Co-search Attention and Stock Return Predictability in Supply-Chains

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Abstract

The ability to make prediction based on online searches in various contexts is gaining substantial interest in both research and practice. This study investigates a novel application of correlated online searches in predicting stock performance across supply chain partners. If two firms are economically dependent through supply chain relationship and if information related to both firms diffuses in the market slowly or rapidly then our ability to predict stock returns increases or decreases, respectively. We use online co-searches of stock as a *proxy* for information diffusion across supply-chain related firms. We identify publicly traded supply chain partners using Bloomberg data and construct co-search networks of supply chain partners based on the weekly co-viewing pattern of these firms on Yahoo! Finance. Our analyses show that the co-search intensity across supply chain partners helps determine cross-return predictability. When investors of a focal stock pay less attention to its supply-chain partners, we can use lagged partner returns to predict the future return of the focal stock. When investors' co-attention to focal and partner stocks is high, the predictability is low. Our simulated trading strategy using returns of supply chain partners with low co-attention generates a significant and positive return above the market returns and performs better than the previously established trading strategy using returns of all supply chain partners.

Keywords: Online Search, Correlated Search, User Attention, Network Analysis, Comovement, Stock Returns, Supply Chain

1. Introduction

Online search activity is used as a proxy to measure the level of interest or attention about a product or an asset. The search volume or trend is then used for predicting demand (Choi and Varian 2012), house prices (Wu and Brynjolfsson 2009) and stock price returns (Da et al. 2011; Luo et al. 2013). Leung et al. (2015) investigated correlated searches – that is, search related to multiple items – to understand return behaviors of a cluster of stocks. This research builds upon this work to understand investor attention and information diffusion among supply chain partners using correlated searches and use that information to predict stock returns among those partners.

Stock returns of economically linked firms such as supply chain partners are correlated due to correlated fundamentals (Hong et al. 2007) and profits (Menzly and Ozbas 2010). It is then expected that investors must pay attention to all stocks in the supply chain and information diffuses quickly in the market. However, due to limited attention and investor specialization, it is possible that the information diffuses slowly in the market (Hong et al. 2007) and across economically linked assets (Cohen and Frazzini 2008; Menzly and Ozbas 2010). This slow information diffusion can lead to a lagged return correlation between supply chain partners, which in turn can be used to predict the current returns of a focal firm (Cohen and Frazzini 2008; Hou 2007; Menzly and Ozbas 2010). Further, investor attention can vary across supply chain partners over time. High investor attention across supply chain partners can represent higher level of information diffusion that would lead to return comovement – i.e., returns tend to move together in the same direction – for such stocks in the same time period (Barberis et al. 2005). In that case, lagged correlation in stocks is less likely among partner stocks with high level of co-attention as compared to lagged correlation among partner stocks with low level of co-attention. The main thesis of this paper is that if there are different levels of attention among supply chain partners then online correlated searches of partner firms should reveal such behaviors. That is, the extent of online correlated searches can be a proxy for the extent of information diffusion across supply chain partners. This proxy can then be used to cross-predict stock returns across supply chain partners.

Da et al. (2011) show that aggregate online search is a proxy for investor attention. Likewise, Leung et al. (2015) show that correlated online searches reveal co-attention to stocks, and can be associated with investment habitats and stock comovement. Thus, correlated searches for supply chain partner stocks can reveal investor co-attention to these stocks. In other words, if investors co-search partner stocks along with a focal stock, it would indicate that investors are paying high attention to these partner stocks. This high attention can represent higher extent of information diffusion between the focal stock and the partner stocks. We should then expect low lagged return correlation between the focal stock and partner stocks. On the contrary, partner stocks that are not co-searched with the focal stock receive low co-attention and may indicate lower information diffusion between the partner stocks and the focal stock. In such a case, we expect lagged return correlation between the low co-attention partner stocks and the focal stock. Further, as investors' attention changes, the nature of correlated search patterns may also evolve, which reflects that over time there may be varying intensity of information diffusion across supply chain partners. Thus, correlated searches can potentially be used for predicting the returns of individual stocks in the supply chain using the returns of partners with low attention as revealed through the co-search pattern.

Previous studies (Da et. al. 2011; Luo et al. 2013) have primarily relied on online search to predict returns of individual stocks. Leung et al. (2015) consider correlated searches to identify investment habitats based on search clusters and show high contemporaneous return correlation among cluster stocks. However, they do not investigate whether correlated searches can represent the extent of information diffusion across economically linked assets such as supply chain partners. Additionally, while they show that search-based habitats can be used to predict stock returns they do not evaluate whether co-search patterns can be used for cross-predictions across supply chain partners. This research focuses on using co-search patterns to investigate information diffusion and cross-predictions across supply chain partners.

Using the online co-search data from Yahoo! Finance of Russell 3000 index stocks, we construct a correlated search network for the supply chain stocks, where the nodes represent stocks and the edges represent the co-search intensity across stocks of supply chain partners. We obtained the supply chain partners from Bloomberg Supply Chain Analysis (SPLC) module. We analyze cross-firm stock return predictability on a weekly basis from mid-September 2011 to December 31, 2012 and how it varies with co-search intensity.

Our results show that when supply-chain stocks are co-searched frequently (i.e., exhibit co-attention), the ability of lagged returns of the supply chain partners to predict the current returns of focal stocks reduces. However, in the absence of such co-attention there is significant cross predictability across supply-chain stocks when the supply chain stocks are not co-owned by institutional investors or co-covered by equity analysts. We control for the effects of commonly used risk factors and news related to the stocks that can impact the returns. We also control for factors that can drive investor attention such as institutional holdings and analyst coverage, and factors that influence co-search for supply chain partners such as stock popularity, industry membership, news co-mentions and investment styles. Even after accounting for these known determinants of investor attention and co-attention, we find that the co-search intensity can still explain the cross-predictability of stocks. We also verify that our results hold even after accounting for unobservable cross-sectional differences across partners that could potentially drive the outcome.

Our results suggest that the online co-search intensity across supply chain stocks could be a proxy for the extent of information diffusion. High co-search intensity may represent high information diffusion and as a consequence, results in weaker cross predictability of stocks. Further, the results show that the effect of high co-search intensity persists even after accounting for the known drivers of such information diffusion. This suggests that co-search intensity reveals the extent of information diffusion above and beyond the known drivers. We also find evidence of buy-sell asymmetry in our results, which is a characteristic of the retail attention. Thus, only positive partner returns can cross predict the focal stock returns. Further, the focal stock returns show a reversion in subsequent weeks.

We also evaluate if we can formulate a trading strategy to exploit this cross predictability based on the co-search pattern across supply chain stocks. We consider a trading strategy where we buy stocks whose low co-attention partners have the most positive returns in the previous week and sell focal stocks whose low co-attention partners have the most negative returns in the previous week. Our simulated trading strategy shows that we can earn average weekly returns of 35 basis points (annualized alpha of 20.77%) using out of sample data for the year 2013. We also compare it with a trading strategy suggested in finance literature (Menzly and Ozbas 2010) where all partners are considered. We find that our trading strategy significantly improves the return predictability over that already established in the literature. This provides additional evidence that use of co-search intensity can improve the cross-predictability of stocks.

This study makes several contributions. It brings different methodologies from distinct areas (i.e., IS and finance) to study an emerging phenomenon. For instance, behavioral finance literature has discussed attention and information diffusion to cross predictability of stock returns. However, network analysis of co-searches used in this study shows the extent of attention and information diffusion at various points in time to help improve prediction. Past studies in this area (e.g., Cohen and Frazzini 2008) rely on passive measures of investor co-attention, such as institutional ownership and analyst coverage, to show extent of information diffusion across supply chain stocks. We believe this is an important contribution that co-search network can reveal attention or inattention by retail investors and use this to represent the level of information diffusion across supply chain stocks. Further, our study contributes to the finance literature that co-attention of retail investors is useful in cross-prediction when partner stocks are not co-followed by analysts or co-owned by institutions. This study also differentiates from other studies in that co-search measure can be used to evaluate the cross predictability at a more granular level instead of the industry level analysis in the existing finance literature (Cohen and Frazzini 2008; Menzly and Ozbas 2010). Additionally, our simulated trading strategy shows that a prediction model, which incorporates investors' co-search behavior, works better than the strategy that considers pure supply-chain relationship strength (e.g., Menzly and Ozbas 2010). Hence, this study makes valuable contributions to understand phenomenon with greater clarity using search digital footprint.

Second, we are adding to the growing body of literature on using search data from digital footprint for prediction. Past IS and finance literatures have studied the role of search and online reviews as external data sources to predict performance of a single products/assets (e.g., Dellarocas et al. 2007; Gu et al. 2012; Lu et al. 2013; Luo et al. 2013). However, individuals often search for a portfolio of assets (e.g., stocks, products) and this study expands existing research to exploit correlated search to improve prediction of market performance.

Third, related to the above stream of research, this study contributes to emerging literature on economic networks that has considered correlated purchases to identify aggregate user preferences for products (Oestreicher-Singer and Sundararajan 2012a; Oestreicher-Singer and Sundararajan 2012b; Oestreicher-Singer and Zalmanson 2013) and to make predictions (Dhar et al. 2014). We show that correlated searches exhibit existing economic associations that can be exploited meaningfully for prediction on a real-time basis.

2. Related Work

This research is related to the literature on user attention, limited attention, and information diffusion in the context of stock markets. Further, we use literature on the impact of retail investors on the stock market performance. We review these two streams of literature below.

2.1 Attention, Limited Attention, and Information Diffusion

Previous research shows that users do not pay attention to everything due to limited processing capability (Lachman et al. 1979; Van der Heijden 1992) and limited cognitive resources (Kahneman 1973). According to the Model of Working Memory Capacity, individuals can only remember seven plus or minus two items (Miller 1956). With the advent of information technology, the amount of information increases but not the processing capacity of human beings (Simon 1973). The plethora of information may lead to information overload (Mendelson and Pillai 1998). As a result, individuals do not pay attention to all types of news and take immediate action. In the context of investment, investors may be more selective in information processing due to limited attention (Peng and Xiong 2006).

This limited investor attention has an impact on the market performance. For example, investors may overlook important public accounting information due to scant attention and lead to stock mispricing (Hirshleifer and Teoh 2003). Previous research has also found that timing and outlets of information affect investors' attentiveness. Dellavigna and Pollet (2009) find that investors' attention is more diverted on Friday and their responses to earnings announcements on Friday are less vigorous than other weekdays. Huberman and Regev (2001) find that investors respond to the news of a cancer-curing drug by EntreMed more vigorously when it appears on New York Times than its earlier appearance in the academic journal *Nature*. This suggests that the attention of investors to external information is not always consistent. As a result, they may overlook some important information in their stock valuation. Further, this can have an impact on the information diffusion across economically linked assets.

When investors pay little attention to an asset they cannot incorporate the related information in their investment decision. This can lead to slow reception of important supply-chain partner information, which may lead to lagged market reaction to that information. Extant research in finance has argued that due to limited attention and investor specialization, information diffuses slowly in the market (Hong et al. 2007) and even across supply chain stocks (Cohen and Frazzini 2008; Menzly and

Ozbas 2010). Investor inattention generates market friction that slows down stock price response to new information (Hou and Moskowitz 2005). In fact, the slow information diffusion of industry news may open up opportunities for stock return prediction (Hong et al. 2007). In contrast, if investors' attention is high, information diffusion is likely to be faster.

A number of studies have shown that rapid information diffusion in the same investment habitats leads to returns comovement for stocks associated with the habitat. These include habitats such as S&P 500 (Barberis et al. 2005; Vijh 1994); geography (Kumar et al. 2013; Pirinsky and Wang 2006); and volatility (Huberman and Dorn 2009). More recently, Leung et al. (2015) show that stocks within the same co-search habitats receive high attention from investors and such habitats exhibit high similarity in stock returns or comovement. Similar behavior applies to supply chain stocks.

If investors pay attention to the partner firms, then the information diffusion is likely to be high and as a result, the stocks are more likely to co-move. This in turn would reduce the lagged correlation and cross predictability across such partners. Past research has shown that online searches of individual stocks can serve as a proxy for investor attention (Da et al. 2011; Luo et al. 2013). This research investigates whether co-search of supply chain partners serves as a proxy for information diffusion and investors' co-attention across the value chain, which can be then be used for cross predictions of stock returns.

Further, the investor attention has been associated with short term mispricing and eventual correction. For example, Barberis et al. (2005) show that factors such as sentiment and market friction may cause stock markets to become inefficient in the short run. Da et al. (2011) show that that the search volume leads to positive price pressure immediately and reversion in the subsequent periods. Similarly, slow information diffusion across partner stocks can lead to mispricing of stocks in the short run and reversion in the subsequent periods.

2.2 Impact of Retail Investors

There is a growing body of literature that relies on user-generated data from retail investor-oriented Internet platforms for stock prediction. Da et al. (2011) use Google search volume index (SVI) as a proxy for retail investor attention and find that SVI can be used to predict stock returns in the next two weeks. Luo et al. (2013) compare social media metrics (Web blogs and consumer ratings) and online behavioral metrics (e.g. Google SVI and Web traffics) in predicting future equity value and find that the former performs better. Similarly, sentiments collected from messages posted in online forums (e.g., Yahoo! Message Boards, Raging Bull, and The Lion) can be used for stock prediction (Das and Chen 2007; Sabherwal et al. 2008; Tumarkin and Whitelaw 2001). Antweiler and Frank (2004) find that online messages can help predict stock volatility. Chen et al. (2014) find that investors' opinions expressed on Seeking Alpha can be used to predict future stock returns and earnings surprise.

Apart from stock market prediction, the behavior of retail investors have also attracted attention in both IS and Finance. Gu et al. (2007) investigate network externalities among three retail-investor oriented virtual investment communities (VICs), namely, Yahoo! Finance, Silicon Investor, and Raging Bull, and found that VICs face tradeoff between information quantity and information quality. Kumar and Lee (2006) analyze retail investor transactions and find that retail investor sentiment can be used to determine return comovement among stocks with high retail concentration.

Our study aims to extend this growing body of literature on retail investors and the associated data for determining market behavior using search data. More specifically, we aim to evaluate the cross predictability of stock returns based on online co-search behaviors which can be attributed to retail investors.

3. Data and Search Network for Supply Chain Partners

3.1 Co-searches

We use Yahoo! Finance "also-viewed" data to capture the co-search pattern across supply chain stocks. While this feature has been discontinued since May 2015 for unknown reasons, it provided valuable information as to what people searched for various stocks together[1]. Similar feature is available in Sina.com in China and Nasdaq.com.[2] Yahoo! Finance is one of the most popular investment portals among investors and it consistently ranks number one in terms of the popularity and the number of visitors.[3] It has an average monthly traffic of over 45 million visitors[4]. Yahoo! Finance listed top six co-viewed stocks for each stock on the stock summary page. Stocks are ranked based on their co-viewing frequency, and the top six co-viewed stocks are displayed to users. Yahoo! computed this co-viewed data based on visitors' cookies and uses a threshold to upload the most recent data to Yahoo! Finance.[5] Figure 1 shows an example of Yahoo! Finance stock summary page for a particular stock. The circled area shows the top six "also-viewed" stocks. When the majority of Yahoo! users who search stock A (e.g. AMD in Figure 1) also search B (e.g. INTC in Figure 1), stock B appears in the "also-viewed" list of stock A. These co-viewed stocks may also include supply chain partners. For example, DELL is a supply chain partner of AMD.

Using a Perl script, we collected daily co-viewing data for all Russell 3,000 stocks at 4pm CST every day during the period from September 15, 2011 to December 31, 2013. We use the co-viewing data to identify subsets of partner stocks that attract investor attention in every time period. Note that co-viewing data includes other firms, which are not supply chain partners of the focal firm. We exclude those firms. As we only consider partners that are publicly listed in US stock exchanges, we remove some stocks from the analysis because they do not have any US listed partners. Furthermore, we remove small focal stocks with market capitalization less than 20th percentile on NYSE by the end

[1] Despite the unavailability of this information from Yahoo! Finance for future research, this research demonstrates the usefulness of co-search data in prediction.
[2] Nasdaq.com shows a pop up with the co-viewing information provided by http://themarketiq.com.
[3] Top 15 popular business websites: http://www.ebizmba.com/articles/business-websites; Top 10 financial news and research websites: http://www.comscore.com/Press_Events/Press_Releases/2008/07/Yahoo!_Finance_Top_Financial_News_and_Research_Site_in_US.
[4] http://www.ebizmba.com/articles/business-websites
[5] Cookies allow a website to identify and track all user activities, including search for different items (in our case stocks). We have separately verified the data generation process directly with the customer service at Yahoo! Finance.

of year 2011 because those thinly traded stocks are more volatile to market changes and may confound our cross-predictability results (Menzly and Ozbas 2010). Our estimation sample contains 102,910 firm-week data that comprise of 1,619 focal firms in 66 trading weeks for the period from September 15, 2011 to December 31, 2012. We use the data from January 01, 2013 to December 31, 2013 for out-of-sample prediction for our trading strategy.

[Insert Figure 1 Here]

3.2 Supply-chain Relationship

We use Bloomberg SPLC to determine supply-chain relationship among Russell 3000 stocks. SPLC classifies supply-chain partners into suppliers and customers, and summarizes trading amount between focal stock and each supply-chain partners. The trading amount is based on the data reported by firms in their quarterly and annual earnings reports, and estimates by Bloomberg analysts. SPLC also provides data on revenue percentage and cost percentage of a focal stock and its supply chain partners.

The use of Bloomberg's dataset provides several advantages. Prior studies use Center for Research in Security Price (CRSP) Segment database to identify supplier and customer relationship and sales between two parties. However, CRSP Segment database only reports a small fraction of supplier-customer relationship data based on the regulation Statement of Financial Accounting Standards (SFAS) No. 131. The SFAS requires firms to only disclose the identity of customers with more than 10% of total sales in quarterly reports (Cohen and Frazzini 2008). Also, customer names in the database are sometimes vague and researchers have to manually match the names to existing stocks in Compustat database, which may result in some data loss (Pandit et al. 2011).

Some studies (e.g. Menzly and Ozbas 2010) rely on Benchmark Input-Output Surveys of the Bureau of Economic Analysis (BEA) to identify the magnitude of trading between industries. Using the survey data, researchers can only identify supply-chain relationship among industries but not individual firms. As a result, cross-prediction in prior studies is mostly restricted to intra-industry analysis. Furthermore, the survey is conducted once every 5 years by BEA and researchers assume that the industry supply-chain relationship does not change dramatically within 5 years. To overcome this limitation, we retrieve data from SPLC, which provides pairwise supply-chain data with the most recent trading amount between two firms. Furthermore, suppliers and customers are identified using Bloomberg tickers and it can alleviate the problems of manual matching of company names.

3.3 Co-search Network for Supply Chain Stocks

We construct a dynamic co-search network for supply chain stocks, which further characterizes the existing associations in a supply chain network using the co-search intensity between partner stocks. In this network, stocks of supply chain firms represent the nodes and the co-search intensity across stocks of supply chain partners represents the edges. The co-search intensity captures the attention among the investors for supply chain partners. If a partner stock appears in the "also-viewed" list of a focal stock on Yahoo! Finance in a week at least once, we assume co-search intensity of the focal stock investors for the "also-viewed" partner stock is high for that week. Otherwise, we consider the co-search intensity for the partner stock to be low for that week.

To illustrate, Figure 2 shows the local co-search network associated with AMD at two different times. AMD has multiple supply-chain partners, for example, DELL, HPQ, IBM and ORCL. We observe that in the week ending 12/9/2011, most investors of AMD also search DELL (bolded line) but do not pay attention to other partners. Thus, the co-search intensity of AMD investors for the DELL stock is high in that particular week. However, in the week ending 2/17/2012, we find that DELL does not appear in the co-viewing list of AMD. This suggests that the co-search intensity for DELL is low. Similarly, Figure 3 shows the local co-search network associated with DELL and how it links DELL with its top supply-chain partners. It should be noted that while, AMD investors pay attention to DELL in the week ending 12/9/2011, the reverse is not true. We capture this asymmetric co-attention in our co-search network and utilize it for cross-predictability of stocks of supply chain partners.

[Insert Figures 2-3 Here]

4. Research Model and Results

Our key objective is to determine if the co-search intensity across supply chain partners can help cross return predictability. Our empirical approach is as follows:

a) In each time period, we classify partners for each focal stock into high and low co-search intensity groups based on whether or not focal stock investors pay attention to these partners in that period. We then determine if average returns of each group can be used to predict the returns of the focal stock even after accounting for known common drivers for stock prediction. We also control for measures such as co-news mentions, which could influence the co-searches.
b) We determine if the co-search pattern can be attributed to factors such as size similarity, growth rate, industry, institutional attention, and stock popularity. In order to evaluate that co-search information is useful beyond known factors, we repeat the analysis after accounting for the effect of these factors.
c) Finally, in order to account for unobservable factors that can explain partner classification in low and high co-search intensity groups, we repeat the analysis with only those partners which belong to both groups in different time periods.

We explain our main model and results below. In section 5, we establish our results after accounting for the effects of known and unobservable factors. In section 6, we evaluate the characteristics of the cross-predictions relying on co-search based attention.

4.1 Model

We analyze the cross-predictability of supply-chain partners using the approach adopted by Menzly and Ozbas (2010). Specifically, we estimate the following time series model:

$$Ret_{i,t} = \beta_0 + \beta_1 Ret^L_{P_i,t-1} + \beta_2 Ret^H_{P_i,t-1} + \beta_3 Ret_{i,t-1} + \beta_4 MktRf_t + \beta_5 SMB_t + \beta_6 HML_t + \beta_7 MOM_t + \beta_8 Analyst_{i,t-1} + \beta_9 InstHldg_{i,t-1} + \beta_{10} News_{i,t} + \beta_{11} News_{i,t-1} + \beta_{12} CoNews^L_{P_i,t} + \beta_{13} CoNews^L_{P_i,t-1} + \beta_{14} CoNews^H_{P_i,t} + \beta_{15} CoNews^H_{P_i,t-1} + \varepsilon_{i,t} \quad (1)$$

The dependent variable is focal firm *i*'s contemporary weekly return $Ret_{i,t}$. We follow prior finance research and use compounded daily return to compute weekly return (e.g., Hou 2007; Mech 1993; Rosenthal and Young 1990). $Ret^L_{P_i,t-1}$ and $Ret^H_{P_i,t-1}$are supply-chain strength weighted partner returns with 1 week lag for the high and low co-search intensity partners. If the partner returns can predict the returns of the focal stock then we should expect the coefficient of $Ret_{P_i,t-1}$ to be positive and significant.

If supply-chain partners of a focal firm are listed in the co-searching list of the focal firm in any one day of the previous week, we consider these partners as part of the high co-search intensity group (H). Otherwise, they are categorized as part of the low co-search intensity group (L). We compute supply-chain strength (SC) weighted average partner returns separately for both groups. The main advantage of using a composite partner return is that it can reduce the number of parameters to be estimated while being model-justified. Menzly and Ozbas (2010) use the same approach to compute composite partner returns.

We control for short-term reversal by including the lagged return of focal firm $Ret_{i,t-1}$ (Jegadeesh and Titman 1993; Menzly and Ozbas 2010). We also account for various market risk factors using the Fama-French 4 factors (i.e., *MktRf*, *SMB*, *HML* and *MOM*). We further control for analyst coverage (*Analyst*) and institutional ownership (*InstHldg*) as they represent attention that may influence a stock's return as shown in prior studies (e.g., Menzly and Ozbas 2010). Finally, we control for news mention in our prediction model because news may capture investors' attention (Barber and Odean 2008). In addition to the news for the focal stock, co-mentions of the focal stock with its supply chain partners in the news can also influence the returns for the focal stock. For example, it may be the case that investors co-search a focal stock with some of its supply chain partners because of news co-mentions. In that case, one can use the news co-mentions instead of co-searches to explain the cross-predictability across supply chain partners. We control for the effect of news co-mentions across supply chain partners for each co-search intensity group (i.e., low and high) in the current week (i.e., $CoNews^{L}_{P_i,t}$ and $CoNews^{H}_{P_i,t}$) and the previous week (i.e., $CoNews^{L}_{P_i,t-1}$ and $CoNews^{H}_{P_i,t-1}$). Appendix A provides details of the control variables in Equation (1) and how these were constructed.

If a focal firm has both publicly traded buyers and suppliers, we define $Ret_{P_i,t-1}$ as the average of dependency weighted buyer returns $Ret_{B_i,t-1}$ (Equation 2) and exposure weighted customer returns $Ret_{S_i,t-1}$ (Equation 3). Dependency is the trading amount between a focal firm and a buyer divided by the total revenue of the focal firm. Exposure is the trading amount between the focal firm and a supplier divided by the total cost of goods sold associated with the focal firm. If the focal firm only has one type of partner, then we use the corresponding supply chain (SC) weighted average partner return (i.e. $Ret_{B_i,t-1}$ or $Ret_{S_i,t-1}$) as $Ret_{P_i,t-1}$.

$$Ret_{B_i,t-1} = \sum_{j\in B_i} Dep_{ij} \times Ret_{j,t-1} \Big/ \sum_{j\in B_i} Dep_{ij} \tag{2}$$

$$Ret_{S_i,t-1} = \sum_{j\in S_i} Exp_{ij} \times Ret_{j,t-1} \Big/ \sum_{j\in S_i} Exp_{ij} \tag{3}$$

where Dep_{ij} is i's dependency on buyer j and Exp_{ij} is i's exposure to supplier j, and $Ret_{j,t-1}$ is weekly return of partner j at t-1. Appendix B shows a numerical example for the calculation of the SC weighted partner returns. The stock return data for each stock during the study period is obtained from the Center for Research on Security Prices (CRSP) database.

Table 1 shows summary statistics of our sample data and Table 2 shows correlation matrix. The correlation among independent variables is low except for the news variables. However, the variation inflation factor (VIF) of our regression result is less than six suggesting that multi-collinearity is not an issue. Nevertheless, we have also tried combining contemporary news and lagged news together and re-run the regression. The VIF is below four and the research findings are qualitatively similar.

[Insert Tables 1-2 Here]

We estimate our research model using two-dimensional clustering at firm and week level. Two dimensional clustering is a commonly used approach in finance to account for cross-sectional correlation and auto-correlation in the analysis of stock returns (Petersen 2009).

4.2 Results

Table 3 shows the main results. Column 1 provides parameter estimates using the two dimensional clustering. The coefficient of lagged partner returns of low co-search intensity group is significant and positive. However, the coefficient of lagged partner returns of high co-search intensity group is not significant. These results suggest that there is a lagged reaction to the partner stocks where the co-search intensity is low. Lagged reaction to partner stocks is expected due to the slow information diffusion across supply chain stocks (Cohen and Frazzini 2008; Menzly and Ozbas 2010). However, as premised, there is no lagged reaction to the partner stocks with high co-search intensity. A plausible explanation is that the information diffusion is high across partners with high co-search intensity and, hence, partner stocks quickly incorporate new information. This removes any potential lag for prediction capabilities. Thus, co-search intensity can reveal the extent of information diffusion and can be used to determine the cross-predictability among supply chain stocks.

The lagged return of focal stocks is significant and negative. This supports the short-term reversion as documented in earlier research (Jegadeesh and Titman 1993). The Fama-French four factors are all significant except HML. Further, $Analyst_{i,t-1}$ and $InstHldg_{i,t-1}$ are not significant implying that the two measures for attention have limited impact on weekly predictions. The coefficient for current focal stock news is significant and positive. It shows that investors of focal stocks are aware of the news of stocks they invest and take immediate action. The coefficient of lagged focal news is significant and negative. This is similar to the effect of lagged focal stock return due to short-term reversion. The current and lagged co-mention news coefficients are not significant implying that investors do not always incorporate supply-chain partner news in their focal stock valuation.

We repeat the analysis using Fama-MacBeth regression with Newey-West correction for auto-correlation. This is another common method used in Finance literature for times series regression (Petersen 2009) and has been also used for cross predictability analysis (Menzly and Ozbas 2010). In Fama-Macbeth regression procedure, we run cross-sectional regressions for different time periods and then use these estimates for individual time periods to derive the overall estimates. Results are shown in column 2 of Table 3 and are qualitatively similar.

Finally, to account for the stock specific-effects, we run OLS regression with one period lag for Newey-West estimator correction for each focal stock.[6] This estimation approach is commonly used in finance literature to account for stock specific effects in a time series regression (Boyer 2011; Chen et al. 2013; Da et al. 2011; Edgerton 2012). We report the average of regression estimates and average R^2. We compute the standard error for the average estimates using asymptotic theory (see Appendix C) and determine the p-value by block bootstrapping. We compute the *p*-value using block bootstrap samples by randomly drawing a block of cross-sectional data 1,000 times[7] (see Appendix D). Corresponding results are shown in column 3 of Table 3 and are consistent with our main analysis. The negative coefficient for the return of high attention partners suggests that there is reversion due to temporary price pressure.

[Insert Table 3 here]

5. Additional Analysis

In this section, we present additional analysis to determine the factors that could potentially drive the co-search pattern and evaluate the cross-predictability after accounting for the effects of different drivers for co-search.

5.1 Co-viewing Analysis

[6] In individual OLS regressions, 47 stocks are eliminated due to insufficient number of observations.
[7] We also try block bootstrapping with 10,000 repeated random drawings. The results are qualitatively similar.

We investigate the factors that are likely to cause investors of a focal stock to search a partner stock. Prior studies (e.g., Froot and Teo 2008; Graham and Kumar 2006; Green and Hwang 2009; Greenwood 2008; Huberman and Dorn 2009; Kumar et al. 2013; Pindyck and Rotemberg 1993; Pirinsky and Wang 2006; Vijh 1994) show that investors are interested in buying stocks with similar characteristics together. These characteristics may include size, growth ratio, and industry. These factors can also influence the investor decision to search for partners along with a focal firm. Further, institutional attention can also play a role. For example, investors may pay attention to a partner stock that is also owned by the institutional investors along with the focal stock or covered by analysts with the focal stock. For each focal-partner pair in our data, we determine the probability of investors not paying attention to the partner (low attention) in period *t* as a function of the characteristics of the partner stock and the shared characteristics between the focal and the partner stock in previous time period. This probability can be expressed as [8]

$$Pr\left(isLow_{i,P_i,t} = 1\right) = \beta_0 + \beta_1 MktCap_{P_i,t-1} + \beta_2 P2B_{P_i,t-1} + \beta_3 News_{P_i,t-1} + \beta_4 DiffMktCap_{i,P_i,t-1} + \beta_5 DiffP2B_{i,P_i,t-1} + \beta_6 isSameSIC2_{i,P_i,t-1} + \beta_7 isSameAnalyst_{i,P_i,t-1} + \beta_8 isSameInst_{i,P_i,t-1} + \beta_9 CoNews_{i,P_i,t-1} + \sum_k \beta_{10,k} SIC2_{P_i,t-1} + \varepsilon_{i,P_i,t} \quad (4)$$

where $Pr\left(isLow_{i,P_i,t} = 1\right)$ is the probability that investors of focal stock *i* pay low attention to a partner stock P_i in week *t*; *MktCap* is log of one plus market capitalization; *P2B* is log of one plus price to book ratio; *News* is news volume, $DiffMktCap_{i,P_i,t-1}$ is log of one plus absolute difference in *MktCap* between *i* and P_i; $DiffP2B_{i,P_i,t-1}$ is log of one plus absolute difference in P2B between *i* and P_i; *isSameSIC2* is an indicator variable whether two firms have the same initial 2 digits of SIC indicating that they belong to the same industry; *isSameAnalyst* is an indicator variable whether the two firms are co-followed by one or more analysts; *isSameInst* is an indicator variable whether the

[8] We define the attention is low when partner P_i does not appear on the "also-viewed" list of stock *i* in week *t*.

two firms are co-owned by one or more institutions; *CoNews* is log of one plus volume of news that co-mentioned the two firms; $SIC2_{P_i,t-1}$ is a dummy variable based on the 2 digits of SIC to control for the effect of the industry of partner firm P_i.

We estimate the above model using logistic regression with two-dimensional clustering at firm-partner and week levels. Our results (Table 4) show that an investor is more likely to pay attention when both focal and partner firms are similar in size (positive coefficient of $DiffMktCap$), belong to the same industry (negative coefficient of *isSameSIC2)*, and co-followed by the same analysts (negative coefficient of *isSameAnalyst)*, and have high co-mentioned news volume (negative coefficient of *CoNews)*. Further, the news about the partners is likely to draw investor attention to the partner.

Our analysis reveals that co-search pattern for supply chain partners can be explained by certain factors. Thus, it is important to determine if the co-search information is useful beyond these factors. R^2 for logistic regression allows us to determine to what extent our independent variables can explain the variation in our main dependent variable (Cameron and Windmeijer 1997). MacFadden R^2 value of 0.23 suggests that while many of these factors help explain the co-search pattern, there is still lot of unexplained variation in the co-search pattern. It is also possible that some variation in co-search could be just noise. However, noise is not likely to give us any reliable results. Next, we investigate whether co-search is useful for cross predictions even after accounting for these drivers.

[Insert Table 4 here]

5.2 Size of Partners

It is possible that supply chain partners who do not appear in the co-viewing list are most likely to be small stocks. In general, information of small firms diffuses slowly to the public (Hong et al. 2000; Hong and Stein 1999). If most investors pay very little attention to small partners, it may result in slow information diffusion and, thus, positive cross-predictability. To control for the effect of small size of supply chain partners, we re-estimate our model after eliminating small supply chain partners from the high and low co-search intensity groups. We follow Menzly and Ozabas (2010) and remove small partner stocks with market capitalization less than 20th percentile in NYSE by the end of year 2011. We create a new group called others (or "O"), which include all small partner firms.[9] We control for the effect of the lagged returns associated with this group ($Ret^{O}_{P_i,t-1}$). We also control for the current and lagged SC weighted news co-mentions ($CoNews^{O}_{P_i,t}$ and $CoNews^{O}_{P_i,t-1}$) for these partner firms in the "other' group. Our updated model can be expressed as

$$Ret_{i,t} = \beta_0 + \beta_1 Ret^{L}_{P_i,t-1} + \beta_2 Ret^{H}_{P_i,t-1} + \beta_3 Ret^{O}_{P_i,t-1} + \beta_4 Ret_{i,t-1} + \beta_5 MktRf_t + \beta_6 SMB_t + \beta_7 HML_t + \beta_8 MOM_t + \beta_9 Analyst_{i,t-1} + \beta_{10} InstHldg_{i,t-1} + \beta_{11} News_{i,t} + \beta_{12} News_{i,t-1} + \beta_{13} CoNews^{L}_{P_i,t} + \beta_{14} CoNews^{L}_{P_i,t-1} + \beta_{15} CoNews^{H}_{P_i,t} + \beta_{16} CoNews^{H}_{P_i,t-1} + \beta_{17} CoNews^{O}_{P_i,t-1} + \beta_{18} CoNews^{O}_{P_i,t-1} + \varepsilon_{i,t} \quad (5)$$

Table 5 column 1 under Panel A shows the corresponding results. The coefficient of lagged return for partners belonging to the low co-search intensity group is still significant and positive. However, the magnitude slightly reduces from 0.0174 to 0.0158. This suggests that the co-search intensity can capture useful information and can help determine cross-predictability of supply chain stocks even after accounting for the effect of small stocks.

[Insert Table 5 here]

5.3 Style Investing

Previous studies (e.g., Barberis and Shleifer 2003) show that investors may invest in a style that performs consistently well in the past. Wahal and Yavuz (2013) show that stocks in the same style exhibit return comovement. Thus, it is possible that investors co-view supply chain partner stocks because these belong to the same style. Note that our co-viewing analysis points to similarity of size as a driver for co-viewing, which is one of the factors using to determine the style. In that case, we

[9] 14 focal firms which do not have any big partners are eliminated from the analysis.

can just identify these styles and use these to determine the cross predictability across supply chain partners.

To determine if co-search intensity has useful information even beyond the known styles, we remove supply-chain partners that fall into the same style as focal firms. We use the approach followed by the Wahal and Yavuz (2013) to identify investment style. We split all stocks available in CRSP into quintiles based on previous year's market capitalization and market-to-book ratio. Each quintile combination of market capitalization and market-to-book ratio represents a style. Then we map each focal stock to a style and identify supply chain partners that belong to the same style.[10] We estimate Equation (5), after including only those partners which do not belong to the same style as the focal firms in the calculation of $Ret_{P_i,t-1}^{L}$ and $Ret_{P_i,t-1}^{H}$. We classify partners with the same style as focal firms into group, "O".

Column 2 in Panel A, Table 5, shows the corresponding results. We find that only the coefficient of returns for low co-search intensity partners is significant and positive. The coefficient of returns for high co-search intensity partners is not significant. Thus, our results are consistent with our original analysis. This confirms that the co-search intensity provides more information than the effect of different investing styles.

5.4 Popularity Effect

Investors may be more aware of popular stocks, for example, Dow Jones Industrial Average (DJIA) component stocks[11] and this may explain the co-search pattern. To control for the popularity effect, we conduct additional analysis that focuses only on stocks whose partners are members of DJIA. For each focal firm, we consider only those partners that are part of Dow Jones Industry Average (DJIA) index. We find that not all DJIA partners are always co-searched. We further classify these partners in high attention and low attention groups in every time period and classify all other non-Dow Jones

[10] There are 33 newly listed focal stocks without previous year's market capitalization and market-to-book ratio. We remove these stocks from the analysis.

[11] We thank an anonymous reviewer for suggesting to use Dow Jones Industrial Average component stocks as a measure of stock popularity.

partners in a group called "Others". Note that we only consider those firms who have at least one partner in the DJIA index.

We expect that the higher ranked firms (in terms of market capitalization) among the DJIA firms are more popular and may receive higher attention. However, we find that the average rank of partners for both high and low attention groups is similar in our data panel. Specifically, the average rank of the firms appearing in high attention group is 15.5 and that in the low attention group is 14.8. The difference is not statistically significant. This suggests that investor attention among DJIA partners is not driven by their rank or popularity.

Next, we re-estimate Equation (5) using this alternative classification of partners. Corresponding results are shown in Table 5, Panel A, column 3. We find that among the DJIA partners of the firm, the lagged returns of low attention group have significant and positive impact on the returns of the focal firm. Thus, our results show that co-search information is useful to determine cross-predictability even for popular stocks.

5.5 Analyst Co-following and Institutional Co-ownership

We further investigate whether analyst co-following and institutional co-ownership have any effect on stock cross-predictability. Analysts and institutions represent professional investors who may have more private information on some firms than retail investors. We conjecture that information diffusion is faster among partner stocks when analysts (institutions) co-follow (co-own) the stocks. Therefore, retail investors' co-attention intensity on co-followed or co-owned stocks may not have much influence on cross-predictability. In contrast, if some partner stocks are not co-followed (co-owned) by analysts (institutions), retail investors' co-attention may have more influence. In every time period, for every focal stock, we further divide high and low attention partner groups into two subgroups representing whether or not the partner stocks have be co-covered by analyst (or co-owned by mutual fund). [12] We then determine whether the lagged returns of these groups are correlated with the focal stock return using Equation (6) where L and H represent low and high attention group, respectively; CA represents analyst co-covered (or institution co-owned) partners; and NA represents stocks that are not co-covered by analysts or co-owned by institutions.

$$Ret_{i,t} = \beta_0 + \beta_1 Ret^{L,NA}_{P_i,t-1} + \beta_2 Ret^{H,NA}_{P_i,t-1} + \beta_3 Ret^{L,CA}_{P_i,t-1} + \beta_4 Ret^{H,CA}_{P_i,t-1} + \beta_5 Ret_{i,t-1} + \beta_6 MktRf_t + \beta_7 SMB_t + \beta_8 HML_t + \beta_9 MOM_t + \beta_{10} Analyst_{i,t-1} + \beta_{11} InstHldg_{i,t-1} + \beta_{12} News_{i,t} + \beta_{13} News_{i,t-1} + \beta_{14} CoNews^{L,NA}_{P_i,t} + \beta_{15} CoNews^{L,NA}_{P_i,t-1} + \beta_{16} CoNews^{H,NA}_{P_i,t} + \beta_{17} CoNews^{H,NA}_{P_i,t-1} + \beta_{18} CoNews^{L,CA}_{P_i,t-1} + \beta_{19} CoNews^{L,CA}_{P_i,t-1} + \beta_{20} CoNews^{H,CA}_{P_i,t-1} + \beta_{21} CoNews^{H,CA}_{P_i,t-1} + \varepsilon_{i,t} \quad (6)$$

Our results (Please see Table 5, Panel B columns 1 and 2 for details) show that the coefficient of $Ret^{L,NA}_{P_i,t-1}$ is positive and significant. However, coefficient of $Ret^{L,CA}_{P_i,t-1}$ is not significant. Our results suggest that lack of attention revealed by low co-search intensity leads to lagged information diffusion only across those partners that are not co-covered (or co-owned). Co-coverage by analysts or co-ownership by institutions may influence the speed of information diffusion and overcome any information lag between partners represented by the co-search behavior of retail investors on Yahoo! Finance.

However, note that of all the possible partner-pair time combinations in our panel data only 12.8% are co-covered by analysts. Further, among the high attention group only 31.1% partner pairs are co-covered by analysts. Similarly, only 40.4% of the partner-pair time combinations are co-owned by the institutions and among the high attention group only 48.0% partner pairs are co-owned by institutional investors.[13] Thus, our results suggest that retail co-attention can be useful for cross

[12] We consider two stocks to be co-followed by analysts if at least one analyst releases earnings per share forecast on two stocks within a year. Similarly, we consider two stocks to be co-owned by institutions if at least one institution owns shares of two stocks in a fiscal quarter. We establish mutual fund co-ownership based on the Thomson Reuters Institutional (13F) Holdings Database. For our purpose, we consider a mutual fund company to be an owner of a stock as long as it holds some shares of the listed firm.
[13] Same partner pair may or may not be co-covered (co-owned) at different points in time.

predictability across a large number of supply chain partners which not co-covered by analysts or co-owned by mutual funds.

5.6 Industry Effect

Our co-viewing analysis suggests that investors interested in a particular industry may pay more attention to partners within the same industry. To control for the industry effect, in every time period for every focal stock, we further divide high and low attention partner groups into two subgroups representing whether or not the partner stocks belong to the same industry (CA) or different industry (NA). We use Standard Industrial Classification (SIC) initial two digits and North American Industry Classification System (NAICS) initial two digits to determine whether a partner firm belongs to the same industry as a focal firm. We re-estimate Equation (6) using the above partner classification. The results are shown in Table 5, Panel B columns 3 and 4. We find that coefficients of lagged returns for the low attention groups, $Ret^{L,NA}_{P_i,t-1}$ and $Ret^{L,CA}_{P_i,t-1}$, are both positive and significant whereas the lagged returns of high attention groups have no effect on the focal stock returns. Our results suggest that the variation in investor attention occurs for partners irrespective of their industry affiliation and can be used for cross-predictability of stocks.

5.7 Unobservable Cross-Sectional Differences

One other possibility of high cross-predictability among low attention partner group is that there are firm specific unobservable characteristics that drive the classification of partners into high and low co-search intensity groups. These may be known to investors, but are unobservable to us. Thus, unobservable cross-sectional differences across the high and low co-search intensity groups may be driving our results.

To alleviate this concern, we repeat our analysis where we consider only those partners that belong to both high and low co-search intensity groups at different points in time during the panel. If the co-search intensity for a partner does not change during the panel period then we classify such a partner into “others” group (or “O”) in our research model represented by Equation (6). Out of 1,619 focal firms, 796 firms have partners that have the same co-search intensity throughout the panel period. We do not consider these firms for our analysis.

We also compute how often the partner co-search intensity is changing for each focal firm and analyze a smaller sample of firms with different levels of change frequency: above 0%, 40% or above, and 60% or above. Using this approach, we guarantee that the co-search intensity level of partners of a focal firm is changing during the panel period.

Table 6 Panel A columns 1-3 show the related results. The lagged returns of low co-search intensity group partners have positive and significant impact on the returns of the focal stock even after removing firms whose partner co-search intensity do not change in the research period. This suggests that our results hold even after accounting for the unobservable cross-sectional differences across high and low co-search intensity groups. At the same time, control variables remain qualitatively similar to our main model. When change frequency increases, the magnitude of the coefficient associated with the lagged returns of the low co-search intensity group also increases. The results show that the cross predictability is even stronger among firms whose investors shift attention frequently among supply-chain partners.

It is possible that the changing attention can be explained by co-coverage by analysts as co-viewing is correlated with analyst co-coverage (Table 4). In order to account for the effect of this behavior we also verify that our results hold when attention changes for partners even without analyst co-coverage. We repeat the analysis by splitting each attention group into two subgroups CA and NA based on whether or not the partners are followed by analysts or owned by institutions. We only consider those partners that have a non-zero change frequency during the panel period. The results as shown in Table 6 column 4 are consistent with our prior findings.

We also validate our results using individual regressions to account for stock specific effects (Boyer 2011; Chen et al. 2013; Da et al. 2011; Edgerton 2012). Specifically, we run OLS regression with one period lag for Newey-West estimator correction for each focal stock. We report the average of regression estimates and average R^2 (Table 6, Panel B). We compute the standard error for the average estimates using asymptotic theory (see Appendix C) and determine the p-value by block bootstrapping (see Appendix D). Results in Panel B of Table 6 are consistent with our findings. Lagged returns of low co-search intensity group partners that are not followed by analysts, have positive and significant impact on the returns of the focal stock. We also compute the difference in coefficients for high attention and low attention lagged returns of partner stocks. We find that this difference is significant (Table 6 Panel B). [14] This confirms the lagged returns of low co-search intensity group have a much higher predictability on the focal stock returns than the lagged returns of high co-search intensity group.

Furthermore, we use Davidson and MacKinnon (1981)'s non-nested J-test (see Appendix E for detail) to investigate whether the lagged return of low attention group in the above analyses contributes more to the model specification than that of high attention group. The test has been used in prior research to determine the relative importance of variables (e.g., Anderson et al. 2003; Edell and Burke 1987; Freeman and Tse 1992; Greene and Hodges 2002; Loh and Venkatraman 1992; Ramasubbu et al. 2008). The results show that the return of low attention group adds more value in our prediction models.

[Insert Table 6 here]

6. Characteristics of the Co-search based Attention

6.1 Buy-Sell Asymmetry

Yahoo! co-searches are more likely due to retail investors. Barber and Odean (2008) show that there is buy-sell asymmetry in retail attention-driven stocks. Retail investors without financial constraints can buy any stocks at will; however, they can only sell stocks they have already purchased and, therefore, attention has limited impact on stock selling (Barber and Odean 2008). If a major partner stock experiences significantly positive returns, it may trigger more investors to buy a related focal

[14] We thank the anonymous reviewer for suggesting the calculation of the statistical difference.

stock. However, if a partner stock experiences negative returns, investors may sell a focal stock subject to their prior ownership. If this is true, the predictability of lagged return of low attention partners will be more significant if they experience positive returns than does that of low attention partners with negative lagged returns. We validate this by re-estimating Equation (6), where NA (CA) is the group with positive (negative) lagged returns. The result shown in Table 7 confirms our conjecture that only partners with positive returns have significant and positive predictability. Thus, our results suggest that co-search as a proxy for co-attention, is more useful for cross-predicting positive partner returns. We also validate our results using individual regressions and report the difference in the coefficient estimates in Table 7. We find that return of the focal stock has significant lagged correlation only with positive returns of low attention partners. Additionally, the difference between coefficients of positive low-attention partner returns and positive high-attention partner returns is statistically significant.

[Insert Table 7 here]

6.2 Price Pressure and Reversion

We conduct further analysis to determine whether the price movement we detected in earlier analysis has some temporary price pressure due to retail attention. If this is true, the positive return correlation will be reverted at later time as arbitrageurs will pay attention to the mispricing. Such efforts would move prices closer to the fundamental value. We re-run the cross predictability regression using future returns of the focal stock as the dependent variable. Results in Table 8 show that the coefficient of the low-attention partner return becomes insignificant beyond the first week and is negative and significant in week 8. These results suggest that there may be some temporary price pressure associated with the positive return predictability detected in the first week.

[Insert Table 8 here]

6.3 Impact of Yahoo on Cross Return Predictability

A potential concern is that the co-viewing data from Yahoo! Finance may influence the stocks that are searched. This conjecture is reasonable as individual investors are net buyers of attention grabbing stocks (Barber and Odean 2008). Thus, users may be drawn to the partner stocks because they appear in the co-viewing list on Yahoo! Finance. Although there is no evidence to believe that stock prices are influenced by the searching behavior of investors on a single site like Yahoo! Finance, the co-viewing list may distort the attention levels and information diffusion across partner firms, which may impact our ability to cross-predict. We exploit the discontinuation of co-viewing feature to determine whether Yahoo! Finance did have an impact on the information diffusion and, hence, the cross predictability of stocks. If co-viewing pattern shown by Yahoo! Finance has an effect on the information diffusion across supply chain partners then in the absence of the co-viewing feature, focal stock return should start showing lagged correlation with returns of those partners which are being co-viewed along with the focal stock i.e. high attention partners.

In order to verify this, we collected additional data for our sample firms before and after the Yahoo! finance site discontinued the co-viewing feature on May 23, 2015.[15] We assume the co-attention represented by the co-viewing pattern in the last week before this event does not change for a few weeks even after the event. This assumption is reasonable as the analysis of the co-viewing pattern few weeks before this event shows that co-search pattern is not changing for most of the focal stocks. We estimate the following model:

$$Ret_{i,t} = \beta_0 + \beta_1 Ret^L_{P_i,t-1} + \beta_2 Ret^H_{P_i,t-1} + \beta_3 Post_t + \beta_4 Post_t \times Ret^H_{P_i,t-1} + \beta_5 Ret_{i,t-1} + \beta_6 MktRf_t + \beta_7 SMB_t + \beta_8 HML_t + \beta_9 MOM_t + \beta_{10} Analyst_{i,t-1} + \beta_{11} InstHldg_{i,t-1} + \beta_{12} News_{i,t} + \beta_{13} News_{i,t-1} + \beta_{14} CoNews^L_{P_i,t} + \beta_{15} CoNews^L_{P_i,t-1} + \beta_{16} CoNews^H_{P_i,t} + \beta_{17} CoNews^H_{P_i,t-1} + \varepsilon_{i,t} \tag{7}$$

[15] Our script was tracking the co-viewing patterns until the site stopped showing the co-viewing data. We collected data for only those firms which were still included in Russell 3000 index.

$Post_t$ is the dummy representing the dis-continuation event. We set it to zero for four weeks before and one week after the feature was discontinued. This allows us to capture the effect of Yahoo co-viewing in the week after discontinuation. We set the dummy to one for week two to week five after the event. $Post_t \times Ret^H_{P_i,t-1}$ is the interaction term between this dummy and the lagged returns for high attention partners. Corresponding estimates are shown in Table 9. The coefficient for $Ret^L_{P_i,t-1}$ is positive and significant. However, coefficients for variables $Ret^H_{P_i,t-1}$ and $Post_t \times Ret^H_{P_i,t-1}$ are not significant. This suggests that focal stock return shows lagged correlation with returns of low attention partners. However, it does not show lagged correlation with returns of high attention partners both before and after the disabling of the co-viewing feature.[16] This confirms that Yahoo does not influence the extent of information diffusion and, hence, the cross-predictability across stocks.

It is possible that inherent high attention to some partners may lead to rapid diffusion of information to focal stocks and may not result in lagged correlation of focal stock return with returns of such partners even in the absence of the co-viewing feature. Effect of Yahoo on information diffusion, if any, may only appear in the return correlation in the same period and not in the lagged return correlation. In that case, we can expect the return comovement between the focal stock and the high attention partners to reduce after the co-viewing feature is dis-continued. So we repeat the above analysis using contemporary partner returns to establish the effect of Yahoo! Finance on the comovement between partner and focal stocks. We set the dummy $Post_t$ to zero for four weeks before and one for all five weeks after the discontinuation. We find that the coefficient for partner returns is significant for both high and low attention partners (Table 9). This is expected as returns for focal stock and its partners should show some return comovement due to correlated fundamentals. However, the coefficient of the interaction term $Post_t \times Ret^H_{P_i,t}$ is not significant. This suggests that the comovement pattern between focal stocks and their high attention partners is not changing after

[16] Our results are qualitatively similar for different time periods before and after the dis-continuation event.

the co-viewing feature was discontinued. This again confirms that Yahoo has no effect on the extent of information diffusion between partners and hence, the cross-predictability.

[Insert Table 9 here]

7. Trading Strategy

Our results show that partners with low co-search intensity can predict the future returns of a stock. However, partners with high co-search intensity show no such effect. Next we explore if we can improve cross-predictability of supply chain stocks using the co-search information. We formulate a trading strategy similar to the one discussed in Menzly and Ozbas (2010) and incorporate co-search intensity of supply chain stocks to improve trading decisions.

Before the market opens, we sort all stocks according to their SC weighted partner returns in previous week. We group them into quintile (Q1: lowest and Q5: highest). Q5 (Q1) consists of stocks whose supply-chain partners have the most positive (negative) lagged returns. We form a value-weighted stock portfolio in each quintile. Due to slow information diffusion, positive (negative) returns of partner stocks in previous week may lead to higher (lower) returns of focal firms in the current week. We can construct a trading strategy and make positive gains by buying focal stocks whose partners have the most positive returns in previous week (i.e. Q5) and selling focal stocks whose partners have the most negative returns in previous week (i.e. Q1). The trading strategy is similar to the one adopted by Menzly and Ozabas (2010) for supply-chain related stocks. To account for systematic market risks that may influence the raw portfolio returns, we compute portfolio alpha by running regression model in Equation (8).

$$Ret_{Port_{i},t} = \alpha + \beta_1 MktRf_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \varepsilon_{i,t} \quad (8)$$

We apply the above trading strategy to stocks with (1) low co-search intensity supply-chain partner stocks only; (2) high co-search intensity supply-chain partner stocks only; and (3) all supply-chain partner stocks regardless of co-search intensity. To avoid sample bias, we use out-of-sample data (Jan 1, 2013 to Dec 31, 2013) for the trading strategy.

Table 10 shows the average weekly return of portfolios of stocks in individual quintiles. Our trading strategy is to buy stocks in Q5 and sell stocks in Q1 (H-L). Panel A shows the results of trading only among stocks associated with low co-search intensity partners. Q1 contains stocks whose partners experienced the most negative returns in the previous week and Q5 contains stocks whose partners experienced the most positive returns in the previous week. Our trading strategy (H-L) yields a mean weekly raw portfolio return of 35 basis points.

Additionally, the alpha of portfolio in Q1 is negative but not significant and that of portfolios in Q5 is 32 basis points and significant at 5%. The insignificant alpha of Q1 may suggest that the focal stock investors do not incorporate the bad news of partner stocks immediately. As suggested by Hong et al. (2000), bad news diffuses slowly to the public. Further, as co-search represents retail attention, these investors may not be able to take a short position. The portfolio of H-L generates the highest alpha of 36 basis points and is significant at 5%. The annualized alpha of low co-search intensity (H-L) portfolio is 20.77%.[17] The primary source of profits of our suggested portfolio comes from buying stocks in Q5.

Panel B shows the portfolio returns using stocks associated with high co-search intensity partners. The portfolio of H-L yields an insignificant alpha of 7 basis points or an annualized alpha of 3.68%. This confirms our main results that high-attention partners are less likely to show cross-predictability. Furthermore, the portfolio returns between Q1 and Q5 are relatively similar. As the co-search intensity of the related partners is high, these stocks may have already incorporated information due to faster information diffusion and may not benefit from the lagged performance of the partners. This is consistent to the attention theory that increased attention may lead to faster information diffusion.

[17] Annualized alpha is weekly alpha compounded over 52 weeks, $(1+\alpha)^{52}-1$.

Panel C shows the portfolio returns for stocks where all supply chain partners are considered. The weekly alpha is only 21 basis points and significant at 10%. The annualized alpha is only 11.51%. The results show that by trading supply-chain related stocks regardless of the co-search information does not generate a high portfolio returns. The weekly alpha is much lower than that reported in Panel A. The results suggest that by incorporating co-search intensity in our investment strategy, it is possible to earn higher portfolio returns.

As a robustness check, we repeat the trading strategy with all supply chain partners by using BEA's definition of supply-chain partners. It is the same approach used by Menzly and Ozbas (2010). The weekly alpha of H-L, as shown in Appendix F, is not significant. A plausible reason is that BEA's supply-chain definition is based on NAICS code, which is too broad and not as precise as Bloomberg's supply-chain definition, which is based on individual firms.

8. Discussion and Conclusion

This study extends extant literature on online user search by focusing on correlated searches across economically linked assets and investigating its usefulness for cross predictability of stock returns. The main thesis is that online search of supply chain partners is a *proxy* for investor attention and information diffusion, which can be exploited for return predictability. We use correlated searches for supply chain stocks on Yahoo! Finance to investigate our thesis. It is important to recognize that search on a single site such as Yahoo! Finance cannot impact stock prices, but the co-search patterns can suggest the level of co-attention. After controlling for numerous known variables, we find co-search intensity can improve cross predictability of returns of supply chain partners. Lagged returns of partners that are not co-searched with the focal stock can be used to predict the returns of a focal stock. However, the same does not hold for partners that are co-searched with the focal stock. We argue that this is due to high attention among supply chain partners and, hence, faster information diffusion. Thus, our results show that co-search intensity can be a proxy for the extent of information diffusion across supply chain stocks. Our results hold even after accounting for several known and unobservable drivers for information diffusion.

The results are insightful as past research in finance shows evidence of limited information diffusion across supply chain partners, but does not distinguish among partner stocks based on the extent of attention. Our results show that we can assess the extent of attention by analyzing the aggregate co-search pattern. We further demonstrate that incoporating co-search intensity information in the trading strategy leads to significant improvement in the cross predictability across supply chain stocks relative to a strategy without co-attention.

Our study has important implications. We illustrate the economic value of capturing and analyzing publicly available online investor search data for investment decisions. Such information can reveal more details about the economic activity and market performance and help make better decisions. More specifically, our study shows that online co-search data such as the Yahoo! Finance "also-viewed" list has several advantages over other measures of co-attention used in prior finance research. Many of the existing measures are either passive or indirect. For example, Cohen and Frazzini (2008) use mutual funds' joint holdings of supplier/customer stocks as a proxy for investor attention. Other conventional attention proxies include news, extreme past returns and trading volume (Barber and Odean 2008; Hou et al. 2008) are indirect measures of attention. Online investor data, such as correlated searches, provide active measure of investor attention. Further, co-search data are available publicly and can be used to capture user economic activities at a granular level and can be exploited faster than transactional data. Traditional publicly available data in finance cannot reveal investor activities at a granular level. In addition, detailed data are typically proprietary and are fragmented across multiple traders. Finally, this study makes methodological contributions to use network analysis to understand information diffusion across economically linked assets (i.e., nodes in a network) and to make predictions.

There are several limitations in our analysis that can be the basis for future research. We determine co-search intensity based on the co-appearance of stocks on Yahoo! Finance. While Yahoo! Finance attracts millions of investors, it is worthwhile to explore alternative sources of co-attention such as other search platforms and message boards and evaluate the effectiveness of these platforms to reveal the extent of information diffusion. Further, we do not consider the actual co-search volume, which can help further differentiate between supply chain partners in terms of the co-search intensity. Future research should explore other data sources such as message boards to better measure the co-search intensity across partners and use the precise measure to determine the cross-predictability of stocks. Also, our dataset reveals only the search data, and not the actual transaction data. This analysis can be further improved if access to transactional data is also available for the same user base. Last, it would also be useful to identify unknown factors that drive investor co-search pattern and stock cross predictability. Though we demonstrate that similarities in terms of size, value, and industry and institutional attention may cause investors to search some stocks simultaneously, there may be other attention grabbing factors that influence the search behaviors of investors. Future research should investigate other drivers of this co-search behavior.

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Figure 1. Example of Co-viewing Data in Yahoo! Finance

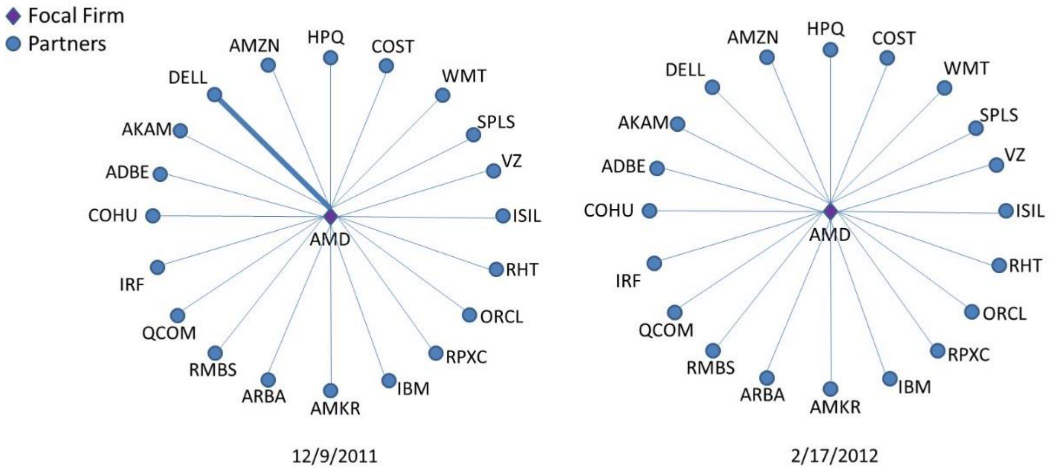

Figure 2. Example of Co-Search Supply-Chain Network

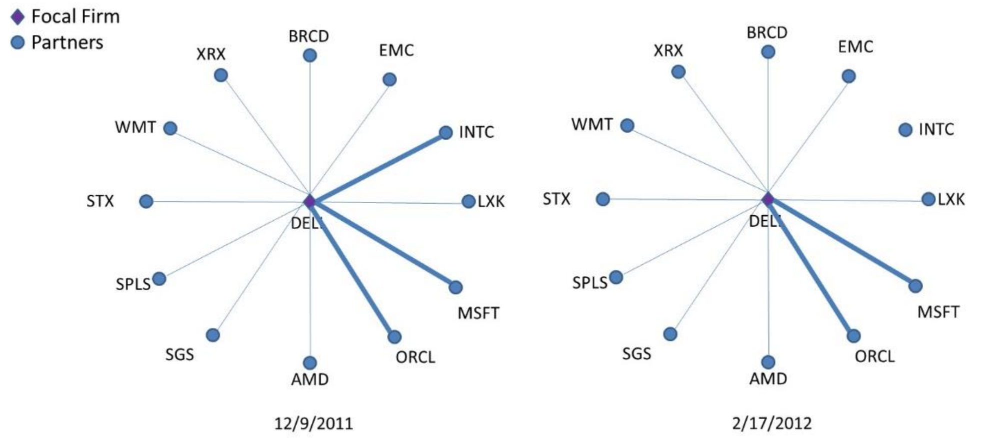

Figure 3. Co-Search Supply-Chain Network for DELL

Table 1. Summary Statistics

Variable	N	Mean	SD	Min	Max
$Ret^{L}_{P_i,t-1}$	102,910	0.00	0.06	-0.74	1.49
$Ret^{H}_{P_i,t-1}$	102,910	0.00	0.04	-0.66	0.92
$Ret_{i,t-1}$	102,910	0.00	0.02	-0.48	0.47
$MktRf_t$	102,910	0.00	0.06	-0.74	1.49
SMB_t	102,910	0.00	0.02	-0.05	0.08
HML_t	102,910	0.00	0.01	-0.03	0.03
MOM_t	102,910	0.00	0.01	-0.02	0.02
$Analyst_{i,t-1}$	102,910	0.00	0.02	-0.04	0.03
$InstHldg_{i,t-1}$	102,910	1.66	0.78	0.00	3.91
$News_{i,t}$	102,910	0.56	0.13	0.00	1.20
$News_{i,t-1}$	102,910	2.44	1.39	0.00	8.64
$CoNews^{L}_{P_i,t}$	102,910	2.39	1.46	0.00	8.64
$CoNews^{L}_{P_i,t-1}$	102,910	0.11	0.34	0.00	5.42
$CoNews^{H}_{P_i,t}$	102,910	0.07	0.30	0.00	5.42
$CoNews^{H}_{P_i,t-1}$	102,910	0.13	0.53	0.00	6.06
$Fraction\ of\ High\ Attention\ Partners_{P_i,t-1}$	102,910	0.04	0.14	0.00	1.00

Table 2. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) $Ret_{i,t}$	1	-0.03	-0.01	-0.06	0.54	0.31	-0.02	-0.37	-0.03	0.01	0.02	-0.01	0.01	0.00	0.00	0.00
(2) $Ret^{L}_{P_i,t-1}$	-0.02	1	0.22	0.46	-0.08	0.09	-0.13	0.00	-0.01	0.00	0.01	0.01	0.01	0.01	0.00	0.00
(3) $Ret^{H}_{P_i,t-1}$	0.00	0.21	1	0.21	-0.03	0.06	-0.06	0.01	0.00	0.00	0.02	0.02	0.02	0.02	0.05	0.04
(4) $Ret_{i,t-1}$	-0.04	0.38	0.20	1	-0.07	0.04	-0.09	0.01	-0.01	0.01	0.01	0.02	0.01	0.01	0.00	0.00
(5) $MktRf_t$	0.49	-0.07	-0.02	-0.07	1	0.35	0.06	-0.65	-0.04	0.00	0.01	-0.02	0.02	0.01	0.00	0.00
(6) SMB_t	0.31	0.07	0.04	0.03	0.43	1	-0.31	-0.31	0.00	0.00	0.01	0.00	0.02	0.01	0.01	0.00
(7) HML_t	-0.02	-0.09	-0.05	-0.05	0.03	-0.30	1	-0.20	0.02	0.00	0.00	-0.01	-0.01	-0.01	0.00	0.00
(8) MOM_t	-0.34	0.02	0.02	0.02	-0.64	-0.34	-0.22	1	0.05	0.00	-0.01	0.03	-0.01	0.00	-0.01	0.00
(9) $Analyst_{i,t-1}$	-0.03	-0.01	0.00	-0.01	-0.04	-0.01	0.02	0.05	1	0.09	0.20	0.24	0.13	0.14	0.09	0.09
(10) $InstHldg_{i,t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	1	-0.07	-0.07	-0.05	-0.08	-0.06	-0.08
(11) $News_{i,t}$	0.02	0.01	0.02	0.01	0.01	0.01	-0.01	-0.01	0.23	-0.04	1	0.77	0.47	0.39	0.32	0.30
(12) $News_{i,t-1}$	-0.01	0.01	0.02	0.01	-0.02	0.00	-0.01	0.02	0.26	-0.04	0.82	1	0.40	0.40	0.29	0.30
(13) $CoNews^{L}_{P_i,t}$	0.01	0.01	0.02	0.01	0.01	0.01	-0.01	-0.01	0.12	-0.04	0.41	0.35	1	0.71	0.38	0.36
(14) $CoNews^{L}_{P_i,t-1}$	0.00	0.00	0.01	0.01	0.00	0.00	-0.01	0.00	0.12	-0.04	0.34	0.35	0.77	1	0.39	0.42
(15) $CoNews^{H}_{P_i,t}$	0.00	0.00	0.03	0.00	0.00	0.01	0.00	-0.01	0.10	-0.05	0.38	0.36	0.39	0.38	1	0.84
(16) $CoNews^{H}_{P_i,t-1}$	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.11	-0.06	0.36	0.36	0.37	0.40	0.90	1

Upper Triangle: Spearman Correlation Matrix; Lower Triangle: Pearson’s Correlation Matrix

Table 3. Cross Prediction Results

Variables	**(1)**	**(2)**	**(3)**
$Ret^{L}_{P_i,t-1}$	0.0174**	0.0392***	0.0327**
	(0.0070)	(0.0067)	(0.0160)
$Ret^{H}_{P_i,t-1}$	0.0066	-0.0509	-0.0970
	(0.0149)	(0.0635)	(0.0346)
$Ret_{i,t-1}$	-0.0214**	-0.0479***	-0.0505**
	(0.0090)	(0.0036)	(0.0111)
$MktRf_t$	1.0677***	1.0566***	1.0443***
	(0.0156)	(0.0147)	(0.0211)
SMB_t	0.6194***	0.6032***	0.6016***
	(0.0280)	(0.0234)	(0.0395)
HML_t	-0.0157	-0.0375	-0.0529
	(0.0339)	(0.0275)	(0.0504)
MOM_t	-0.1041***	-0.1242***	-0.1543***
	(0.0255)	(0.0215)	(0.0321)
$Analyst_{i,t-1}$	-0.0004	0.0015*	0.0012
	(0.0004)	(0.0009)	(0.0015)
$InstHldg_{i,t-1}$	0.0022	-0.0303	0.0181
	(0.0021)	(0.0716)	(0.0536)
$News_{i,t}$	0.0015***	0.0025***	0.0026**
	(0.0005)	(0.0005)	(0.0005)
$News_{i,t-1}$	-0.0011***	-0.0001	-0.0004
	(0.0004)	(0.0003)	(0.0006)
$CoNews^{L}_{P_i,t}$	0.0007	0.0062	0.0058
	(0.0018)	(0.0105)	(0.0128)
$CoNews^{L}_{P_i,t-1}$	-0.0004	-0.0604	-0.0419
	(0.0015)	(0.0811)	(0.0458)
$CoNews^{H}_{P_i,t}$	-0.0004	-0.0002	-0.0021
	(0.0011)	(0.0011)	(0.0008)
$CoNews^{H}_{P_i,t-1}$	-0.0002	-0.0101	-0.0042
	(0.0010)	(0.0081)	(0.0029)
Constant	-0.0012	0.0151	0.0283*
	(0.0019)	(0.0281)	(0.0174)
	Two Dimensional Clustering	Fama-MacBeth	Individual Regression
N	102,910	102,910	101,429
R^2	0.2545	0.1794	0.5318

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 4. Co-Viewing Analysis

Variables	$Pr\left(isLow_{i,P_i,t} = 1\right)$
$MktCap_{P_i,t-1}$	-0.5844***
	(0.0434)
$P2B_{P_i,t-1}$	0.1592*
	(0.0940)
$DiffMktCap_{i,P_i,t-1}$	0.1927***
	(0.0240)
$DiffP2B_{i,P_i,t-1}$	0.1102*
	(0.0576)
$SameSIC2_{i,P_i,t-1}$	-1.5326***
	(0.1202)
$isCoAnalyst_{i,P_i,t-1}$	-0.7734***
	(0.0816)
$isCoInst_{i,P_i,t-1}$	0.2315*
	(0.1379)
$News_{P_i,t-1}$	-0.6384***
	(0.0507)
$CoNews_{P_i,t-1}$	-0.2100***
	(0.0347)
Constant	7.2819***
	(0.6708)
N	1,256,275
MacFadden R^2	0.23

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 5. Additional Cross Prediction Results

Panel A. Size, Investment Style, and Dow Jones Partners

Variables	**(1)Big Partners**	**(2) Partners with Different Investment Style**	**(3) Dow Jones Partners**
$Ret^{L}_{P_i,t-1}$	0.0158**	0.0193***	0.0293**
	(0.0074)	(0.0058)	(0.0126)
$Ret^{H}_{P_i,t-1}$	0.0085	0.0104	-0.0149
	(0.0136)	(0.0133)	(0.0219)
$Ret^{O}_{P_i,t-1}$	0.0060	-0.0084	0.0015
	(0.0046)	(0.0136)	(0.0096)
$Ret_{i,t-1}$	-0.0214**	-0.0193**	-0.0195**
	(0.0091)	(0.0093)	(0.0097)
$MktRf_t$	1.0672***	1.0684***	1.0515***
	(0.0155)	(0.0154)	(0.0211)
SMB_t	0.6152***	0.6234***	0.6191***
	(0.0281)	(0.0278)	(0.0364)
HML_t	-0.0201	-0.0141	-0.0862*
	(0.0339)	(0.0331)	(0.0463)
MOM_t	-0.1015***	-0.1069***	-0.1497***
	(0.0257)	(0.0257)	(0.0377)
$Analyst_{i,t-1}$	-0.0003	-0.0003	0.0000
	(0.0004)	(0.0004)	(0.0000)
$InstHldg_{i,t-1}$	0.0023	0.0014	0.0013
	(0.0021)	(0.0021)	(0.0016)
$News_{i,t}$	0.0015***	0.0014***	0.0013**
	(0.0005)	(0.0004)	(0.0005)
$News_{i,t-1}$	-0.0011***	-0.0010**	-0.0010**
	(0.0004)	(0.0004)	(0.0005)
$CoNews^{L}_{P_i,t}$	0.0010	0.0011	0.0015
	(0.0017)	(0.0018)	(0.0013)
$CoNews^{L}_{P_i,t-1}$	-0.0007	-0.0009	-0.0018
	(0.0015)	(0.0015)	(0.0012)
$CoNews^{H}_{P_i,t}$	-0.0001	-0.0008	-0.0011
	(0.0010)	(0.0012)	(0.0011)
$CoNews^{H}_{P_i,t-1}$	-0.0004	0.0003	0.0016
	(0.0010)	(0.0011)	(0.0026)
$CoNews^{O}_{P_i,t}$	-0.0090*	-0.0017	0.0002
	(0.0048)	(0.0015)	(0.0011)
$CoNews^{O}_{P_i,t-1}$	0.0042	0.0012	-0.0009
	(0.0039)	(0.0014)	(0.0021)
Constant	-0.0014	-0.0009	-0.0014
	(0.0018)	(0.0018)	(0.0017)
N	102,053	98,797	55,092
R^2	0.2542	0.2545	0.2701

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Panel B. Analyst Co-followed, Institutional Co-ownership, and Industry Effect

Variables	**(1) Analyst Co-followed (CA)**	**(2) Institution Co-ownership (CA)**	**(3) Industry – SIC2 (CA)**	**(4) Industry – NAICS2 (CA)**
$Ret_{P_i,t-1}^{L,NA}$	0.0162**	0.0162**	0.0173**	0.0168**
	(0.0081)	(0.0079)	(0.0075)	(0.0081)
$Ret_{P_i,t-1}^{H,NA}$	0.0106	0.0004	-0.0021	0.0098
	(0.0131)	(0.0215)	(0.0139)	(0.0158)
$Ret_{P_i,t-1}^{L,CA}$	0.0021	0.0027	0.0149**	0.0163**
	(0.0096)	(0.0139)	(0.0076)	(0.0078)
$Ret_{P_i,t-1}^{H,CA}$	-0.0029	-0.0087	0.0082	0.0010
	(0.0172)	(0.0124)	(0.0152)	(0.0120)
$Ret_{i,t-1}$	-0.0211**	-0.0132	-0.0240**	-0.0242**
	(0.0092)	(0.0106)	(0.0096)	(0.0097)
$MktRf_t$	1.0677***	1.0363***	1.0645***	1.0646***
	(0.0159)	(0.0230)	(0.0159)	(0.0158)
SMB_t	0.6077***	0.3806***	0.6042***	0.6038***
	(0.0283)	(0.0342)	(0.0292)	(0.0291)
HML_t	-0.0232	-0.0933*	-0.0179	-0.0168
	(0.0343)	(0.0508)	(0.0345)	(0.0341)
MOM_t	-0.1010***	-0.1496***	-0.0969***	-0.0966***
	(0.0259)	(0.0367)	(0.0261)	(0.0260)
$Analyst_{i,t-1}$	-0.0003	0.0000	-0.0003	-0.0003
	(0.0004)	(0.0005)	(0.0004)	(0.0004)
$InstHldg_{i,t-1}$	0.0027	0.0024	0.0021	0.0021
	(0.0021)	(0.0027)	(0.0019)	(0.0019)
$News_{i,t}$	0.0016***	0.0022***	0.0016***	0.0015***
	(0.0004)	(0.0007)	(0.0005)	(0.0005)
$News_{i,t-1}$	-0.0011***	-0.0017***	-0.0011***	-0.0011***
	(0.0004)	(0.0006)	(0.0004)	(0.0004)
$CoNews_{P_i,t}^{L,NA}$	0.0011	0.0048**	-0.0010	0.0000
	(0.0018)	(0.0023)	(0.0019)	(0.0019)
$CoNews_{P_i,t-1}^{L,NA}$	-0.0013	-0.0035*	-0.0008	-0.0001
	(0.0015)	(0.0019)	(0.0014)	(0.0016)
$CoNews_{P_i,t}^{L,CA}$	0.0001	0.0010	-0.0003	-0.0004
	(0.0013)	(0.0024)	(0.0015)	(0.0014)
$CoNews_{P_i,t-1}^{L,CA}$	-0.0002	-0.0010	0.0009	0.0006
	(0.0011)	(0.0021)	(0.0014)	(0.0013)
$CoNews_{P_i,t}^{H,NA}$	-0.0017	-0.0032**	-0.0002	-0.0013
	(0.0016)	(0.0016)	(0.0012)	(0.0013)
$CoNews_{P_i,t-1}^{H,NA}$	0.0014	0.0021	-0.0005	0.0003
	(0.0014)	(0.0013)	(0.0009)	(0.0010)
$CoNews_{P_i,t}^{H,CA}$	-0.0005	0.0002	-0.0003	0.0009
	(0.0015)	(0.0012)	(0.0015)	(0.0014)
$CoNews_{P_i,t-1}^{H,CA}$	-0.0002	-0.0006	0.0002	-0.0012
	(0.0014)	(0.0012)	(0.0015)	(0.0014)
Constant	-0.0017	-0.0023	-0.0013	-0.0012
	(0.0018)	(0.0021)	(0.0017)	(0.0017)
N	100,052	47,442	100,189	100,189

R^2	0.2539	0.2374	0.2590	0.2590

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 6. Cross Predictability with Varying Co-Search Intensity of Partners

Panel A: Two-Dimensional Clustering

Variables	**(1) Change Freq > 0**	**(2) Change Freq ≥ 0.4**	**(3) Change Freq ≥ 0.6**	**(4) Analyst (CA) – Change Freq > 0**
$Ret^{L}_{P_i,t-1}$	0.0208**	0.0210*	0.0523***	
	(0.0097)	(0.0124)	(0.0199)	
$Ret^{H}_{P_i,t-1}$	0.0233	0.0057	0.0201	
	(0.0181)	(0.0312)	(0.0517)	
$Ret^{L,NA}_{P_i,t-1}$				0.0365***
				(0.0100)
$Ret^{H,NA}_{P_i,t-1}$				0.0113
				(0.0124)
$Ret^{L,CA}_{P_i,t-1}$				-0.0276**
				(0.0139)
$Ret^{H,CA}_{P_i,t-1}$				-0.0181
				(0.0176)
$Ret^{O}_{P_i,t-1}$	-0.0154	-0.0251**	-0.0071	0.0012
	(0.0103)	(0.0112)	(0.0171)	(0.0087)
$Ret_{i,t-1}$	-0.0225**	-0.0173	-0.0393**	-0.0249**
	(0.0089)	(0.0141)	(0.0196)	(0.0106)
$MktRf_t$	1.0594***	1.0150***	0.9360***	1.0665***
	(0.0257)	(0.0388)	(0.0336)	(0.0265)
SMB_t	0.4818***	0.2822***	-0.0255	0.4694***
	(0.0496)	(0.0691)	(0.0683)	(0.0508)
HML_t	-0.1575**	-0.2959***	-0.3204***	-0.1577**
	(0.0627)	(0.0988)	(0.0864)	(0.0668)
MOM_t	-0.1739***	-0.2910***	-0.2185***	-0.1682***
	(0.0470)	(0.0687)	(0.0771)	(0.0468)
$Analyst_{i,t-1}$	-0.0003	-0.0001	0.0003	-0.0002
	(0.0004)	(0.0005)	(0.0005)	(0.0004)
$InstHldg_{i,t-1}$	0.0026	-0.0010	0.0026	0.0031
	(0.0019)	(0.0031)	(0.0038)	(0.0019)
$News_{i,t}$	0.0016***	0.0014*	0.0006	0.0017***
	(0.0005)	(0.0008)	(0.0011)	(0.0006)
$News_{i,t-1}$	-0.0011**	-0.0012	0.0001	-0.0012**
	(0.0005)	(0.0007)	(0.0011)	(0.0005)
$CoNews^{L}_{P_i,t}$	0.0025	-0.0006	0.0014	
	(0.0019)	(0.0022)	(0.0022)	
$CoNews^{L}_{P_i,t-1}$	-0.0018	0.0009	-0.0016	
	(0.0019)	(0.0022)	(0.0019)	

$CoNews^{H}_{P_i,t}$	-0.0004 (0.0012)	0.0001 (0.0014)	0.0001 (0.0011)	
$CoNews^{H}_{P_i,t-1}$	-0.0004 (0.0011)	-0.0008 (0.0015)	-0.0008 (0.0012)	
$CoNews^{L,NA}_{P_i,t}$				0.0020 (0.0016)
$CoNews^{L,NA}_{P_i,t-1}$				-0.0013 (0.0016)
$CoNews^{H,NA}_{P_i,t}$				0.0001 (0.0012)
$CoNews^{H,NA}_{P_i,t-1}$				-0.0001 (0.0010)
$CoNews^{L,CA}_{P_i,t}$				0.0010 (0.0017)
$CoNews^{L,CA}_{P_i,t-1}$				-0.0018 (0.0014)
$CoNews^{H,CA}_{P_i,t}$				-0.0002 (0.0019)
$CoNews^{H,CA}_{P_i,t-1}$				-0.0011 (0.0019)
$CoNews^{O}_{P_i,t}$	-0.0008 (0.0020)	-0.0023 (0.0015)	-0.0031** (0.0015)	-0.0017 (0.0019)
$CoNews^{O}_{P_i,t-1}$	0.0009 (0.0017)	0.0023* (0.0013)	0.0021 (0.0014)	0.0017 (0.0016)
Constant	-0.0016 (0.0015)	0.0009 (0.0016)	-0.0032*** (0.0011)	-0.0021 (0.0015)
N	53,176	17,284	5,634	46,561
R^2	0.2791	0.2989	0.3135	0.2833
Firms	823	267	87	723
Weeks	66	66	66	66

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Panel B: Individual Regressions

Variables	**(1) Change Freq > 0**	**(2) Change Freq ≥ 0.4**	**(3) Change Freq ≥ 0.6**	**(4) Analyst (CA) – Change Freq > 0**
$Ret^{L}_{P_i,t-1}$	0.0295*** (0.0034)	0.0429** (0.0176)	0.0594** (0.0180)	
$Ret^{H}_{P_i,t-1}$	0.0045 (0.0093)	0.0091 (0.0092)	0.0018 (0.0156)	
$Ret^{L,NA}_{P_i,t-1}$				0.0295** (0.0116)
$Ret^{H,NA}_{P_i,t-1}$				-0.0070 (0.0104)
$Ret^{L,CA}_{P_i,t-1}$				-0.0062 (0.0040)
$Ret^{H,CA}_{P_i,t-1}$				-0.0088* (0.0047)
$Ret^{O}_{P_i,t-1}$	-0.0025	-0.0065	-0.0071	0.0226**

	(0.0040)	(0.0076)	(0.0090)	(0.0115)
$Ret_{i,t-1}$	-0.0547 (0.0491	-0.0594 (0.0144)	-0.0673 (0.0140)	-0.0620 (0.0412)
$MktRf_t$	1.0532*** (0.0231)	1.0141*** (0.0475)	0.9186*** (0.0206)	1.0634*** (0.3628)
SMB_t	0.4741*** (0.0501)	0.2684*** (0.0863)	-0.0420 (0.0384)	0.4755*** (0.1124)
HML_t	-0.1757 (0.1001)	-0.3001 (0.1050)	-0.3167 (0.0509)	-0.1586 (0.1073)
MOM_t	-0.1752 (0.0981)	-0.2769 (0.0677)	-0.2250 (0.0306)	-0.1690 (0.1034)
$Analyst_{i,t-1}$	0.0015 (0.0090)	0.0003 (0.0007)	0.0016* (0.0007)	0.0012 (0.0020)
$InstHldg_{i,t-1}$	-0.0234 (0.0035)	0.3352 (1361.9794)	-0.0504 (0.0674)	0.2041 (0.1500)
$News_{i,t}$	0.0027*** (0.0011)	0.0012** (0.0009)	0.0007 (0.0012)	0.0024*** (0.0011)
$News_{i,t-1}$	0.0001 (0.0012)	0.0009** (0.0007)	0.0020* (0.0009)	0.0002 (0.0004)
$CoNews^{L}_{P_i,t}$	0.0000 (0.0008)	0.0003 (0.0015)	-0.0005 (0.0019)	
$CoNews^{L}_{P_i,t-1}$	0.0032 (0.0010)	0.0012 (0.0007)	0.0025 (0.0017)	
$CoNews^{H}_{P_i,t}$	0.0012 (0.0006)	0.0021 (0.0018)	-0.0024 (0.0023)	
$CoNews^{H}_{P_i,t-1}$	0.0004 (0.0020)	-0.0018 (0.0022)	0.0001 (0.0024)	
$CoNews^{L,NA}_{P_i,t}$				-0.0018 (0.0009)
$CoNews^{L,NA}_{P_i,t-1}$				0.0002 (0.0003)
$CoNews^{H,NA}_{P_i,t}$				0.0004 (0.0011)
$CoNews^{H,NA}_{P_i,t-1}$				0.0000 (0.0002)
$CoNews^{L,CA}_{P_i,t}$				0.0019** (0.0006)
$CoNews^{L,CA}_{P_i,t-1}$				0.0000 (0.0002)
$CoNews^{H,CA}_{P_i,t}$				-0.0012 (0.0007)
$CoNews^{H,CA}_{P_i,t-1}$				-0.0001 (0.0002)
$CoNews^{O}_{P_i,t}$	-0.0094 (0.0113)	-0.0044 (0.0056)	-0.0018 (0.0048)	-0.0110 (0.0131)
$CoNews^{O}_{P_i,t-1}$	0.0261 (0.0102)	0.0052 (0.0110)	-0.0081 (0.0139)	0.0257 (0.0126)
N	53,176	17,284	5,634	46,561
Avg. R^2	0.5356	0.5604	0.5692	0.5517

Firms	823	267	87	723
Weeks	66	66	66	66
$Ret^{L}_{P_i,t-1} - Ret^{H}_{P_i,t-1}$	0.0251** (0.0099)	0.0338** (0.0199)	0.0576** (0.0238)	
$Ret^{L,NA}_{P_i,t-1} - Ret^{H,NA}_{P_i,t-1}$				0.0365** (0.0156)

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 7 Buy-Sell Asymmetry

Variables	Two Dimensional Clustering (NA: Positive Parner Returns; CA: Negative Partner Returns)	Individual Regression (NA: Positive Parner Returns; CA: Negative Partner Returns)
$Ret^{L,NA}_{P_i,t-1}$	0.0216 ** (0.0108)	0.0390*** (0.0146)
$Ret^{H,NA}_{P_i,t-1}$	0.0096 (0.0098)	0.0166 (0.0161)
$Ret^{L,CA}_{P_i,t-1}$	0.0064 (0.0206)	0.0066* (0.0049)
$Ret^{H,CA}_{P_i,t-1}$	0.0145 (0.0211)	0.0077 (0.0048)
$Ret_{i,t-1}$	-0.0216** (0.0088)	-0.0525*** (0.0111)
$MktRf_t$	1.0650*** (0.0159)	1.0625*** (0.0259)
SMB_t	0.6114*** (0.0285)	0.6059*** (0.0465)
HML_t	-0.0219 (0.0338)	-0.0310 (0.0574)
MOM_t	-0.1029*** (0.0259)	-0.1074*** (0.0368)
$Analyst_{i,t-1}$	-0.0001* (0.0000)	-0.0010 (0.0001)
$InstHldg_{i,t-1}$	0.0017 (0.0013)	-0.0775 (0.0289)
$News_{i,t}$	0.0015*** (0.0005)	0.0021*** (0.0003)
$News_{i,t-1}$	-0.0010** (0.0004)	-0.0001 (0.0002)
$CoNews^{L,NA}_{P_i,t}$	0.0008 (0.0020)	-0.0115 (0.0087)
$CoNews^{L,NA}_{P_i,t-1}$	-0.0003	-0.0028

	(0.0018)	(0.0048)
$CoNews^{L,CA}_{P_i,t}$	-0.0002	0.0075
	(0.0018)	(0.0025)
$CoNews^{L,CA}_{P_i,t-1}$	0.0001	0.0001
	(0.0016)	(0.0014)
$CoNews^{H,NA}_{P_i,t}$	-0.0007	0.0006*
	(0.0011)	(0.0002)
$CoNews^{H,NA}_{P_i,t-1}$	0.0001	0.0000
	(0.0016)	(0.0002)
$CoNews^{H,CA}_{P_i,t}$	0.0004	-0.0004*
	(0.0010)	(0.0002)
$CoNews^{H,CA}_{P_i,t-1}$	0.0003	0.0002
	(0.0024)	(0.0001)
Avg. R^2	0.2572	0.5318
N	101,855	101,855
Week	66	66
$Ret^{L,NA}_{P_i,t-1} - Ret^{H,NA}_{P_i,t-1}$		0.0224**
Block bootstrap p-value of diff		(0.0420)

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 8 Reversion Results

Variables	(1) DV = $Ret_{i,s}$ s=t+1	(2) DV = $Ret_{i,s}$ s=t+3	(3) DV = $Ret_{i,s}$ s=t+5	(4) DV = $Ret_{i,s}$ S=t+7
$Ret^{L}_{P_i,t-1}$	0.0060	+0.0000	-0.0040	-0.0093**
	(0.0065)	(0.0063)	(0.0060)	(0.0046)
$Ret^{H}_{P_i,t-1}$	-0.0118	0.0022	-0.0072	0.0034
	(0.0160)	(0.0156)	(0.0179)	(0.0128)
$Ret_{i,s-1}$	-0.0209**	-0.0207**	-0.0182**	-0.0188**
	(0.0085)	(0.0085)	(0.0086)	(0.0090)
$MktRf_s$	1.0571***	1.0477***	1.0509***	1.0529***
	(0.0146)	(0.0138)	(0.0139)	(0.0138)
SMB_s	0.6240***	0.6225***	0.6152***	0.6064***
	(0.0292)	(0.0282)	(0.0280)	(0.0266)
HML_s	-0.0008	0.0144	0.0099	0.0248
	(0.0324)	(0.0324)	(0.0352)	(0.0316)
MOM_s	-0.1169***	-0.1225***	-0.1131***	-0.1237***
	(0.0260)	(0.0252)	(0.0259)	(0.0256)
$Analyst_{i,s-1}$	-0.0004	-0.0004	-0.0005	-0.0006
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
$InstHldg_{i,s-1}$	0.0014	0.0011	0.0008	0.0011
	(0.0022)	(0.0021)	(0.0022)	(0.0021)
$News_{i,s}$	0.0008***	0.0008***	0.0008***	0.0008***

	(0.0003)	(0.0002)	(0.0002)	(0.0002)
$News_{i,s-1}$	-0.0006*	-0.0004*	-0.0004*	-0.0004**
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
$CoNews^{L}_{P_i,t}$	0.0006	-0.0007	0.0005	-0.0006
	(0.0009)	(0.0009)	(0.0006)	(0.0008)
$CoNews^{L}_{P_i,t-1}$	-0.0007	-0.0001	-0.0008	0.0007
	(0.0011)	(0.0008)	(0.0009)	(0.0008)
$CoNews^{H}_{P_i,t}$	0.0006	0.0001	0.0008	-0.0009
	(0.0008)	(0.0007)	(0.0008)	(0.0008)
$CoNews^{H}_{P_i,t-1}$	-0.0012*	-0.0004	-0.0015*	0.0004
	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Constant	0.0004	-0.0001	0.0001	0.0001
	(0.0018)	(0.0017)	(0.0017)	(0.0017)
N	102,714	102,522	102,327	102,127
R^2	0.2630	0.2435	0.2343	0.2379

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 9. Impact of Yahoo on Cross-Predictability

Variables	Lagged Partner Returns	Current Partner Returns
$Ret^{L}_{P_i,t-1}$	0.1125**	
	(0.0449)	
$Ret^{H}_{P_i,t-1}$	0.0451	
	(0.0377)	
$Ret^{L}_{P_i,t}$		0.1467**
		(0.0569)
$Ret^{H}_{P_i,t}$		0.2341**
		(0.1067)
$Post_t$	-0.0014	-0.0027
	(0.0029)	(0.0025)
$Post_t \times Ret^{H}_{P_i,t-1}$	0.1745	
	(0.1135)	
$Post_t \times Ret^{H}_{P_i,t}$		0.0673
		(0.1247)
$Ret_{i,t-1}$	0.0026	0.0033
	(0.0189)	(0.0190)
$MktRf_t$	0.1922	0.1908
	(0.2823)	(0.2266)
SMB_t	-0.0348	-0.0120
	(0.1337)	(0.1330)
HML_t	-0.2125	-0.3036
	(0.2504)	(0.2126)
MOM_t	-0.3620***	-0.3701***
	(0.0819)	(0.0748)
$Analyst_{i,t-1}$	0.0001	0.0000
	(0.0006)	(0.0006)
$InstHldg_{i,t-1}$	-0.2171	-0.1858
	(0.1354)	(0.1532)

$News_{i,t}$	-0.0003 (0.0004)	0.0001 (0.0003)
$News_{i,t-1}$	0.0001 (0.0003)	-0.0001 (0.0003)
$CoNews^{L}_{P_i,t}$	0.0017*** (0.0005)	0.0021*** (0.0005)
$CoNews^{L}_{P_i,t-1}$	-0.0007 (0.0007)	-0.0012* (0.0007)
$CoNews^{H}_{P_i,t}$	-0.0004 (0.0014)	-0.0012 (0.0015)
$CoNews^{H}_{P_i,t-1}$	0.0001 (0.0010)	0.0008 (0.0010)
Constant	0.0039* (0.0022)	0.0038** (0.0019)
N	9,116	9,116
R^2	0.0634	0.0792

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 10 Trading Strategy

Panel A: Weekly Excess Returns on Value-Weighted Portfolios of Firms associated with Low Co-search Intensity Partners

Strategies	Low (1)	(2)	(3)	(4)	High (5)	High - Low
Mean	0.0056	0.0079	0.0068	0.0084	0.0091	0.0035
SD	0.0160	0.0174	0.0170	0.0147	0.0149	0.0098
Sharpe Ratio	0.3499	0.4531	0.3997	0.5677	0.6113	0.3600
4-Factor Alpha (Standard Error)	-0.0004 (0.0011)	0.0006 (0.0009)	-0.0001 (0.0009)	0.0024*** (0.0008)	0.0032*** (0.0009)	0.0036** (0.0015)

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Panel B: Weekly Excess Returns on Value-Weighted Portfolios of Firms associated with High Co-search Intensity Partners

Strategies	Low (1)	(2)	(3)	(4)	High (5)	High - Low
Mean	0.0066	0.0056	0.0065	0.0064	0.0064	-0.0001
SD	0.0160	0.0148	0.0162	0.0145	0.0139	0.0084
Sharpe Ratio	0.4109	0.3814	0.4028	0.4404	0.4638	-0.0162
4-Factor Alpha (Standard Error)	0.0002 (0.0010)	0.0000 (0.0009)	0.0002 (0.0008)	0.0010 (0.0008)	0.0009 (0.0008)	0.0007 (0.0012)

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Panel C: Weekly Excess Returns on Value-Weighted Portfolios of Firms associated with All Partners

Strategies	Low (1)	(2)	(3)	(4)	High (5)	High - Low
Mean	0.0057	0.0073	0.0066	0.0071	0.0078	0.0021
SD	0.0149	0.0156	0.0162	0.0146	0.0141	0.0079

Sharpe Ratio	0.3843	0.4682	0.4056	0.4875	0.5530	0.2640
4-factor Alpha	0.0000	0.0007	-0.0002	0.0013*	0.0021***	0.0021* (0.0011)
(Standard Error)	(0.0008)	(0.0007)	(0.0006)	(0.0008)	(0.0006)	

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Appendix A

Control Variables for the Main Model

Variable	Definition	Description
$MktRf_t$	Market return in period *t*	Value weighted return of all CRSP (Center for Research in Security Prices) firms incorporated in the US less one-month Treasury bill rate
SMB_t	Fama-French size risk factor in period *t*	We obtain factor returns from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
HML_t	Fama-French value risk factor in period *t*	
MOM_t	Carhart momentum risk factor in period *t*	
$Analyst_{i,t-1}$	Log(1 + the number of analysts following the stock *i* in period *t*)	We obtain the analyst coverage information from the I/B/E/S database. We follow Menzly and Ozabas (2010) to compute the number of analysts following. We assume that an analyst follows a stock in the same month when he/she releases an earnings per share forecast.
$InstHldg_{i,t-1}$	Log(1 + percentage of institutional holding for stock *i* in period *t*)	We follow Menzly and Ozabas (2010) to compute the percentage of institutional holding. The percentage of institutional holding, which is calculated as the percentage of outstanding shares owned by institutions, is available on a quarterly basis. We assume that it does not change within a quarter and is applicable for all weeks within a quarter. We obtain the institutional holding data from Thomson Financial's 13F Holdings database.
$News_{i,t}$	Log(1+ total number of news articles related to stock *i* in period *t*)	We control for news of focal firms by including news in the current week $News_{i,t}$ and news in previous week, $News_{i,t-1}$. We calculate news volume as log (1+ total number of news articles related to the focal firms). Da et al. (2011) uses similar approach in their calculation of news volume.
$CoNews^L_{P_i,t}$	Log(1+supply-chain strength weighted average number of news articles that contain both stock *i* and low attention supply-chain partners of stock *i* in period *t*)	We obtain news volume and co-mention news volume from all sources of news available in Factiva news database. We count the number of articles in the Factiva database associated with co-mentions of focal stock and each partner. We search individual stock on Factiva in each time period and download the list of top most mentioned companies on Factiva. The top most mentioned companies are companies that are also mentioned with the focal stock appearing in the news database. Apart from the name of companies that are co-mentioned with the focal stock,
$CoNews^H_{P_i,t}$	Log(1+supply-chain strength weighted average number of news articles that contain both stock *i* and high attention supply-chain partners of stock *i* in period *t*)	the number of news articles that mention both companies are also shown. We use this information for the calculation of news co-mention volume. We weigh the number of co-mentions for each pair with the supply chain strength. $CoNews_{P_i,t}$ is log[1 + $(CoNews_{BP_i,t} + CoNews_{SP_i,t})/2$]. If a focal firm has only one type of partners, then we either use $\log(1 + CoNews_{BP_i,t})$ or $\log(1 + CoNews_{SP_i,t})$, where $CoNews_{BP_i,t} = \sum_{j \in B_i} Dep_{ij} \times News_{i,j,t} \big/ \sum_{j \in B_i} Dep_{ij}$ and $CoNews_{SP_i,t} = \sum_{j \in S_i} Exp_{ij} \times News_{i,j,t} \big/ \sum_{j \in S_i} Exp_{ij}$. $News_{i,j,t}$ is the total

number of news articles with both companies i and j at time t.

Appendix B

Calculation of Supply Chain Strength (SC) Weighted Returns

We define dependency as the trading amount between a focal firm and a buyer divided by the total revenue of the focal firm and exposure as the trading amount between the focal firm and a supplier divided by the total cost of goods sold of the focal firm. The tables below show the returns of NPSP's customers and suppliers in the week ending 9/30/2011 and their corresponding dependency and exposure.

US-listed Customer	Return of Customer (in %)	Trading Amount between AWI and Customer (in million US$)	Revenue of AWI (in million US$)	Dependency (in %)
HD	-2.52	60.4	715	8.45
LOW	-2.02	46.8	715	6.55

US-listed Supplier	Return of Supplier	Trading Amount between AWI and Buyer	Cost of Goods Sold of AWI (in million US $)	Exposure (in %)
OMN	12.58	3.17	547	0.58
PPG	2.67	0.54	547	0.10

SC weighted partner returns of NPSP in the week ending 9/30/2011 is calculated as

$$\left(\frac{-2.52\% \times 8.45\% - 2.02\% \times 6.55\%}{8.45\% + 6.55\%} + \frac{12.58\% \times 0.58\% - 2.67\% \times 0.10\%}{0.58\% + 0.10\%}\right)\Big/_{2} = 4.4\%$$

Appendix C

Computation of Standard Error of Average Beta

As a robustness test, we regress the return of each individual focal stock on the lagged returns of its supply-chain partners by running Equation (1) separately. Then we obtain average betas ($\bar{\beta}$) for each individual focal stocks. As the stocks may overlap in the same time period, we have to take into consideration the cross-sectional dependence. To address this issue, we compute the standard error of average beta $\bar{\beta}$, as the square root of following equation. This approach has been adopted by Boyer (2011).

$$Var(\bar{\beta}) = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} Cov(\beta_i, \beta_j)$$

where

n is number of stocks;

Cov(β_i, β_j) is the covariance of beta obtained from stock *i* and that from stock *j*.

Assuming that the residuals of each regression are i.i.d. across time but correlated cross-sectionally, we can estimate the variance covariance matrix across regressions as below:

$$\widehat{\Sigma_{ij}} = \left(X_i^{'} X_i\right)^{-1} X_i^{'} \left(\frac{\hat{\epsilon}_i^{'} \hat{\epsilon}_j}{T}\right) \Omega_{ij} X_j \left(X_j^{'} X_j\right)^{-1}$$

where

X_i is the matrix of independent variables of stock *I;*

$\hat{\epsilon}_i$ is the residual of regression of stock *I;*

T is the number of days used in the regression;

Ω_{ij} is a matrix where element (*a*, *b*) equal to 1 if the a^{th} row of X_i and the b^{th} row of X_j are observed on the same date and 0 otherwise;

Cov(β_i,β_j) where i $\neq$ j is an element of the diagonal matrix of $\widehat{\Sigma_\iota}$.

Appendix D

Block Bootstrapping Approach in Computing *p*-Value

Consider following regression model in Equation (1):

$$Ret_{i,t} = \beta_0 + \beta_1 Ret^L_{P_i,t-1} + \beta_2 Ret^H_{P_i,t-1} + \beta_3 Ret_{i,t-1} + \beta_4 MktRf_t + \beta_5 SMB_t + \beta_6 HML_t + \beta_7 MOM_t$$
$$+ \beta_8 Analyst_{i,t-1} + \beta_9 InstHldg_{i,t-1} + \beta_{10} News_{i,t} + \beta_{11} News_{i,t-1} + \beta_{12} CoNews^L_{P_i,t}$$
$$+ \beta_{13} CoNews^L_{P_i,t-1} + \beta_{14} CoNews^H_{P_i,t} + \beta_{15} CoNews^H_{P_i,t-1} + \varepsilon_{i,t}$$

The abbreviated equation as follows:

$$Y_{i,t} = \beta X_{i,t-1} + \varepsilon_{it}$$

where Y is the dependent variable $Ret_{i,t}$, X is a vector of independent variables, β is a vector of coefficients, ε is a disturbance term, i = 1, 2, …, N is panel variable, and t = 1, 2, …, T is time variable.

To address the temporal and cross-sectional dependence issues in OLS regression, we adopt a block bootstrap approach.

First, we organize the panel data into overlapping blocks with a temporal block size of L. We follow the approach of Politis and White (2004) and Patton et al. (2009) to find the optimal block size. Patton shares the MatLab code on his website (http://public.econ.duke.edu/~ap172/code.html) and we use the program to find the optimal block size.

Block 1 contains following data:

{x_{it}, y_{it}} where i = 1, 2, …, N and t = 1, 2, …, L;

Block 2 contains following data:

{x_{it}, y_{it}} where i = 1, 2, …, N and t = 2, 3, …, L+1;

Block T-L+1 contains following data:

$\{x_{it}, y_{it}\}$ where $i = 1, 2, \ldots,$ N and $t = T\text{-}L+1, T\text{-}L+2, \ldots, T$.

Second, we draw randomly from the above blocks $K = T/L$ times with replacement and form a bootstrap sample.

Third, we run an OLS regression using the bootstrap sample and determine the coefficient estimate $\hat{\beta}^1$.

Fourth, we repeat the sampling and regression estimation procedures in steps two and three 1,000 times to obtain 1,000 bootstrap sample estimates $\{\hat{\beta}^1, \hat{\beta}^2, \ldots, \hat{\beta}^{1,000}\}$.

Finally, we determine the p-value by computing the proportion of bootstrap sample estimates $\hat{\beta}^j < 0$, where $j = 1, 2, \ldots, 1{,}000$ if the coefficient of estimated coefficient (β) is positive. If β is negative, we compute the p-value by finding the proportion of bootstrap sample estimates $\hat{\beta}^j > 0$.

Appendix E

Davidson and MacKinnon (1981)'s non-nested J test

J-test is a model specification test on linear models. The null hypothesis is that a competing model does not provide any additional value. The results may provide some guidance on model selection. The main steps of the test adapted to our research context are summarized as below.

There are two competing models (i) and (ii), which are adapted from model (5) where (i) is model (5) without $Ret^{H}_{P_i,t-1}$ and (ii) is model (5) without without $Ret^{L}_{P_i,t-1}$. First we estimate regression model (i), which is model (5) without $Ret^{H}_{P_i,t-1}$ and obtain a predicted value of $\widehat{Ret^{L}_{\iota,t}}$. Second, we estimate regression model (ii), which is model (5) without $Ret^{L}_{P_i,t-1}$ and obtain a predicted value of $\widehat{Ret^{H}_{\iota,t}}$. Third, we plug in $\widehat{Ret^{H}_{\iota,t}}$ to (i) and re-estimate the regression model as (iii). Fourth, we plug in $\widehat{Ret^{L}_{\iota,t}}$ to (ii) and re-estimate the regression model as (iv).

$$Ret_{i,t} = \beta_0 + \beta_1 Ret^{L}_{P_i,t-1} + \beta_2 Ret^{O}_{P_i,t-1} + \beta_3 Ret_{i,t-1} + \beta_4 MktRf_t + \beta_5 SMB_t + \beta_6 HML_t + \beta_7 MOM_t + \beta_8 Analyst_{i,t-1} + \beta_9 InstHldg_{i,t-1} + \beta_{10} News_{i,t} + \beta_{11} News_{i,t-1} + \beta_{12} CoNews^{L}_{P_i,t} + \beta_{13} CoNews^{L}_{P_i,t-1} + \beta_{14} CoNews^{H}_{P_i,t} + \beta_{15} CoNews^{H}_{P_i,t-1} + \beta_{16} CoNews^{O}_{P_i,t-1} + \beta_{17} CoNews^{O}_{P_i,t-1} + \varepsilon_{i,t} \quad \text{(i)}$$

$$Ret_{i,t} = \beta_0 + \beta_1 Ret^{H}_{P_i,t-1} + \beta_2 Ret^{O}_{P_i,t-1} + \beta_3 Ret_{i,t-1} + \beta_4 MktRf_t + \beta_5 SMB_t + \beta_6 HML_t + \beta_7 MOM_t + \beta_8 Analyst_{i,t-1} + \beta_9 InstHldg_{i,t-1} + \beta_{10} News_{i,t} + \beta_{11} News_{i,t-1} + \beta_{12} CoNews^{L}_{P_i,t} + \beta_{13} CoNews^{L}_{P_i,t-1} + \beta_{14} CoNews^{H}_{P_i,t} + \beta_{15} CoNews^{H}_{P_i,t-1} + \beta_{16} CoNews^{O}_{P_i,t-1} + \beta_{17} CoNews^{O}_{P_i,t-1} + \varepsilon_{i,t} \quad \text{(ii)}$$

$$Ret_{i,t} = \beta_0 + \beta_1 \widehat{Ret^{H}_{\iota,t}} + \beta_2 Ret^{L}_{P_i,t-1} + \beta_3 Ret^{O}_{P_i,t-1} + \beta_4 Ret_{i,t-1} + \beta_5 MktRf_t + \beta_6 SMB_t + \beta_7 HML_t + \beta_8 MOM_t + \beta_9 Analyst_{i,t-1} + \beta_{10} InstHldg_{i,t-1} + \beta_{11} News_{i,t} + \beta_{12} News_{i,t-1} + \beta_{13} CoNews^{L}_{P_i,t} +$$

$$\beta_{14} CoNews^{L}_{P_i,t-1} + \beta_{15} CoNews^{H}_{P_i,t} + \beta_{16} CoNews^{H}_{P_i,t-1} + \beta_{17} CoNews^{O}_{P_i,t-1} + \beta_{18} CoNews^{O}_{P_i,t-1} + \varepsilon_{i,t}$$

(iii)

$$Ret_{i,t} = \beta_0 + \beta_1 \widehat{Ret^{L}_{\iota,t}} + \beta_2 Ret^{H}_{P_i,t-1} + \beta_3 Ret^{O}_{P_i,t-1} + \beta_4 Ret_{i,t-1} + \beta_5 MktRf_t + \beta_6 SMB_t + \beta_7 HML_t + \beta_8 MOM_t + \beta_9 Analyst_{i,t-1} + \beta_{10} InstHldg_{i,t-1} + \beta_{11} News_{i,t} + \beta_{12} News_{i,t-1} + \beta_{13} CoNews^{L}_{P_i,t} + \beta_{14} CoNews^{L}_{P_i,t-1} + \beta_{15} CoNews^{H}_{P_i,t} + \beta_{16} CoNews^{H}_{P_i,t-1} + \beta_{17} CoNews^{O}_{P_i,t-1} + \beta_{18} CoNews^{O}_{P_i,t-1} + \varepsilon_{i,t}$$

(iv)

There are different scenarios associated with the significance of estimates of $\widehat{Ret^{H}_{\iota,t}}$ and $\widehat{Ret^{L}_{\iota,t}}$ in (iii) and (iv), respectively. If the t-statistic associated with $\widehat{Ret^{H}_{\iota,t}}$ is significant (not significant), we reject (fail to reject) the null hypothesis that model (i) provide any additional value. If the t-statistic associated with $\widehat{Ret^{H}_{\iota,t}}$ is significant (not significant), we reject (fail to reject) the null hypothesis that model (ii) does not add value. As models (i) and (ii) differ in terms of the presence of $Ret^{L}_{P_i,t-1}$ and $Ret^{H}_{P_i,t-1}$, the J-test results may provide insights to whether a variable is more important in improving predictability.

We conduct J-test to our models in Table 6 columns 1-4. We find that $\widehat{Ret^{H}_{\iota,t}}$ in (iii) is not significant with a t-statistics (p-value) of 1.29 (0.20), 0.18 (0.85), and 0.39 (0.70) that correspond to columns 1-3 respectively. In contrast, $\widehat{Ret^{L}_{\iota,t}}$ in (iv) is significant with a t-statistics (p-value) of 2.14 (0.03), 1.69 (0.09), 2.63 (0.01) that correspond to columns 1-3 respectively. Again for column 4, we find that only $\widehat{Ret^{L,NA}_{\iota,t}}$ is positive and significant with a t-statistics (p-value) of 3.66 (0.00). $\widehat{Ret^{H,NA}_{\iota,t}}$, $\widehat{Ret^{H,CA}_{\iota,t}}$ and $\widehat{Ret^{L,CA}_{\iota,t}}$ coefficients have test statistics values of 0.91 (0.36), 1.03 (0.30) and 1.99 (0.05). Thus, our J-test results suggest that the low attention partner group add more value to the prediction model than does the high attention partner group.

Appendix F

Trading Strategies Based on BEA Partner Definition

Instead of using Bloomberg's definition, we use BEA's definition of customer and supplier and re-run our weekly trading strategy based on all supply chain partners. This approach is similar to that of Menzly and Ozbas (2010). We use the most recent BEA survey results in 2007 to identify supplier and customer industries of a focal firm using NAICS. Any US-listed firms that belong to the supplier and customer industries are considered to be supply-chain partners of the focal firm. In our trading strategy, we first sort all focal firms into quintiles based on SC weighted lagged returns of the partners. The weight of supplier is defined as the share of total purchase of focal firm's industry from other industries whereas the weight of customer is defined as the share of total sales of focal firm's industry to other industries (Menzly and Ozbas 2010). Then in the beginning of a week, we buy focal stocks whose partners have the most positive returns in previous week (or month) (i.e. Q5) and sell focal stocks whose partners have the most negative returns in previous week (or month) (i.e. Q1).

Table F1 shows the average weekly return of portfolios of stocks in individual quintiles where stocks were sorted based on the lagged weekly returns of the partners. Table F2 shows the average weekly return of portfolios of stocks in individual quintiles where stocks were sorted based on the lagged monthly returns of the partners. Note that the second approach (i.e. sorting based on lagged monthly returns) is used by Menzly and Ozbas (2010). As shown in the tables, we do not see any significant results in the column of "High - Low" (H-L). Plausible explanation is that the BEA data is less precise. BEA data relate a focal firm to its partners using NAICS codes. Thus, partners are classified at the industry level and not at the firm level. As a consequence, the impact on the stock return is based on the information related to partner industries not specific partners and may be diffusing very slowly to have a lagged weekly reaction

(Menzly and Ozbas (2010) use a monthly trading strategy). Bloomberg data, on the other hand, provide firm level partner information.

Table F1: Weekly Excess Returns on Value-Weighted Portfolios of Firms associated with BEA partner industries (based on previous weekly returns)

Strategies	Low (1)	(2)	(3)	(4)	High (5)	High - Low
Mean	0.0075	0.0076	0.0070	0.0064	0.0055	-0.0020
SD	0.0161	0.0132	0.0146	0.0158	0.0148	0.0082
Sharpe Ratio	0.4685	0.5732	0.4804	0.4062	0.3735	-0.2441
4-factor Alpha	0.0010	0.0022***	0.0012	-0.0003	-0.0004	-0.0013
(Standard Error)	(0.0008)	(0.0005)	(0.0008)	(0.0007)	(0.0008)	(0.0012)

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table F2: Weekly Excess Returns on Value-Weighted Portfolios of Firms associated with BEA partner industries (based on previous monthly returns)

Strategies	Low (1)	(2)	(3)	(4)	High (5)	High - Low
Mean	0.0069	0.0072	0.0074	0.0065	0.0066	-0.0003
SD	0.0160	0.0152	0.0150	0.0149	0.0144	0.0099
Sharpe Ratio	0.4340	0.4707	0.4912	0.4378	0.4583	-0.0327
4-factor Alpha	0.0007	0.0012	0.0012*	0.0005	0.0008	0.0001
(Standard Error)	(0.0008)	(0.0008)	(0.0006)	(0.0008)	(0.0009)	(0.0014)

*** Significant at 1%, ** Significant at 5%, * Significant at 10%