to June of year *t*).

Table 4.1 (continued): Summary statistics

Variable	N	Mean	Stdev	p25	p50	p75
Rec	708,907	3.85	0.60	3.43	3.89	4.25
ΔRec	690,679	0.04	0.68	-0.33	0.00	0.35
$Corr_{\text{MGMT}}$	562,391	-0.04	0.26	-0.19	-0.03	0.11
$Corr_{\text{PERF}}$	547,000	0.04	0.26	-0.11	0.04	0.19
$\|\Delta Rec_{individual}\|$	383,782	1.06	0.74	1.00	1.00	2.00
$AllStar$	574,954	0.09	0.29	0.00	0.00	0.00
$Concurrent\ Rec$	574,954	0.14	0.35	0.00	0.00	0.00
Pre-earnings	574,954	0.05	0.21	0.00	0.00	0.00
Post-earnings	574,954	0.07	0.26	0.00	0.00	0.00
$Away\ from\ consensus$	574,954	0.21	0.41	0.00	0.00	0.00
$Accuracy$	540,404	0.27	0.29	0.14	0.31	0.45
$Ln(FirmExp + 1)$	558,358	4.98	2.94	3.50	6.10	7.17
$Ln(TotalExp + 1)$	572,400	7.75	1.47	7.31	8.18	8.65
$Ln(BrokerSize)$	574,954	5.95	1.15	5.21	6.14	6.82
$Ln(Size)$	463,736	14.35	1.80	13.09	14.28	15.56
$MOM_{(-21,-1)}$	455,419	1.02%	15.87%	-6.94%	0.94%	8.45%
$MOM_{(-252,-22)}$	429,339	16.13%	55.67%	-15.29%	8.87%	35.15%
$Volatility$	446,408	3.04%	1.93%	1.76%	2.55%	3.73%
$Coverage$	574,954	9.57	6.54	5.00	8.00	13.00
$Average\ Size$	44,087	14.87	1.50	13.84	14.90	15.91
$Mutual\ Fund\ Net\ buys$	55,251	1.47%	5.63%	-1.20%	0.95%	3.94%

Table 4.2: Informativeness of anomaly signals

This table reports average monthly raw returns and alphas for the long-short portfolios of the 11 prominent anomalies and two composite mispricing measures. We classify the 11 anomalies into two clusters following Stambaugh and Yuan (2017). MGMT (PERF) stands for the composite mispricing measure of the first (second) cluster. Panel A (Panel B) reports the raw returns of Cluster 1 (Cluster 2) anomalies. Panel C (Panel D) reports the Fama-French three-factor alphas of Cluster 1 (Cluster 2) anomalies. The *t*-statistics in parentheses are based on Newey-West standard errors with optimal lag length. The sample period is 1993-2014.

Panel A: Cluster 1 (Raw returns)							
	MGMT	NSI	CEI	Accrual	NOA	AG	IA
Long	1.25%	1.23%	1.21%	1.14%	1.19%	1.26%	1.18%
	(3.80)	(3.94)	(4.29)	(2.82)	(3.34)	(3.18)	(3.09)
Short	0.53%	0.67%	0.76%	0.78%	0.57%	0.50%	0.59%
	(1.18)	(1.57)	(1.82)	(1.82)	(1.39)	(1.11)	(1.31)
Long – Short	0.72%	0.57%	0.44%	0.35%	0.62%	0.76%	0.60%
(*t*-stat)	(3.12)	(2.50)	(1.73)	(2.02)	(2.91)	(3.56)	(3.33)
Panel B: Cluster 2 (Raw returns)							
	PERF	Distress	O-score	MOM	GP	ROA	
Long	1.33%	1.29%	1.15%	1.28%	1.33%	1.33%	
	(3.82)	(4.15)	(3.41)	(3.15)	(3.73)	(3.67)	
Short	0.58%	0.81%	0.88%	0.62%	0.83%	0.51%	
	(1.30)	(2.11)	(1.97)	(1.34)	(2.36)	(0.93)	
Long – Short	0.75%	0.48%	0.27%	0.66%	0.50%	0.82%	
(*t*-stat)	(3.54)	(2.57)	(1.41)	(2.07)	(2.69)	(2.81)	
Panel C: Cluster 1 (Alphas)							
	MGMT	NSI	CEI	Accrual	NOA	AG	IA
Long	0.23%	0.26%	0.32%	0.00%	0.17%	0.13%	0.07%
	(2.77)	(2.73)	(3.72)	(-0.01)	(1.61)	(1.20)	(0.72)
Short	-0.62%	-0.48%	-0.37%	-0.35%	-0.55%	-0.63%	-0.57%
	(-4.91)	(-4.87)	(-3.95)	(-3.28)	(-3.88)	(-5.09)	(-4.25)
Long – Short	0.86%	0.75%	0.68%	0.35%	0.72%	0.76%	0.64%
(*t*-stat)	(5.18)	(6.03)	(5.24)	(2.61)	(2.62)	(4.31)	(3.80)
Panel D: Cluster 2 (Alphas)							
	PERF	Distress	O-score	MOM	GP	ROA	
Long	0.36%	0.37%	0.13%	0.24%	0.29%	0.32%	
	(3.85)	(3.43)	(1.30)	(1.64)	(2.99)	(3.09)	
Short	-0.63%	-0.33%	-0.31%	-0.62%	-0.18%	-0.77%	
	(-4.56)	(-2.43)	(-2.49)	(-3.27)	(-1.24)	(-4.75)	
Long – Short	0.99%	0.69%	0.45%	0.86%	0.47%	1.09%	
(*t*-stat)	(5.63)	(3.95)	(2.94)	(2.95)	(2.13)	(4.69)	

Table 4.3: Analyst consensus recommendations for anomaly stocks

This table reports the average level (Column "Rec") and change (Column "ΔRec") of consensus recommendations for quintile portfolios sorted by the anomaly variables. We classify 11 anomalies into two clusters following Stambaugh and Yuan (2017). MGMT (PERF) stands for the composite mispricing measure of the first (second) cluster. Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The *t*-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is 1993-2014.

Panel A: Cluster 1 (Recommendation level or change)

	MGMT		NSI		CEI		Accrual	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.52	-0.06	3.62	-0.09	3.54	-0.06	3.69	-0.06
2	3.63	-0.05	3.63	-0.05	3.60	-0.05	3.66	-0.05
3	3.76	-0.02	3.73	-0.03	3.76	-0.08	3.77	-0.01
4	3.90	-0.02	3.86	0.00	3.89	-0.03	3.89	0.00
Short	4.07	0.02	4.00	0.02	4.00	0.04	4.04	0.01
Long – Short	-0.55***	-0.08***	-0.38***	-0.10***	-0.46***	-0.10***	-0.35***	-0.06***
(*t*-stat)	(-13.47)	(-9.48)	(-11.31)	(-9.71)	(-10.70)	(-12.52)	(-9.05)	(-5.15)

	NOA		AG		IA	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.71	-0.04	3.61	-0.06	3.68	-0.01
2	3.70	-0.03	3.62	-0.04	3.74	-0.03
3	3.71	-0.02	3.74	-0.04	3.78	-0.03
4	3.77	-0.03	3.88	-0.02	3.86	-0.03
Short	4.00	-0.03	4.05	0.01	3.99	-0.02
Long – Short	-0.28***	-0.01	-0.44***	-0.06***	-0.32***	0.01
(*t*-stat)	(-12.04)	(-1.30)	(-10.02)	(-7.76)	(-7.62)	(0.66)

Panel B: Cluster 2 (Recommendation level or change)

	PERF		Distress		O-score		MOM	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.89	0.04	3.82	0.01	3.87	-0.02	3.89	0.07
2	3.83	0.01	3.83	0.01	3.80	0.01	3.76	0.00
3	3.77	-0.03	3.81	-0.01	3.77	-0.01	3.72	-0.01
4	3.69	-0.06	3.72	-0.03	3.75	-0.03	3.71	-0.06
Short	3.71	-0.11	3.64	-0.09	3.85	-0.05	3.77	-0.15
Long – Short	0.18***	0.15***	0.19***	0.10***	0.01	0.03**	0.12***	0.22***
(*t*-stat)	(5.62)	(5.58)	(9.03)	(3.86)	(0.36)	(2.35)	(4.36)	(7.33)

	GP		ROA	
	Rec	ΔRec	Rec	ΔRec
Long	3.83	-0.01	3.91	0.03
2	3.83	-0.02	3.83	0.01
3	3.83	-0.03	3.74	-0.03
4	3.73	-0.02	3.63	-0.07
Short	3.68	-0.06	3.81	-0.09
Long – Short	0.15***	0.05**	0.10**	0.12***
(*t*-stat)	(7.34)	(2.45)	(1.99)	(4.13)

Table 4.4: Abnormal returns of anomaly portfolios conditional on analyst recommendations

This table reports the monthly Fama-French three-factor alphas of portfolios sorted independently by anomaly characteristics and the level of analyst consensus recommendations. At the end of each June, stocks are sorted into three groups based on the level of analyst consensus recommendations and independently into quintiles based on each anomaly characteristic. Up (Middle, Down) refers to stocks in the top (middle, bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Consistent (Inconsistent) refers to the long-short portfolio where analyst recommendations are in congruent with (contradictory to) the anomaly prescriptions. Diff is the difference in alphas between Inconsistent and Consistent portfolios. The *t*-statistics in parentheses are based on Newey-West standard errors. Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The sample period is from 1993 to 2014.

Panel A: Cluster 1 (Fama-French three-factor alphas)

	MGMT			NSI			CEI			Accrual		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	0.40%	0.27%	0.17%	0.37%	0.32%	0.23%	0.44%	0.35%	0.27%	0.10%	-0.19%	0.07%
	(3.09)	(1.92)	(1.87)	(3.13)	(2.19)	(1.93)	(3.11)	(2.87)	(2.32)	(0.75)	(-1.20)	(0.57)
Short	-0.83%	-0.42%	-0.44%	-0.63%	-0.29%	-0.45%	-0.51%	-0.10%	-0.21%	-0.64%	-0.09%	-0.07%
	(-5.20)	(-3.31)	(-3.48)	(-4.94)	(-3.08)	(-3.98)	(-4.11)	(-1.07)	(-1.80)	(-4.65)	(-0.79)	(-0.65)
Consistent		0.85%			0.81%			0.65%			0.18%	
		(4.87)			(5.30)			(3.91)			(1.00)	
Inconsistent		1.00%			0.87%			0.77%			0.72%	
		(5.07)			(4.43)			(4.38)			(3.80)	
Diff: Incon – Con		0.16%			0.05%			0.12%			0.54%	
		(0.85)			(0.29)			(0.65)			(2.34)	

	NOA			AG			IA		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	0.08%	0.30%	0.18%	0.22%	0.18%	0.06%	0.11%	0.02%	0.14%
	(0.50)	(2.50)	(1.37)	(1.45)	(1.23)	(0.67)	(0.93)	(0.13)	(1.31)
Short	-0.69%	-0.44%	-0.48%	-0.84%	-0.41%	-0.44%	-0.85%	-0.44%	-0.38%
	(-4.21)	(-3.07)	(-3.39)	(-5.25)	(-3.53)	(-3.04)	(-5.00)	(-2.86)	(-2.21)
Consistent		0.56%			0.66%			0.48%	
		(1.53)			(3.40)			(2.93)	
Inconsistent		0.87%			0.90%			0.99%	
		(3.21)			(4.09)			(4.54)	
Diff: Incon – Con		0.31%			0.24%			0.51%	
		(1.56)			(1.22)			(2.41)	

Table 4.4 (continued): Abnormal returns of anomaly portfolios conditional on analyst recommendations

Panel B: Cluster 2 (Fama-French three-factor alphas)

	PERF			Distress			O-score			MOM		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	0.40%	0.39%	0.47%	0.36%	0.21%	0.36%	0.08%	0.15%	0.22%	0.40%	0.54%	0.41%
	(3.48)	(3.96)	(4.11)	(2.69)	(1.58)	(3.24)	(0.72)	(1.30)	(2.01)	(2.65)	(2.75)	(2.94)
Short	-1.09%	-0.54%	-0.50%	-0.71%	-0.08%	-0.27%	-0.55%	-0.22%	-0.18%	-1.09%	-0.68%	-0.45%
	(-5.87)	(-3.42)	(-4.13)	(-4.26)	(-0.46)	(-1.84)	(-3.08)	(-1.50)	(-1.23)	(-4.87)	(-2.88)	(-2.14)
Consistent		0.90%			0.63%			0.26%			0.85%	
		(5.21)			(2.98)			(1.54)			(2.75)	
Inconsistent		1.57%			1.07%			0.76%			1.50%	
		(6.47)			(5.34)			(3.72)			(4.44)	
Diff: Incon – Con		0.67%			0.44%			0.50%			0.65%	
		(2.96)			(1.96)			(2.31)			(3.29)	

	GP			ROA		
	Up	Middle	Down	Up	Middle	Down
Long	0.22%	0.34%	0.37%	0.28%	0.42%	0.49%
	(2.10)	(2.94)	(2.69)	(2.30)	(3.72)	(3.23)
Short	-0.39%	-0.04%	-0.11%	-1.07%	-0.70%	-0.63%
	(-2.26)	(-0.28)	(-0.65)	(-5.79)	(-3.82)	(-4.31)
Consistent		0.33%			0.91%	
		(1.86)			(4.34)	
Inconsistent		0.76%			1.56%	
		(2.78)			(6.65)	
Diff: Incon – Con		0.43%			0.65%	
		(2.27)			(3.06)	

Table 4.5: Fama-MacBeth regressions

This table reports the Fama and MacBeth (1973) regressions of stock returns (in percentage) on anomaly characteristics interacted with analyst consensus recommendations. Long (short) is a dummy variable that equals one for stocks in the most undervalued (overvalued) quintile based on anomaly characteristics and zero otherwise. RecUp (RecMid, RecDown) is a dummy variable that equals one for stocks in the top (middle, bottom) tercile based on analyst consensus recommendations and zero otherwise. We run the Fama-MacBeth regression of the form:

$$Ret_{i,t+1} = \alpha + \beta_1 Long \times RecUp + \beta_2 Long \times RecMid + \beta_3 Long \times RecDown + \beta_4 Short \times RecUp + \beta_5 Short \times RecMid + \beta_6 Short \times RecDown + \beta_7 Missing + \sum \beta_k X_{k,i,t} + \epsilon_{i,t+1},$$

where $X_{k,i,t}$ stands for a set of control variables, including firm size (Ln(Size)), short-term reversal (Rev), book-to-market ratio (Ln(BM)), idiosyncratic volatility (IVOL), past 12-month average turnover (Turnover), analyst forecast dispersion (Disp), and maximum daily return (MaxReturn). We replace the missing value of a control variable with its cross-sectional monthly median value and add a dummy variable $Missing$ that equals one when there is at least one missing value for any of the control variables and zero otherwise. Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The t-statistics in parentheses are based on Newey-West standard errors. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 1993 to December 2014.

Panel A: Cluster 1

	MGMT	NSI	CEI	Accrual	NOA	AG	IA
Long×RecUp	0.127	0.024	0.144	0.151	-0.055	0.308**	0.015
	(1.02)	(0.22)	(0.99)	(1.17)	(-0.32)	(2.34)	(0.15)
Long×RecMid	0.191	0.023	0.093	0.013	0.133	0.267	0.005
	(1.52)	(0.17)	(0.79)	(0.11)	(0.84)	(1.62)	(0.04)
Long×RecDown	0.033	0.029	-0.120	0.257*	-0.046	0.177	0.231*
	(0.34)	(0.26)	(-1.04)	(1.94)	(-0.28)	(1.37)	(1.93)
Short×RecUp	-0.810***	-0.645***	-0.330**	-0.570***	-0.660***	-0.753***	-0.755***
	(-6.19)	(-4.84)	(-2.32)	(-3.76)	(-4.97)	(-4.50)	(-4.54)
Short×RecMid	-0.337**	-0.226	0.089	-0.027	-0.520***	-0.318*	-0.186
	(-2.19)	(-1.36)	(0.79)	(-0.12)	(-3.68)	(-1.85)	(-1.01)
Short×RecDown	-0.579***	-0.474***	-0.326**	-0.269*	-0.541***	-0.492***	-0.462**
	(-3.68)	(-3.28)	(-2.07)	(-1.71)	(-3.97)	(-2.92)	(-2.56)
Rev	-1.294**	-1.291**	-2.182***	-1.293**	-1.395**	-1.261**	-1.276**
	(-2.13)	(-2.10)	(-3.32)	(-2.14)	(-2.28)	(-2.04)	(-2.14)
Ln(Size)	-0.072	-0.056	-0.029	-0.086	-0.074	-0.073	-0.088*
	(-1.46)	(-1.14)	(-0.57)	(-1.51)	(-1.52)	(-1.50)	(-1.68)
Ln(BM)	0.041	0.032	-0.025	0.033	0.064	0.029	0.046
	(0.42)	(0.33)	(-0.24)	(0.34)	(0.66)	(0.30)	(0.47)
IVOL	-12.811**	-12.376**	-18.837***	-14.446***	-13.737**	-13.106**	-14.192***
	(-2.44)	(-2.39)	(-3.38)	(-2.66)	(-2.53)	(-2.52)	(-2.70)
Turnover	0.573	0.301	0.196	-0.038	0.493	0.418	0.257
	(0.69)	(0.35)	(0.21)	(-0.05)	(0.59)	(0.51)	(0.33)
Disp	-0.004	-0.293	-0.193	0.098	0.039	0.001	0.045
	(-0.04)	(-1.22)	(-0.49)	(0.76)	(0.40)	(0.01)	(0.47)
MaxReturn	-1.131	-0.929	-1.647	-0.550	-0.879	-1.188	-0.801
	(-0.81)	(-0.69)	(-1.08)	(-0.39)	(-0.60)	(-0.86)	(-0.55)
Missing	0.160*	0.262***	0.382***	0.341***	0.191**	0.186**	0.241**
	(1.71)	(2.67)	(3.25)	(2.83)	(1.97)	(2.06)	(2.35)
Intercept	2.459***	2.247***	1.903**	2.590***	2.487***	2.395***	2.680***
	(3.10)	(2.89)	(2.37)	(2.84)	(3.10)	(3.06)	(3.15)
Observations	668,865	650,129	605,441	513,929	667,793	669,836	575,196
Adjusted R^2	0.063	0.065	0.072	0.063	0.066	0.065	0.062

Table 4.5 (continued): Fama-MacBeth regressions

Panel B: Cluster 2						
	PERF	Distress	O-score	MOM	GP	ROA
Long×RecUp	0.319***	0.285*	-0.003	0.413**	0.281**	0.482***
	(2.78)	(1.92)	(-0.02)	(2.24)	(2.24)	(3.80)
Long×RecMid	0.365**	0.056	0.111	0.503**	0.499**	0.602***
	(2.40)	(0.37)	(0.76)	(2.53)	(2.56)	(3.54)
Long×RecDown	0.300**	0.361*	0.189	0.527**	0.487***	0.591***
	(2.18)	(1.95)	(1.59)	(2.33)	(3.28)	(3.85)
Short×RecUp	-1.041***	-0.798***	-0.474**	-0.701***	-0.537***	-0.800***
	(-4.67)	(-3.49)	(-2.57)	(-2.88)	(-2.63)	(-2.85)
Short×RecMid	-0.336**	0.062	-0.146	0.087	-0.157	-0.270
	(-1.99)	(0.32)	(-0.80)	(0.33)	(-0.74)	(-1.02)
Short×RecDown	-0.547***	-0.537***	0.032	-0.091	-0.402*	-0.268
	(-3.53)	(-3.16)	(0.21)	(-0.37)	(-1.87)	(-1.19)
Rev	-1.390**	-2.990***	-1.235**	-1.548**	-1.239**	-1.257**
	(-2.34)	(-4.41)	(-2.03)	(-2.44)	(-2.09)	(-2.04)
Ln(Size)	-0.098*	-0.055	-0.103*	-0.042	-0.074	-0.081
	(-1.92)	(-1.01)	(-1.83)	(-0.81)	(-1.53)	(-1.61)
Ln(BM)	0.114	0.159	0.045	0.036	0.129	0.116
	(1.18)	(1.31)	(0.50)	(0.37)	(1.26)	(1.31)
IVOL	-13.172**	-12.398*	-13.776**	-16.137***	-15.576***	-14.979***
	(-2.42)	(-1.69)	(-2.55)	(-2.91)	(-2.92)	(-3.09)
Turnover	-0.126	-1.094	-0.045	-0.511	0.117	0.137
	(-0.15)	(-0.87)	(-0.05)	(-0.62)	(0.14)	(0.18)
Disp	0.202**	-1.108	0.100	0.241	0.049	0.133
	(1.97)	(-1.32)	(0.87)	(1.24)	(0.46)	(1.55)
MaxReturn	-0.570	-0.123	-0.396	-1.578	-1.488	-1.011
	(-0.42)	(-0.07)	(-0.27)	(-1.15)	(-1.04)	(-0.75)
Missing	0.242**	0.185	0.366***	0.259***	0.180*	0.158
	(2.59)	(0.35)	(3.37)	(2.74)	(1.88)	(1.64)
Intercept	2.791***	2.247**	2.768***	2.059***	2.568***	2.554***
	(3.49)	(2.56)	(3.04)	(2.61)	(3.27)	(3.14)
Observations	661,412	359,496	522,326	616,331	673,591	691,037
Adjusted R^2	0.068	0.075	0.064	0.079	0.069	0.067

Table 4.6: Mutual fund net buys in anomaly portfolios conditional on analyst recommendations

This table reports the change of stock ownership by mutual funds (mutual fund net buys) over the portfolio formation window (July of year *t*-1 to June of year *t*). At the end of each June, we sort stocks into three groups based on the level of analyst consensus recommendations and independently into quintiles based on anomaly characteristics. We calculate the average mutual fund net buys for each portfolio over the portfolio formation window. Up (Middle, Down) refers to stocks in the top (middle, bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Long×RecUp – Long×RecDown (Short×RecUp – Short×RecDown) reports the difference in mutual fund net buys between stocks with the most favorable and most unfavorable consensus recommendations for the long-leg portfolio (short-leg portfolio). Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The Newey-West adjusted *t*-statistics are shown in parentheses. The sample period is from 1993 to 2014.

Panel A: Cluster 1 (Mutual fund net buys)

	MGMT			NSI			CEI			Accrual		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	1.00%	0.69%	0.47%	1.40%	0.73%	0.42%	1.31%	0.77%	0.64%	2.06%	1.24%	0.43%
	(5.06)	(5.32)	(2.86)	(5.70)	(4.67)	(2.61)	(6.92)	(14.97)	(4.60)	(11.36)	(6.31)	(1.96)
Short	3.86%	2.65%	0.91%	4.30%	2.77%	1.12%	4.27%	2.95%	1.42%	3.62%	2.20%	0.62%
	(14.04)	(13.80)	(2.93)	(20.3)	(16.76)	(3.90)	(16.46)	(13.06)	(6.56)	(14.63)	(11.42)	(1.45)
Long×RecUp – Long×RecDown		0.53%			0.98%			0.67%			1.63%	
		(2.65)			(6.00)			(3.97)			(7.65)	
Short×RecUp – Short×RecDown		2.95%			3.18%			2.84%			3.01%	
		(7.16)			(8.41)			(7.43)			(5.15)	

	NOA			AG			IA		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	2.59%	1.52%	0.56%	1.50%	1.06%	0.32%	2.13%	1.32%	0.52%
	(15.69)	(13.27)	(2.52)	(9.34)	(6.05)	(1.80)	(11.48)	(6.72)	(2.53)
Short	2.93%	1.65%	0.30%	4.00%	2.55%	0.95%	3.21%	1.87%	0.52%
	(9.60)	(8.20)	(1.14)	(17.02)	(13.44)	(3.15)	(12.59)	(8.67)	(1.63)
Long×RecUp – Long×RecDown		2.03%			1.18%			1.61%	
		(13.08)			(6.17)			(11.19)	
Short×RecUp – Short×RecDown		2.63%			3.05%			2.69%	
		(7.95)			(8.01)			(5.94)	

Table 4.6 (continued): Mutual fund net buys in anomaly portfolios conditional on analyst recommendations

Panel B: Cluster 2 (Mutual fund net buys)

	PERF			Distress			O-score			MOM		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	2.95%	1.59%	0.95%	2.35%	1.21%	0.84%	3.12%	1.53%	0.72%	3.22%	2.15%	0.94%
	(10.52)	(7.90)	(5.35)	(8.16)	(5.43)	(4.14)	(12.39)	(7.02)	(2.28)	(12.43)	(8.94)	(5.62)
Short	2.23%	1.36%	0.32%	1.92%	1.47%	0.64%	2.41%	1.59%	-0.31%	2.46%	1.27%	0.39%
	(12.19)	(8.16)	(1.83)	(11.59)	(5.51)	(2.19)	(11.21)	(6.16)	(-1.80)	(21.51)	(6.65)	(1.30)
Long×RecUp – Long×RecDown		2.00%			1.52%			2.40%			2.28%	
		(8.13)			(8.50)			(5.26)			(11.58)	
Short×RecUp – Short×RecDown		1.91%			1.28%			2.71%			2.07%	
		(9.13)			(4.14)			(13.54)			(8.64)	

	GP			ROA		
	Up	Middle	Down	Up	Middle	Down
Long	2.77%	1.43%	0.64%	2.99%	1.57%	0.82%
	(12.81)	(10.57)	(2.61)	(11.07)	(7.27)	(4.73)
Short	2.16%	1.38%	0.61%	2.56%	1.45%	0.17%
	(13.44)	(13.03)	(3.42)	(16.88)	(6.82)	(0.79)
Long×RecUp – Long×RecDown		2.12%			2.17%	
		(8.17)			(8.71)	
Short×RecUp – Short×RecDown		1.55%			2.39%	
		(9.97)			(11.52)	

Table 4.7: Determinants of analyst skills

This table reports the panel regression results of our measure of analyst skill on a set of analyst and firm characteristics. We conduct the panel regression of the form:

$$Corr_{s,i,t} = \alpha + \beta_1 AllStar + \beta_2 Away\ from\ consensus + \beta_3 Accuracy + \beta_4 Ln(FirmExp + 1)$$
$$+\beta_5 Ln(TotalExp + 1) + \beta_6 Ln(BrokerSize) + \beta_7 Coverage + \beta_8 Average\ Size + \epsilon_{i,t}.$$

The dependent variable $Corr_{s,i,t}$ is the rank correlation between stocks' recommendations and two composite mispricing scores, MGMT or PERF, using all recommendations issued by each analyst *i* over the last three years up to year *t*. All other variables are defined in Table 1. Standard errors are double clustered by analyst and year and *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1993 to 2014.

	$Corr_{MGMT}$				$Corr_{PERF}$			
$AllStar$	-0.004	-0.013**	-0.003	-0.010*	0.008	0.013**	0.007	0.012**
	(-0.65)	(-2.06)	(-0.49)	(-1.68)	(1.43)	(2.02)	(1.31)	(1.97)
$Away\ from\ consensus$	-0.001	0.000	-0.001	-0.000	-0.001	-0.003	-0.001	-0.003
	(-0.26)	(0.07)	(-0.36)	(-0.13)	(-0.27)	(-1.01)	(-0.18)	(-0.94)
$Accuracy$	0.011*	0.003	0.011*	0.004	0.014**	0.006	0.013**	0.004
	(1.79)	(0.49)	(1.95)	(0.65)	(2.31)	(1.02)	(2.04)	(0.68)
$Ln(FirmExp + 1)$	-0.000	-0.001	-0.000	-0.001	-0.001	-0.001	-0.000	-0.001
	(-0.57)	(-1.11)	(-0.67)	(-1.29)	(-1.02)	(-1.55)	(-0.62)	(-1.11)
$Ln(TotalExp + 1)$	-0.006***	-0.006**	-0.006***	-0.007***	0.004*	-0.001	0.004**	0.003
	(-3.16)	(-2.44)	(-3.32)	(-2.84)	(1.94)	(-0.34)	(2.20)	(0.99)
$Ln(BrokerSize)$	-0.008***	-0.007***	-0.008***	-0.007***	0.005***	0.002	0.004***	0.002
	(-5.27)	(-3.89)	(-5.31)	(-3.64)	(3.17)	(1.37)	(2.75)	(1.27)
$Coverage$	-0.000	-0.000**	-0.000	-0.000**	0.000	0.000*	0.000	0.000
	(-0.65)	(-2.25)	(-0.55)	(-2.28)	(1.55)	(1.80)	(0.89)	(1.50)
$Average\ Size$	0.003***	0.003*	0.003**	0.001	-0.002	-0.002	0.000	-0.000
	(2.79)	(1.86)	(2.24)	(0.82)	(-1.28)	(-1.10)	(0.15)	(-0.02)
Intercept	0.018	0.023	0.027	0.015	0.004	0.051*	-0.020	0.037
	(0.86)	(0.89)	(1.28)	(0.53)	(0.18)	(1.92)	(-0.89)	(1.29)
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Analyst FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	34,866	34,866	34,866	34,866	33,705	33,705	33,705	33,705
Adjusted R^2	0.002	0.002	0.002	0.004	0.001	0.001	0.001	0.005

Table 4.8: Market reactions to skilled analysts' recommendation changes

This table reports the panel regression results of analyst recommendation announcement returns on our measure of analyst skill. We estimate the panel regression of the form:

$$CAR[0,+1]) = \alpha + \beta_1 Corr_s + \beta_2 |\Delta Rec_{individual}| + \beta_3 AllStar + \beta_4 Concurrent\ Rec$$
$$+\beta_5 Pre\text{-}earnings + \beta_6 Post\text{-}earnings + \beta_7 Away\ from\ consensus + \beta_8 Accuracy$$
$$+\beta_9 Ln(FirmExp+1) + \beta_{10} Ln(TotalExp+1) + \beta_{11} Ln(BrokerSize) + \beta_{12} Coverage$$
$$+\sum \beta_k X_{k,i,t} + \epsilon_{i,t}.$$

The dependent variable ($CAR[0,+1]$) is the 2-day cumulative abnormal returns (in percentage) around recommendation change announcements. $Corr_s$ is the rank correlation between stocks' recommendations and two composite mispricing scores, MGMT or PERF, using all recommendations issued by each analyst over the last three years. All other variables are defined in Table 1. $X_{k,i,t}$ represents the vector of firm characteristics, including $Ln(Size)$, $Volatility$, $MOM_{(-21,-1)}$, and $MOM_{(-252,-22)}$. Panel A (Panel B) reports the results for upgrade (downgrade) recommendation changes. Standard errors are double clustered by firm and analyst and *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Upgrade recommendation changes ($CAR[0,+1]$)						
	Cluster 1			Cluster 2		
$Corr_{MGMT}$	-0.000	0.000	-0.001			
	(-0.43)	(0.39)	(-0.53)			
$Corr_{PERF}$				0.002**	0.003**	0.004*
				(2.26)	(2.21)	(1.86)
$\lvert\Delta Rec_{individual}\rvert$	0.003***	0.005***	0.005***	0.003***	0.005***	0.005***
	(7.74)	(8.71)	(6.84)	(7.85)	(8.94)	(6.92)
$AllStar$	0.006***	0.002**	0.001	0.006***	0.003**	0.002
	(8.77)	(2.28)	(0.94)	(8.83)	(2.42)	(1.36)
$Concurrent\ Rec$	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(30.73)	(28.33)	(19.87)	(30.48)	(28.05)	(19.28)
$Pre\text{-}earnings$	0.005***	0.003***	0.004**	0.004***	0.003***	0.004**
	(4.60)	(3.33)	(2.42)	(4.24)	(2.99)	(2.46)
$Post\text{-}earnings$	0.002**	0.002***	0.002	0.002***	0.002***	0.002*
	(2.45)	(2.79)	(1.47)	(2.65)	(3.14)	(1.69)
$Away\ from\ consensus$	0.002***	0.001***	0.002***	0.002***	0.001**	0.002***
	(4.06)	(2.96)	(3.06)	(3.80)	(2.45)	(2.99)
$Accuracy$	0.006***	0.002	0.001	0.006***	0.002	0.000
	(7.21)	(1.61)	(0.65)	(6.84)	(1.41)	(0.33)
$Ln(FirmExp+1)$	0.000	0.000	-0.000	0.000	0.000	-0.000
	(1.29)	(0.85)	(-0.63)	(1.14)	(0.47)	(-0.38)
$Ln(TotalExp+1)$	0.001***	0.001	0.002	0.001***	0.001	0.003*
	(5.21)	(1.36)	(1.49)	(5.37)	(1.52)	(1.92)
$Ln(BrokerSize)$	0.003***	0.002***	0.002***	0.003***	0.002***	0.002***
	(16.07)	(4.47)	(3.10)	(15.80)	(4.36)	(2.73)
$Coverage$	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-7.10)	(-9.23)	(-4.37)	(-6.70)	(-8.74)	(-4.28)
Intercept	-0.033***	-0.040***	-0.002	-0.031***	-0.038***	-0.002
	(-3.29)	(-3.65)	(-0.08)	(-3.07)	(-3.48)	(-0.08)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	Yes	No	Yes
Analyst FE	No	Yes	Yes	No	Yes	Yes
Observations	94,046	94,046	94,046	91,545	91,545	91,545
Adjusted R^2	0.074	0.080	0.069	0.071	0.076	0.064

Table 4.8 (continued): Market reactions to skilled analysts' recommendation changes

Panel B: Downgrade recommendation changes ($CAR[0,+1]$)						
	Cluster 1			Cluster 2		
$Corr_{MGMT}$	-0.003**	-0.004*	-0.005*			
	(-2.13)	(-1.90)	(-1.76)			
$Corr_{PERF}$				-0.005***	-0.006***	-0.007***
				(-3.34)	(-3.06)	(-2.71)
$\|\Delta Rec_{individual}\|$	-0.008***	-0.013***	-0.014***	-0.009***	-0.013***	-0.015***
	(-11.88)	(-13.50)	(-10.30)	(-11.94)	(-13.32)	(-10.38)
$AllStar$	-0.009***	-0.004**	-0.002	-0.008***	-0.004**	-0.001
	(-8.18)	(-2.57)	(-0.80)	(-7.95)	(-2.41)	(-0.64)
$Concurrent\ Rec$	-0.038***	-0.038***	-0.034***	-0.039***	-0.039***	-0.035***
	(-44.88)	(-41.57)	(-27.21)	(-45.10)	(-41.79)	(-27.50)
$Pre\text{-}earnings$	-0.004***	-0.005***	-0.002	-0.004***	-0.005***	-0.002
	(-2.83)	(-2.93)	(-0.98)	(-3.13)	(-3.15)	(-1.04)
$Post\text{-}earnings$	-0.012***	-0.013***	-0.010***	-0.012***	-0.013***	-0.010***
	(-10.69)	(-10.74)	(-6.16)	(-10.74)	(-10.79)	(-5.85)
$Away\ from\ consensus$	-0.000	-0.002**	-0.001	-0.000	-0.001*	-0.001
	(-0.69)	(-2.09)	(-0.79)	(-0.56)	(-1.77)	(-0.72)
$Accuracy$	-0.008***	-0.003**	-0.001	-0.008***	-0.004**	-0.002
	(-6.69)	(-2.23)	(-0.67)	(-6.90)	(-2.40)	(-0.91)
$Ln(FirmExp+1)$	0.000	0.001***	0.001	0.000	0.001***	0.001
	(0.76)	(3.88)	(1.40)	(0.82)	(3.60)	(0.94)
$Ln(TotalExp+1)$	-0.001***	-0.003*	0.000	-0.001***	-0.002	0.001
	(-3.58)	(-1.86)	(0.22)	(-3.50)	(-1.63)	(0.40)
$Ln(BrokerSize)$	-0.005***	-0.002***	-0.000	-0.005***	-0.002***	-0.000
	(-16.91)	(-3.44)	(-0.50)	(-16.65)	(-3.15)	(-0.10)
$Coverage$	-0.002***	-0.001***	-0.002***	-0.002***	-0.001***	-0.002***
	(-16.08)	(-6.35)	(-9.96)	(-15.39)	(-6.13)	(-9.73)
Intercept	0.019	0.028*	-0.061**	0.029**	0.029*	-0.060**
	(1.37)	(1.78)	(-2.20)	(1.99)	(1.77)	(-2.13)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	Yes	No	Yes
Analyst FE	No	Yes	Yes	No	Yes	Yes
Observations	114,003	114,003	114,003	111,237	111,237	111,237
Adjusted R^2	0.079	0.101	0.079	0.080	0.102	0.078

Table 4.9: Subsample tests in post-publication periods

This table reports the results in post-publication periods. Panel A reports the Fama-French three-factor alphas of long-short portfolios sorted by 11 anomalies. Panel B reports the average level and change of analyst consensus recommendations across quintile portfolios of 11 anomalies. Column "Rec" reports the average level of consensus recommendations and Column "ΔRec" reports the average change of consensus recommendations. The *t*-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Fama-French three-factor alphas						
	NSI	CEI	Accrual	NOA	AG	IA
Long	0.26%	0.10%	0.03%	-0.08%	0.16%	-0.01%
	(2.73)	(0.85)	(0.24)	(-0.50)	(1.42)	(-0.09)
Short	-0.49%	-0.27%	-0.33%	-0.22%	-0.20%	-0.30%
	(-4.87)	(-2.75)	(-2.81)	(-2.77)	(-1.46)	(-2.46)
Long – Short	0.75%	0.37%	0.36%	0.14%	0.36%	0.29%
(*t*-stat)	(6.03)	(2.58)	(2.45)	(0.61)	(1.73)	(1.70)
	Distress	O-score	MOM	GP	ROA	
Long	0.09%	-0.03%	0.24%	0.16%	-0.02%	
	(0.92)	(-0.31)	(1.64)	(1.10)	(-0.25)	
Short	0.20%	0.16%	-0.62%	0.60%	-0.38%	
	(1.49)	(1.49)	(-3.27)	(6.35)	(-2.27)	
Long – Short	-0.11%	-0.20%	0.86%	-0.44%	0.35%	
(*t*-stat)	(-0.56)	(-1.00)	(2.95)	(-2.06)	(1.96)	

Table 4.9 (continued): Subsample tests in post-publication periods

Panel B: Recommendation level or change

	NSI		CEI		Accrual		NOA	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.62	-0.09	3.49	-0.05	3.69	-0.06	3.60	0.01
2	3.63	-0.05	3.51	-0.02	3.67	-0.05	3.59	0.00
3	3.73	-0.03	3.64	-0.02	3.77	-0.01	3.64	0.01
4	3.86	0.00	3.76	0.00	3.88	0.01	3.65	0.00
Short	4.00	0.02	3.84	0.04	4.03	0.01	3.84	0.01
Long - Short	-0.38***	-0.10***	-0.36***	-0.09***	-0.34***	-0.06***	-0.24***	-0.00
(*t*-stat)	(-12.65)	(-9.71)	(-13.95)	(-8.52)	(-10.71)	(-4.93)	(-13.69)	(-0.08)

	AG		IA	
	Rec	ΔRec	Rec	ΔRec
Long	3.58	-0.03	3.60	0.02
2	3.58	0.01	3.67	-0.01
3	3.63	0.00	3.68	0.01
4	3.74	0.02	3.72	0.01
Short	3.91	0.03	3.83	0.01
Long – Short	-0.33***	-0.06***	-0.23***	0.02
(*t*-stat)	(-25.93)	(-9.69)	(-13.31)	(0.91)

	Distress		O-score		MOM		GP	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.70	0.01	3.72	0.00	3.89	0.07	3.72	-0.01
2	3.73	0.01	3.72	0.03	3.76	0.00	3.79	-0.02
3	3.73	0.02	3.70	0.00	3.72	-0.01	3.78	0.01
4	3.65	0.02	3.72	-0.01	3.71	-0.06	3.69	0.00
Short	3.54	-0.02	3.82	-0.01	3.77	-0.15	3.63	0.00
Long – Short	0.16***	0.03***	-0.10**	0.01	0.12***	0.22***	0.09***	-0.01
(*t*-stat)	(5.11)	(2.98)	(-2.60)	(0.53)	(4.36)	(8.24)	(3.17)	(-0.74)

	ROA	
	Rec	ΔRec
Long	3.72	0.02
2	3.72	0.03
3	3.64	0.00
4	3.54	-0.01
Short	3.74	-0.03
Long – Short	-0.02	0.05***
(*t*-stat)	(-0.35)	(3.57)

Table 4.10: Subsample tests based on firm size

This table reports the results for subsamples based on firm size. We define small (big) stocks as those with market capitalization below (above) the 30% size cutoff using the NYSE size breakpoints. Panel A reports the average level and change of analyst consensus recommendations for quintile portfolios sorted by the two composite mispricing scores, MGMT or PERF. Column "Rec" reports the average level of consensus recommendations and Column "ΔRec" reports the average change of consensus recommendations. Panel B reports the monthly Fama-French three-factor alphas of portfolios sorted independently by anomaly characteristics and the level of analyst consensus recommendations. At the end of each June, all stocks are sorted into three groups based on the level of analyst consensus recommendations and independently into quintiles based on the composite mispricing measures. Up (Down) refers to stocks in the top (bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Consistent (Inconsistent) refers to the long-short portfolio where analyst recommendations are in congruent with (contradictory to) the anomaly prescriptions. Diff is the difference in alphas between Inconsistent and Consistent portfolios. The *t*-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is 1993-2014.

	Small Stocks				Big Stocks			
Panel A: Recommendation level or change								
	MGMT		PERF		MGMT		PERF	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.60	-0.07	4.04	0.07	3.46	-0.06	3.81	0.03
2	3.70	-0.07	3.93	-0.02	3.57	-0.03	3.75	0.01
3	3.85	-0.04	3.81	-0.06	3.68	-0.01	3.70	0.00
4	3.97	-0.04	3.72	-0.09	3.82	0.00	3.63	-0.03
Short	4.14	-0.01	3.76	-0.13	3.99	0.04	3.62	-0.08
Long – Short	-0.54***	-0.07***	0.28***	0.20***	-0.53***	-0.10***	0.19***	0.11***
(*t*-stat)	(-24.79)	(-4.37)	(9.11)	(7.54)	(-12.04)	(-10.24)	(6.56)	(4.20)
Panel B: Double sorts (Fama-French three-factor alphas)								
	MGMT		PERF		MGMT		PERF	
	Up	Down	Up	Down	Up	Down	Up	Down
Long	0.52%	0.24%	0.61%	0.67%	0.17%	0.08%	0.26%	0.41%
	(2.98)	(2.04)	(4.36)	(5.10)	(1.54)	(0.81)	(2.18)	(3.19)
Short	-0.86%	-0.51%	-1.29%	-0.61%	-0.71%	-0.31%	-0.82%	-0.36%
	(-4.95)	(-2.57)	(-5.99)	(-3.66)	(-3.84)	(-2.00)	(-3.77)	(-3.45)
Consistent	1.03%		1.22%		0.48%		0.63%	
	(3.23)		(6.21)		(2.49)		(3.47)	
Inconsistent	1.10%		1.96%		0.80%		1.23%	
	(5.14)		(7.56)		(3.67)		(4.04)	
Diff: Incon – Con	0.07%		0.74%		0.32%		0.60%	
	(0.33)		(2.96)		(1.15)		(2.21)	

Table 4.11: Subsample tests based on investor sentiment

This table reports the results for sub-periods based on investor sentiment. We divide the sample into low and high sentiment periods based on the median value of Baker and Wurgler (2006) sentiment index. Panel A reports the average level and change of analyst consensus recommendations for quintile portfolios sorted by the two composite mispricing scores MGMT or PERF. Column "Rec" reports the average level of consensus recommendations and Column "ΔRec" reports the average change of consensus recommendations. Panel B reports the monthly Fama-French three-factor alphas of portfolios sorted independently by anomaly characteristics and the level of analyst consensus recommendations. At the end of each June, we sort stocks into three groups based on the level of analyst consensus recommendations and independently into quintiles based on the composite mispricing measures. Up (Down) refers to stocks in the top (bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Consistent (Inconsistent) refers to the long-short portfolio where analyst recommendations are in congruent with (contradictory to) the anomaly prescriptions. Diff is the difference in alphas between Inconsistent and Consistent portfolios. The *t*-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is 1993-2014.

	Low Sentiment				High Sentiment			
Panel A: Recommendation level or change								
	MGMT		PERF		MGMT		PERF	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.49	-0.08	3.79	0.03	3.55	-0.06	3.96	0.05
2	3.59	-0.06	3.77	0.00	3.66	-0.05	3.87	0.01
3	3.70	0.00	3.72	-0.02	3.81	-0.04	3.80	-0.03
4	3.80	-0.01	3.64	-0.05	3.96	-0.02	3.71	-0.08
Short	3.98	0.01	3.64	-0.10	4.14	0.02	3.74	-0.12
Long – Short	-0.48***	-0.08***	0.15***	0.13***	-0.59***	-0.08***	0.22***	0.17***
(*t*-stat)	(-19.87)	(-5.82)	(3.79)	(2.76)	(-15.87)	(-5.76)	(10.09)	(8.57)
Panel B: Double sorts (Fama-French three-factor alphas)								
	MGMT		PERF		MGMT		PERF	
	Up	Down	Up	Down	Up	Down	Up	Down
Long	0.35%	0.14%	0.27%	0.29%	0.38%	0.09%	0.46%	0.52%
	(2.09)	(1.27)	(1.70)	(2.56)	(2.11)	(0.62)	(2.78)	(3.37)
Short	-0.43%	-0.22%	-0.46%	-0.36%	-1.09%	-0.64%	-1.61%	-0.68%
	(-3.01)	(-1.90)	(-2.12)	(-2.22)	(-4.47)	(-3.27)	(-6.68)	(-3.52)
Consistent	0.56%		0.63%		1.02%		1.14%	
	(2.90)		(2.44)		(4.06)		(4.15)	
Inconsistent	0.56%		0.75%		1.19%		2.14%	
	(2.52)		(3.45)		(3.93)		(6.78)	
Diff: Incon – Con	0.00%		0.12%		0.17%		0.99%	
	(0.00)		(0.40)		(0.60)		(3.19)	

Chapter 5

Summary of Conclusion

My dissertation investigates the implications of market friction in the information acquisition and dissemination process. Behavioral bias and transaction frictions lead to mispricing of information in real life, thus generating market anomalies and the return predictability of behavioral factors.

In Chapter 2, to illustrate how news travels across industries, I propose an effective way to quantify cross-industry news through machine learning and textual analysis. Consistent with high information cost hypothesis, cross-industry news contains valuable information about the firm fundamentals, which cannot be fully captured by the firm specific news or peer industry news in a timely manner. Therefore, the stock price will not immediately reflect cross-industry news, hence predicting stocks returns. In addition, investors' under-reaction to cross-industry news is highly concentrated in stocks with small size, low liquidity, high idiosyncratic volatility and fewer analysts coverage. A long - short portfolio based on cross-industry news generates an annual alpha above 10%.

In Chapter 3, a social network analysis is applied to aggregate the attention spillover effects among individual stocks. Our story suggests that the attention spillover effect, due to short sale constraint, leads to an incorporation of more good information than bad information in the prices of connected stocks. Consistent with this story, the media network based attention index negatively forecasts market return with a monthly in-sample (out-of-sample) R-square 5.97% (5.80%). To further verify the attention spillover effect, I compare Google and Bloomberg searching volume between connected news coverage and unconditional news coverage and find that connected news significantly increases the search volume for both Google and

Bloomberg. Consistent with behavior explanation, the evidence shows that attention spillover leads to over-valuation especially when arbitrage is limited.

On top of that, various market participants may have different purpose and ability to react to a new information. In Chapter 4, I formally examine the interaction effect between analyst recommendations and stock market anomalies. Interestingly, I find that the biased recommendations of analysts might be a source of market friction, which hinders the effective correction of mispricing. Particularly, analysts tend to make more favourable recommendations for overvalued stocks, which earn particularly negative abnormal returns in the future. Meanwhile, those analysts whose recommendations are better aligned with anomaly signals are more skilled and their recommendations receive stronger market reactions.

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