Mining the Value of Network Structure on Stock Performance

Completed Research

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Abstract

We propose a novel Fintech application which models investors’ co-attention to diversified stocks as networks by utilizing visitors’ online correlated searches for a set of stocks. We adopt a sliding-window procedure to capture the dynamics of the co-search networks and develop panel-data models to examine the impact of the network structure on individual stock performance. By arguing the heterogeneous information flows transmitting through the network matter for an ego’s future performance, we explicitly divide the alters of an ego stock into two distinct groups based on their historical return trends. Our empirical results suggest an increase of network centrality and closure among historical winners can positively contribute to an ego’s future return whereas that among historical losers can exert significant and negative impact. We also find a higher level of centrality is associated with a lower level of future volatility.

Keywords

Co-search, network structure, centrality, closure, stock performance, return, volatility.

Introduction

Under the rapid growth of digital revolution in financial sector, topics related to “Fintech” (i.e. Financial Technology) are becoming increasingly popular in both academia and industry. As “a marriage of financial services and information technology” (Arner et al. 2015), a lot of practice has been devoted to Fintech applications that concentrate on technology-enabled financial solutions. One of the promising applications is to apply social network analysis (SNA) to derive a network representation of financial markets. The network structure could model the relational or structural embeddedness among financial instruments and act as channels for information dissemination. Analyzing the structural interrelationships among different entities allows researchers to uncover and explain a myriad of market phenomena (Borgatti et al. 2009), as well as provides guidance on financial investment and asset management for market participants. In this paper, we provide a novel Fintech application by modeling stock market as networks derived from visitors’ digital footprints on a financial web portal. As a large body of literature has recognized the power of visitors’ search histories, click-stream data and other user-generated contents on IT platforms, we identify and collect investors’ online correlated searches for a set of stocks to construct the co-search network that models investors’ co-attention in the stock market. The general concept of our network is quite intuitive: the whole network is a collection of vertices and directed arcs in which each vertex is an individual stock and each arc represents a direct investor co-search between two stocks. In doing so, we are able to capture the underlying interrelationship of investor attention to a collection of stocks derived from actual observed investor behavior, and the network structure allows us to analyze the mutual dependencies among
connected individuals, which has potential in revealing interesting market phenomena and producing insightful financial outcomes.

Despite the increasing interest in applications of the networked systems in financial markets, empirical evidence linking network structure and particular financial outcomes and market phenomena is scarce. Prior research mainly adopts SNA in mapping the banking systems to financial networks in order to uncover the overall network effect on contagious bank failures (Elsinger et al. 2006; Hu et al. 2012), or in detecting the cohesive subgroups of security network to reveal interesting behavioral patterns (e.g. return comovement) within the subnetworks (Leung et al. 2016). Although these studies contribute to network analysis of financial systems, they basically focus on the market- or group- level consequences. However, as social scientists also attach great concern to the node-level outcomes driven by the network effect (Borgatti et al. 2009), it’s important and necessary to conduct a fine-grained analysis of how networks could play a role in influencing individual constituents. In doing so, we have the possibility to obtain insightful individual-level outcomes that may be more relevant and interesting for market participants in making trading decisions. Therefore, to address these gaps, we provide a way to model the stock market as networks by utilizing investors’ online correlated searches to a set of stocks. Our study aims to answer the following questions: What is the effect of network structure on investor-interested financial outcomes? Further, how does the heterogeneous information flow transmitting through networks play a role in individual stock performance?

To solve above questions, we focus on all A-share stocks listed in Chinese stock markets. We construct networks by recognizing and collecting investors’ co-search stock data from a widely-used Chinese financial portal. By applying a sliding-window approach, we empirically investigate the effect of network structure on stock performance by explicitly studying two aspects of network structure: network centrality and network closure. Focusing on egocentric networks, we further split the alters of an ego into two groups based on their historical returns: historical winners and historical losers, and we examine the impact of network centrality and closure within the two sets of alters, respectively. Here, as we are interested in the discrepancy of the individual-level network outcome induced by investors’ co-attention, the egocentric SNA is recommended as it is concerned with the individual entities across different settings as well as how the interaction with alters can shape the individual’s outcomes (Borgatti et al. 2009; DeJordy and Halgin 2008). Our results suggest network structure is playing a significant role in explaining future stock performance, and the impact of network structure within the two groups of alters are quite different: an increase of network centrality/closure with historical winners contribute positively to the ego’s future return whereas the historical loser centrality/closure has significant and negative influence. In terms of the impact on stock volatility, centrality within any group can exert significant and negative influence whereas network closure for the two groups does not exhibit consistent and significant impact on the ego’s future volatility.

This study contributes to several lines of research. First, we add to the emerging literature on Fintech applications by providing a novel approach to constructing financial networks that utilize investors’ digital footprints on a financial web portal. We further extend the stream by examining the dynamic impact of network structure on stock performance. To the best of our knowledge, it is the first study that demonstrates the network structure driven by investors’ co-attention among individual stocks can significantly influence stock performance. Second, we also contribute to prior research on applications of SNA by demonstrating that the impact of network structure is not uniform but dependent of heterogenous information flows channeled by networks.

The rest of paper is organized as follows: we introduce the theoretical backgrounds and propose our research hypotheses in the next section. Then we introduce the data and network construction method. After that, we introduce the measures and variables used in our empirical models. Then we present the estimation results. Finally, we discuss and reach the conclusions of this research.

Theoretical Backgrounds and Hypotheses

To investigate the influence of network structure on individual stock performance, we need to consider both the topological properties of individuals as well as the contents of information flows transmitting through the network. In this research, we combine network theory with the traditional technical approach to stock market prediction. The rationale behind technical analysis is based on the feedback trading which refers to strategies based on historical price trends (Nofsinger and Sias 1999). Further, as empirical evidence
suggestions individual or retail investors rely primarily on the past price information to infer the true value of a stock (Dimpfli and Jank 2016; Wang et al. 2006; Zhang and Zhang 2015), network structure induced by investors’ co-attention also depicts the flows of price information among connected stocks that investors access and process in order to satisfy their information demand and serve for subsequent investment decision-making.

Peng and Dey (2013) provides a perspective to examine the node-level outcomes by focusing on egocentric networks. Egocentric networks are networks anchored around an “ego” node where only the direct neighborhood is considered. It is suggested to formulate egocentric contexts when we are interested in examining individuals across diversified situations (Borgatti et al. 2009). Followed by Peng and Dey (2013), we focus on egocentric networks and two key concepts of network structure: network centrality and network closure. Network centrality measures the extent to which an individual occupies a central position in the network and network with closure usually implies a dense network with individuals strongly interconnected (Burt 2001).

However, the impact of network centrality and closure on stock market performance is not intuitive. In order to find out the exact role of network structure on stock performance, we aim to employ the variation in network structure across different groups by separating the alters of an ego in an egocentric network into two groups. One group is “historical winners” that generate above-average profitability in the past and the other is “historical losers” with below-average historical profitability. And we further focus on the impact of network structure within each of the two groups, respectively.

**Impact of Network Centrality**

Prior literature mainly points a positive influence of centrality on individual-level outcomes because a node with higher level of centrality occupies the central position in the network and tends to gain advantages from access to more information and resources (Borgatti et al. 2009; Ibarra 1993). However, it should be emphasized what kind of information an ego stock receives from its alters because the information fetched and processed by a node is not always beneficial. The impact of network centrality can also be negative when the linkage to more alters does not benefit the ego (Peng and Dey 2013), which suggests we should divide the alters into two groups with different impact on the ego. In our context, when an ego receives information from its alters who are historical losers, such information will more likely to be processed as a “bad signal” to the ego, which makes investors infer the ego will also perform unsatisfactorily in the near future. As a result, the centrality among past losers conveys negative message to the ego, and therefore, leads to a selling pressure which as a result, makes a lower level of future return of the ego stock. On the contrary, if the signal transmitting to the ego is “good” when alters are predominately historical winners, investors with feedback strategies tend to perceive the ego will continue to perform well, thus they are more likely to make buying decisions, resulting in a positive impact of centrality on the focal stock’s return. Therefore, we propose the hypotheses with regard to the impact of network centrality as follows:

**Hypothesis 1A (H1A):** A stock’s network centrality with historical winners can promote its future return.

**Hypothesis 1B (H1B):** A stock’s network centrality with historical losers can reduce its future return.

**Impact of Network Closure**

Current findings of literature on the impact of network closure are not conclusive. Social scientists mainly document the role of network closure from the social capital perspective (Allcott et al. 2007; Burt 2001; Burt 2002; Burt 2005; Coleman 1988; Coleman 1994). The positive-impact school states network closure can contribute to social capital because closure in the social structure plays a role in creating trustworthiness and social norms through facilitating effective sanctions among connected individuals that can increase incentives of cooperation (Allcott et al. 2007; Burt 2001; Coleman 1988; Coleman 1994). The negative view claims network with closure is disadvantageous because brokerages between disconnected elements are considered to be the source of value added (Burt 2002). Contrary to the positive-impact school, this view emphasizes the critical role of structural holes in creating social capital, thus closure is detrimental due to the lack of broker connections in network structure.

Thus, the overall effect of network closure is ambiguous, either. In our context, it’s also necessary to consider the nature of information contents from the two groups of alters (i.e. historical winners and
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If historical winners predominate among the alters, the density among them has potential to increase the likelihood for the ego to be a winner stock as well. This is because, on the one hand, increased network closure promotes the odds for connected individuals to be homogenous and behave in conformity with each other since closed network can help facilitate individuals to undertake concerted actions (Burt 2005). On the other hand, because network with closure can foster learning and knowledge exchanges among interconnected elements (Peng and Dey 2013), investors can obtain more comprehensive information and knowledge about the connected stocks, which reduces the informational asymmetry faced with individual investors who are less sophisticated and promotes their confidence in making trading decisions. As a result, when alters are dominated by historical winners, their historical price information transmitted in the dense network makes investors conjecture the return of the ego also has an uptrend. However, if alters mainly consist of historical losers that release “bad signal” to the ego, network closure may possibly pose negative impact on the ego’s future return. This is because a higher level of closure tends to reinforce existing norms and values within the network (Burt 2005). When alters perform unsatisfactorily in the past, investors with feedback strategies may perceive the profitability of the ego will also present a downward trend. Thus, we propose the following hypotheses:

Hypothesis 2A (H2A): A stock’s network closure with historical winners can promote its future return.

Hypothesis 2B (H2B): A stock’s network closure with historical losers can reduce its future return.

Data and Network Construction

We collect co-search stock data from Sina Finance, which is one of the most widely-used financial portals for Chinese investors. Visitors use the query tool on Sina Finance to search stock information. When a particular stock is searched, another nine stocks visitors most frequently search along with this stock are also presented on the website. Sina Finance computes co-searched stocks based on co-search frequencies captured by visitors’ cookies and displays top nine co-searched stocks to visitors. Using a web crawler written by PERL, we collect daily co-search data of A-share stocks on Sina Finance at 4 p.m. (UTC+8) every day during the period from June 1, 2015 to July 3, 2016. Here, it should be noted that search is a revealed attention measure (Da et al. 2011) because when investors search for a stock, they are undoubtedly paying attention to that stock. Thus, the co-search stock data derived from Sina Finance can be used to model the underlying interrelationships of investor attention to a set of stocks.

We also obtain weekly data of individual stocks’ characteristics (e.g. stock return, capitalization, trading volume, turnover, price-to-book ratio, etc.), daily media coverage data (e.g. news and report) and daily market-level data (e.g. Fama-French’s asset pricing factors) from the China Stock Market & Accounting Research Database (CSMAR database). To account for the influence of investor sentiment, we also collect daily post data from a widely accepted online stock forum - eastmoney.com.

In order to capture the dynamic changes of network structure, we adopt a sliding window approach to construct a series of networks during the period from June 1, 2015 to July 3, 2016. Figure 1 offers a sketch of our sliding window approach. The window size is fixed on four weeks and the sliding size is set as one week. Specifically, we begin to use the initial four-week co-search data to construct the first network, then we slide the window one week forward and construct the second network using the updated co-search data. This procedure is repeated until the last recent network is constructed. As a result, we have a total of 54 different co-search networks.

Figure 1. A Sketch of Sliding-Window Approach

1 eastmoney.com is one of the most popular Chinese financial portals which has an online forum (http://guba.eastmoney.com/) with tremendous posts about stocks.
Measures and Variable Definitions

In this section, we introduce the measures and define the variables in our models. Prior literature suggests two common measures of stock performance: abnormal return and volatility (Dewan and Ren 2007; Luo et al. 2013; Tantaopas et al. 2016; Vozlyublennaia 2014). Abnormal return is defined as actual return minus expected return which is calculated by fitting Fama-French’s asset pricing model (Fama and French 2015) using rolling-window and recursive estimation with the window size set as 250 consecutive trading days prior to the target day. And volatility is the standard deviation of the model residuals (Luo et al. 2013).

Following Peng and Dey (2013), we concentrate on egocentric networks and measure two key aspects of network structure: network centrality and network closure. We exploit in-degree centrality as proxy for centrality in egocentric network. The in-degree centrality implies the popularity or prominence of an ego based on its topological position (De Nooy et al. 2011), and it is a simple and direct measure in our context as we are interested in how heterogenous information flows from alters can influence the ego’s performance. We calculate the in-degree centrality as the number of directed edges pointing to the ego. Besides, the clustering coefficient is a natural measure of network closure, and it quantifies how close the alters are to being a complete graph around an ego (Watts and Strogatz 1998).

For every ego stock, we split its alters based on their monthly abnormal returns into two groups: historical winners and historical losers. The historical winners produce above-average profitability whose actual returns are greater than their expected returns, and vice versa for the historical losers. We further compute network centrality and network closure for the two groups, respectively. As a consequence, we obtain the measures of historical winner centrality, historical loser centrality, as well as the measures of historical winner closure and historical loser closure for every ego stock.

We also include the known determinants of stock performance as control variables to eliminate alternative explanations. In addition to variables related to stock characteristics, we also account for the impact of news (Birz and Lott 2011; Fang and Peress 2009), analyst coverage (Hong et al. 2000), and investor sentiment (Antweiler and Frank 2004; Baker and Wurgler 2007; Brown and Cliff 2004; Sabherwal et al. 2011) on stock returns. We calculate investor sentiment using online stock post data, and we adopt the measure proposed by Antweiler and Frank (2004) to derive the sentiment index. The full variable definitions are displayed in Table 1.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definitions</th>
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<tr>
<td><strong>Stock Performance Measures</strong></td>
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<tr>
<td>AbnormalReturn&lt;sub&gt;it&lt;/sub&gt;</td>
<td>Abnormal return for stock &lt;i&gt;i&lt;/i&gt; on week &lt;i&gt;t&lt;/i&gt;</td>
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<tr>
<td>Volatility&lt;sub&gt;it&lt;/sub&gt;</td>
<td>Volatility for stock &lt;i&gt;i&lt;/i&gt; on week &lt;i&gt;t&lt;/i&gt;</td>
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<td><strong>Network Centrality Measures</strong></td>
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<tr>
<td>Centrality&lt;sub&gt;i,t-4:t-1&lt;/sub&gt;</td>
<td>Overall network centrality for stock &lt;i&gt;i&lt;/i&gt; in the whole egocentric network formed in the past recent four weeks</td>
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<tr>
<td>WinnerCentrality&lt;sub&gt;i,t-4:t-1&lt;/sub&gt;</td>
<td>Network centrality for stock &lt;i&gt;i&lt;/i&gt; in the egocentric network with alters who are historical winners in the past recent four weeks</td>
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<tr>
<td>LoserCentrality&lt;sub&gt;i,t-4:t-1&lt;/sub&gt;</td>
<td>Network centrality for stock &lt;i&gt;i&lt;/i&gt; in the egocentric network with alters who are historical losers in the past recent four weeks</td>
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<td><strong>Network Closure Measures</strong></td>
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<td>Closure&lt;sub&gt;i,t-4:t-1&lt;/sub&gt;</td>
<td>Overall network closure for stock &lt;i&gt;i&lt;/i&gt; in the whole egocentric network formed in the past recent four weeks</td>
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<tr>
<td>WinnerClosure&lt;sub&gt;i,t-4:t-1&lt;/sub&gt;</td>
<td>Network closure for stock &lt;i&gt;i&lt;/i&gt; in the egocentric network with alters who are historical winners in the past recent four weeks</td>
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<td>LoserClosure&lt;sub&gt;i,t-4:t-1&lt;/sub&gt;</td>
<td>Network closure for stock &lt;i&gt;i&lt;/i&gt; in the egocentric network with alters who are historical losers in the past recent four weeks</td>
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Models and Results

In this section, we propose our empirical models and present the estimation results. Recall that we utilize a sliding-window approach to capture the dynamics of network structure, and we derive 54 different co-search networks. Every time when the window moves one week forward, we add one observation per stock into our dataset. As a result, we derive our panel-data models in which the cross-sectional variables are individual stocks and the time-series variables are consecutive trading weeks.

We adopt an incremental regression strategy to investigate the influence of network structure on stock performance. We propose four models in which model (1-1) is the baseline model where we utilize the overall network centrality and network closure measures without the distinction between two groups of alters. Then we extend the baseline model as follows. We add network centrality among historical winners and network centrality among historical losers in model (1-2) to replace the overall centrality measure. Then we utilize historical winner closure and historical loser closure to replace the overall network closure measure in model (1-3). After that, we develop model (1-4) by further substituting historical winner centrality, historical loser centrality, historical winner closure, historical loser closure for the overall centrality and closure measures. Similarly, we also derive models (2-1) - (2-4) to investigate the impact of network structure on stock volatility.

We fit our models using Generalized Least Squares (GLS) estimation for panel-data models and account for group-wise heteroscedasticity and panel-specific AR1 autocorrelation among observations at the same time. The estimation period contains 53 consecutive weeks from June 29, 2015 to July 8, 2016. All the continuous independent variables except for lagged return are included in our models after log transformations. Meanwhile, we also accommodate three different trading boards of A-shares as dummy variables in our models to account for the potential impact. The three trading boards are, namely, Main board, SME board (i.e. Small- and Medium-sized Enterprises) and GEM board (i.e. Growth Enterprise Market). Furthermore, as prior research suggests individual or retail investors with limited attention prefer specific information (Peng and Xiong 2006), we also take the impact of industry into consideration. In our dataset, we have a total of 2,686 A-share stocks belonging to 18 industries. For brevity, we do not display the estimates for dummy variables. The estimation results for models (1-1) - (1-4) are summarized in Table 2.

<table>
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<tr>
<th>AbnormalReturn_{it}</th>
<th>Model (1-1)</th>
<th>Model (1-2)</th>
<th>Model (1-3)</th>
<th>Model (1-4)</th>
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<tr>
<td>Centrality_{i,t-4:t-1}</td>
<td>-0.00226 (0.0086)</td>
<td>-0.0136 (0.0093)</td>
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The number of historical losers reduce in half. Similarly, for a 1% increase in historical winner closure, the coefficient for historical winner closure is positive and significant (p-value<0.05) and that for historical loser closure is negative and significant (p-value<0.05). The estimation results for model (1-4) are consistent with that in models (1-2) and (1-3), which provide even stronger support on H1A, H1B, H2A and H2B. We could explain the effect of centrality in this way: when the number of incoming links from historical winners doubles, the weekly abnormal return of the ego stock will increase on average by 0.0534 (=ln2*0.0771), and the weekly abnormal return can also increase by 0.0690 (=ln(1/2)*0.0996) if the incoming historical losers reduce in half. Similarly, for a 1% increase in historical winner closure, the weekly abnormal return of ego stock can be 0.0021 (=ln1.01*0.216) higher than before, whereas it could decrease by 0.0033 (=ln1.01*0.335) if there is a 1% increase in historical loser closure.

On the other hand, Table 3 provides the results for models (2-1) – (2-4) that focus on investigating the impact of network structure on stock volatility.
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Table 3. Estimation Results for Models (2-1) - (2-4)

The estimates in Table 3 explain whether and how network centrality and network closure can influence stock volatility. The coefficients in models (2-1) – (2-4) jointly indicate, regardless of whether alters are historical winners or historical losers or a mixture of the two types, the impact of network centrality on the ego’s future volatility is always significant (p-value<0.001) and negative. However, the impact of network closure on stock volatility is not clear. The coefficient of historical loser closure in model (2-3) is negative and significant at 1% level, whereas the historical winner closure in model (2-4) has a positive influence with weak significance (p-value<0.05) on stock volatility. Overall, these results suggest compared with network centrality, network closure has relatively weak impact on stock volatility.

Discussions and Conclusions

This research examines the impact of network structure on stock market performance. We provide a novel Fintech application by modeling the stock market as networks derived from investors’ online correlated searches. Rather than focusing on static networks, we adopt a sliding window approach to capture the dynamics of network structure induced by changing investor attention. Our analysis is unique and it contributes to both IS and Finance literature.

First, our study extends the line of research on network analysis of financial markets by demonstrating the effect of network structure on stock performance. Further, we emphasize the influence of network structure is dependent of the heterogeneous information flows. Our analysis suggests whether network topology acts as conduits for “good” information flows or “bad” information flows matters for the ego receiving that information. Our findings on the distinct role played by network structure also contribute to prior literature on individual-level network consequences, which remains relatively unexplored.

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The table shows the estimation results for models (2-1) - (2-4), indicating the impact of network structure on stock volatility. The coefficients are significant and negative, suggesting that network centrality and closure generally reduce stock volatility. The table also notes that the impact of network closure on stock volatility is less clear, with only historical losers showing a significant negative effect.

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The table highlights the importance of network structure in financial markets, particularly in the context of investor attention. It demonstrates how network dynamics can influence stock performance, offering insights for both IS and Finance scholars.

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This research demonstrates the value of network analysis in financial markets, aligning with prior work in IS and Finance. The findings contribute to a better understanding of how network structures affect stock volatility, opening avenues for further exploration into individual-level network consequences.
In addition, we add to IS and Finance literature by empirically investigating the role of online correlated searches in generating interesting financial outcomes. Prior research has devoted to revealing interesting market phenomena (e.g., return comovement) with investors’ correlated searches on IT platforms (Leung et al. 2016). Our research extends this line by further mining the value behind visitors’ digital footprints. Our findings imply investors’ collective searches can be valuable sources of investment advice, and investors are able to translate advancement in information acquisition into superior stock performance in financial markets (Bogan 2008; Zhang and Zhang 2015). These results are consistent with the view that accumulative “wisdom of crowds” on IT platforms can play a significant role in the financial markets (Chen et al. 2014).

Our findings also provide practical implications on stock investment and risk management for individual investors who are less sophisticated and relatively uninformed in stock markets. Our findings indicate stocks in more central positions tend to be less volatile in the future. However, how centrality can influence stock return is not intuitive. In most cases, the overall centrality has a negative but not significant influence on future return. In other words, there exists a return-risk tradeoff. Although more popular stocks (i.e., stocks with higher level of network centrality) will be less volatile, they do not always produce superior profitability. This implies trading on popular stocks may not be a profitable strategy for investors pursuing short-term benefit.

However, there still exist some limitations that can serve as future directions. First, we focus on egocentric networks that only retain one-step neighborhood. Although it’s recommended for the research question concerning individuals across different settings (Borgatti et al. 2009), we still need to generalize our analysis by considering the multistep neighborhood. The second limitation is we assume individual investors hold feedback strategies and it is the price information that primarily captures their attention and affect their trading decisions. However, there still exist other factors, either observed or unobserved (e.g., policies, macroeconomic variables and market rumors), that may potentially influence the behaviors of individual investors. Although our models have accounted for the impact of investor sentiment which enables us to capture a considerable amount of influence from sentiment-induced factors such as market rumors and fads (Da et al. 2014), it’s still necessary to figure out the determinants of investor attention and consider other information contents that may transmit through the network.

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