Heterogeneous Investors and Impact on Systemic Risk

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Abstract

This paper used an investor trading data on KOSPI market to measure the market stability based on the connections among nine investors group. The connections with the direction and strength are estimated by Variance Decomposition. Information source is defined that investors with more information flows than others in investor network. We assume that information flows in the network through information-sharing process among different investor groups. This study found that an individual investors with larger trading volume engage in destabilization regardless of market status. Especially, we reveal that individual investors and listed foreign investors was source of the financial crisis. Our findings suggest that an amount of information flows among heterogeneous investors play a detrimental role on the financial stability.

Keywords: information flow, systemic risk, heterogeneous trading, investor activity, variance decomposition

1. Introduction

How vary an investor behavior under uncertainty over time? Do some investors lead the movement of stock market when they trade? Such questions have considered scholars for some time, and are essential to understanding the effect of investor activity on securities markets and the way in which all relevant information becomes incorporated into market price \cite{1}\cite{2}. The information theory might appear the heterogeneous trading behavior of investors in stock market \cite{3}. There are theoretical motivations identified in
research. First, investors trade stocks through various style such as value stocks or growth stocks [4][5][6]. Several studies have proposed heterogeneous type of investors and distinguished investor strategies using profit or loss calculated by portfolio analysis [7][8][9]. Second, intensive trading contains information about the distribution of future returns [10][11][12]. In other that investors choose their stocks to invest, they could want to get private information from trading activity of other investors. Schneider (2009) has insisted that outside observer of the economy make it is not unclear that investors within the economy acquire a knowledge from trading volume [13]. Third, stock price is reflected by beliefs about value of investors [14]. Noise that investor trade makes incomplete market. Since noisy signal is independent of public information reflected stock prices in this context, we use the concept of information as way of channeling that either allocational or informational shock propagate. As based on connectedness measure, we might reveal not only amount of relative information among heterogeneous investors, but also the investors who is source of market destabilization by contagion of structural shocks.

Far from the theoretical mechanics stemming from efficient market hypothesis, the financial markets exhibit a heterogeneous pattern of interconnectedness that fundamentally forces the propagation of activity [15][16]. Understanding these movements remain as one of primary interest in the field of Econophysics as well as Finance. An underlying assumption of these investigation is that there are rational investors and irrational investors who have bounded rationality [5][17]. The irrationality can have a substantial and long-lived impact on stock prices. We begin with the premise that every participant in the financial market is interested in the private information that others possess. Also, structural shock is rapidly transmitted in the financial market. To be specific, densely connected financial network is easy to propagate negative shocks, leading a more fragile system [18][19][20]. Preis(2013) et al. found negative return on portfolio based on Google query volume reflected the interest of investors was observed during the financial crisis. This study shows that there is a period of increased instability by investor sentiment [21]. Recently, bottom-up studies that try to explain whole financial market by analyzing patterns of investors or companies have emerged [22][23][24].

It is difficult to clearly define to elements of financial stability, because stock market with a high degree of interconnectedness are so volatile. However, interest in systemic risk has continued to grow since the failure of
Lehman Brothers on September 15, 2008[22]. Billio, Getmansky and Pelizzon showed increasing the level of systemic risk in the finance and insurance industries through principle component analysis and granger causality networks [23]. The result just relies on the unidirectional causality and bipartite connection. Diebold and Yilmaz introduced a connectedness measure at various levels from pairwise to system-wide [26] [27]. They said that the methods had similar results with conditional value-at-risk(CoVaR) [28] and Systemic expected shortfall [22]. There are many studies that have measured systemic risk of different scales, but insufficient studies have been made from the perspective of investors, which is a fundamental level.

Our goal in this article is to test that information flow calculated by investor networks is empirically linked to market stability. To do so, we construct a time series of over 3000 networks using daily trading volume for 15 years in Korea Composite Stock Price Index (KOSPI) market. We categorize investors into nine groups and calculate average information flow (AIF) using variance decomposition method (VDM). We would like to extend Diebold and Yilmaz approach [26] to investigate dynamic direction of information flow among investor groups and causality on market stability. Then, we develop an information flow through a directed network, in which nodes represent investors and links between investors denote their contribution on unpredictable error of the aggregated trading volume of common securities.

In our approach, the influence of a investor group is based on the amount of information a investor group obtains from the other investor’s group as their position in the network. The similar paper to our own is that investigated information diffusion in investor networks in the theoretical literature[16]. Also, Colla and Mele [29] showed that information linkages among traders convey positively or negatively correlated signals. Furthermore, Kaniel, Saar, and Titman [30] asserted the interaction between individual trading as liquidity provider and stock returns and allowed us opportunity to broaden our perspective of investor activity in the sense that it is considered as a systematic factor in the financial market.

There are empirical evidences to supports the view that average information flow among investors has an infectious role of market stability based on the theory of systemic risk. A major finding in this paper is that the amount of information increases during global financial crises. Second, individual investors and listed foreign investors transfer structural shock negatively. Third, the relation between average information flow and market stability have statistically significant positive correlation. The results could help shed
light on the bridging between complex networks and finance theory.

The contribution in the paper is that measure of systemic risk calculated
by information flow using investor’s trading volume which is unique type of
database from Republic of Korea. While there has been studies that measure
the connectedness of financial institutions or corporations using stock returns,
there are not enough from the individual investors who are primary decision
maker and critical role of price formation. It is worthwhile to estimate in-
formation flows based on connectivity from the perspective of investors as
cornerstone in financial market. This article is related to the literature on
economic vulnerability, as applying methodology of VDM from economet-
rics to understand economic issues behind behavior economics. Moreover,
it sheds light on the research about the anomaly of asset pricing or agent
based model of heterogeneous investor activity. We conjecture that infor-
mation flow is an important aspect to analyze market stability because they
could provide potential channels for sharing additional information excluded
form fundamentals. We propose information flow of the trading volume of
investors as a new factor that can have impact on market stability. It might
help to regulators and policymakers of country.

The rest of the paper is organized as follows. In Section II, we describe
our data and variance decomposition method used to measure the amount
of information flow. In Section III and Section IV, we present and discuss
main findings related to the market stability, which is relationship between
AIF and market volatility. Section V is the conclusion with briefly summary.

2. Methodology

Here we discuss our database and measures to estimate the amount of
information flow among investors groups. we use vector autoregression and
variance decomposition methods [26].

2.1. Data Description

Our dataset contains trading volume of buyer, seller, and net purchase
that contain volume 1048 stocks which are ordinary common shares traded
on the Korea stock exchange (KRS). Our sample covers survival 480 stocks
actively traded in the market over a 4,000 daily period from January 1, 1997
through December 30, 2014. In other to investigate the relation between
information flow and market volatility, data on stock index prices of Ko-
rea composite Stock Price Index (KOSPI) is collected from FnGuide. The
transactions in the KOSPI market are organized differently from those in the NYSE and Nasdaq exchanges in the sense that there are no specialists or market makers. Considering the trading characteristics of each investor, we group investors into nine types of investor except overlapped groups from FnGuide: individual, financial investment, other financial, other corporate, listed foreign, insurance, pension funds, bank, or investment. We make the aggregate trading volumes of each investor during sample period. In this study, when showing relationship between information flow and market volatility, we calculate logarithmic returns to measure KOSPI index volatility:

\[
  r_t = \ln \left( \frac{p_t}{p_{t-1}} \right)
\]

(1)

\[
  vol_t = \text{std}(r_{t-\text{window}+1} : r_t)
\]

(2)

where \( p_t \) represents the price of an equity market index at time \( t \) and \( r_t \) is the stock index of KOSPI market at time \( t \). We use rolling window is a 250 day.

2.2. Information Flow of Individual Investor Population

In this section, we propose a measure of the information flow designed to change the casual relationship between financial institutions during the shocks of anywhere [26]. It is worth to measure the degree of information flow and the causality among individual investors in order to examine the cascade effect across the market through closely coupled investors. We must take into consideration that the information in this study can be interpreted differently from the general meaning about information. We make use of the term information flow in the sense that, as in the literature, the relationship of each agent is often referred to as connectedness in the asymmetric networks. As Sims [31] argued, a vector autoregressive (VAR) model used to capture the linear linkages among multiple time series is one of familiarly econometric model. All variables in this model are considered symmetrically in a structural sense [32]. The evolution of a set of variables is over the sample period as a linear function of only past values. i.e. we can forecast dynamic correlation and influence among investors. By eliminating the correlation of the error, the response of the shock for each time is analyzed. To do so, we propose using forecast error variance decomposition method (VDM), which is the proportion over time of the variance of a variable due to each fundamental shock. Let \( x_t \) and \( z_t \) be univariate stationary process of the trading
volume of each investor.

\[ x_t = \sum_{i=1}^{p} \alpha_i z_{t-i} + \varepsilon_{x,t} \]  

(3)

\[ z_t = \sum_{i=1}^{p} \beta_i x_{t-i} + \varepsilon_{z,t} \]  

(4)

where \( \varepsilon_{x,t} \) and \( \varepsilon_{z,t} \) are two uncorrelated white noise processes, and \( \alpha_i, \beta_i \) are coefficient of the model. The \( p \) is the lag order of three chosen by Diebold and Yilmaz [26]. Let \( Y_t = [x_t, z_t]' \) and \( \varepsilon_t = [\varepsilon_{x,t}, \varepsilon_{z,t}]' \), that these innovations reflect either changes in output of otehr variable as following equation:

\[ A(L)Y_t = \varepsilon_t \]  

(5)

where \( A(L) = 1 - A_1L - \ldots - A_pL^p \), \( A_p \) is the matrix of estimators. Specifically, we choose window length of a 250-day and H-step of 12 days. The results do not vary depending on the various window lengths and H-steps.

The connectedness horizon is important because it is related to issues of dynamic connectedness as opposed to purely contemporaneous connectedness.

We exploit not the most popular Choleski decomposition but a generalized variance decomposition method (GVDM) to measure the information flow of each investor. That is why Cholesky decomposition have the limitation that exogenous variables have different results when the ordering of variables is changed. The proportion of variables in the prediction errors of estimator using GVDM can be written as

\[ \theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \Sigma_{h=0}^{H-1} (e_i'B_h \Sigma e_j)^2}{\Sigma_{h=0}^{H-1} e_i'B_h \Sigma B_h' e_i} \]  

(6)

where \( \theta_{ij}^g(H) \) is the fraction of variable \( i \) is h-step forecast error variance due to shocks in variable \( j \) and \( H \) is the predictive horizon \( (H = 1, 2, 3, \) we set \( H = 12 \) \), \( \sigma_{jj}^{-1} \) is a diagonal element of covariance matrix estimate error, \( e_j \) is \( j \)-th element = 1 and other element = 0, \( B_h \) is coefficient matrix reflected shock effect, and \( \Sigma \) is covariance matrix of estimate error. This paper generates the proportion of variables in the disturbance matrix. The directional information flow from \( j \) to \( i \) can be written as

\[ C_{ij}(t) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^{N} \theta_{ij}^g(H)} \]  

(7)
Though GVDM, we show the variance decomposition table obtained by aggregating trading volume within the nine investor categories (individual, financial investment, other financial, other corporate, listed foreign, insurance, pension funds, bank, investment) and each component in the table implies the connectedness of the variables. Since the components in above matrix can be interpreted the proportion of response to impact of other variables, the diagonal term is the amount of impact received from itself. This enables us to observe information flows which are removed the diagonal components themselves from each investor. Each row of this matrix describes contribution of own to others, while each column of the matrix describes the contribution of own from other.

2.3. System-wide information flow

Finally, we derive average information flow (AIF) between investors using the average of outflow. We measure AIF as

\[ AIF(t) = \frac{\sum_{i,j=1,i\neq j}^{N} C_{ij}(t)}{N} \]  

We call this system-wide information flow at time t. It is same with the sum of total directional information flow whether to or from in the sense that diagonal terms are ignored. When shocks of micro or macro level break out of equilibrium, the contribution of investors has negative impact on other investors. The most important thing is that the contribution of investors on forecast error each investor did not expect is reflected on AIF. Directional information flow represents the quality of investors’ information in the sense that heterogeneous investors contribute to unpredictable factor of own. We then construct simple investor networks which is the weighted directed networks in that case the weight is more than sum of mean and two standard deviation.

3. Empirical tests of average information flow

In our study, we use vector autoregressive (VAR) the variance decomposition method (VDM). This results represented by heterogeneous trading of investors were compared with market volatility during global financial crises. In this section, the method defined in Section II are implemented using historical data from individual investors corresponding to the nine categories.
Subsection A in Section III contains the results of the VDM that are unconditionally applicable to trading volume. Subsection B in Section III reports the results of rolling window approach including simple visualizations.

3.1. Full Sample Results

Here we provide a full-sample analysis of buying and selling information in Korea stock market. This sub-section examines the pattern of information flows between individual investors in nine groups over the entire sample period. We assume that as market stability decrease, the information flow increases. That is why the global financial crisis is sure to be a serious result of connectedness in the stock market. For example, linkages between financial institutions affects the systemic risk [26]. To better understand the results of our study, let me briefly introduce major financial crises. The dot-com bubble was a historic economic bubble and period of excessive speculation that occurred roughly from 1997 to 2001. In 1999, after the Asian financial crisis, the South Korean government encouraged bank to draw credit cards to as many people as possible as a way to reinforce consumer expenditure. To be specific, the number of credit card is 89.3 in 2001 and 104.8 in 2002 and 95.5 in 2003(million) from Bank of Korea and Financial Supervisory Service of Korea. A large number of credit card issuers were matched against going downhill such as difficult liquidity and solvency condition, which then exposed the financial markets to systemic risk and devastated the real economy in 2003. Since imprudent trading of commodity such as mortgage-backed securities (MBSs), credit default swaps (CDSs) had increased, the collapse of Lehman Brothers happened in 2008. The event has brought global financial markets to a turbulent period of weeks, given the size of the company and its status as a major player in the U.S. and internationally. The Eurozone crisis is a multi-year debt crisis that has been taking place in the European Union since the end of 2009. The crisis has had significant adverse economic effects not only the entire Eurozone but for the entire European Union. Some crisis I said before was impended in the financial market and real word market due to liquidity problem. Therefore, it is valuable to investigate investor activities, which are significant role of liquidity in the financial market.

To begin with, Table 1 shows the results of full-sample analysis obtained using VDM. As can be seen in the Table 1, the degree of information flow as a percent of all possible information flow on condition of database such as buy money, sell money, and net buy money. Moreover, the nine investors in KOSPI market are nominated ID (Individuals), FI (Financial Investment),
Table 1: Full-sample Information Flow Table, Nine-Group Aggregation. This table lists information flow calculated using aggregated trading volume January, 1999 through December, 2014. Information flow (i, j) means the percent of forecast error variance of investor i caused by shocks from investor j that the predictive horizon (h-step) is a 12day. Panel A, B, and C are used the trading volume of buyer, seller, and net purchase, respectively. They are designated by Buy Money, Sell Money, and Net Buy Money. Moreover, the nine investors in KOSPI market are nominated as ID (Individual), FI (Financial Investment), OF (Other Financial), OC (Other Corporate), LF (Listed Foreign), IS (Insurance), PF (Pension Funds), B (Bank), and IV (Investment).

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(a) Panel A: full sample information flow table of buy money

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(b) Panel B: full sample information flow table of sell money

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<td>2.3</td>
<td>0.6</td>
<td>2.9</td>
<td>34.7</td>
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<td>0.7</td>
<td>1.0</td>
<td>1.4</td>
<td>N/A</td>
<td>1.4</td>
<td>0.2</td>
<td>0.5</td>
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</tr>
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<td>0.1</td>
<td>0.2</td>
<td>5.7</td>
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<td>2.0</td>
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</tr>
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<td>0.4</td>
<td>0.9</td>
<td>0.5</td>
<td>1.1</td>
<td>0.5</td>
<td>0.0</td>
<td>N/A</td>
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</tr>
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<td>0.5</td>
<td>12.0</td>
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<td>1.7</td>
<td>0.3</td>
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<td>2.6</td>
<td>6.2</td>
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<td>-1.4</td>
<td>-6.1</td>
<td>12.8</td>
<td>-2.4</td>
<td>-2.9</td>
<td>-0.9</td>
<td>-13.4</td>
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</tr>
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</table>

(c) Panel C: full sample information flow table of net buy money
OF (Other Financial), OC (Other Corporate), LF (Listed Foreign), IS (Insurance), PF (Pension Funds), B (Bank), and IV (Investment). The $ij$-th entry in Table 1 is the estimated contribution to the forecast error variance of investor $i$ coming from innovations to investor $j$. In addition, degrees of information flow involve the non-diagonal element of information flow table. The off-diagonal row sums (labeled From) or column sums (labeled To) represent contributions from others or contributions to others, and NET means the value of from minus to. To be specific, the sum of off-diagonal elements in first column gives the shares of the H-step forecast error variance of first investor.

Let us discuss several characteristics of the information flow table. The entries in the from column cannot exceed 100% because it means sum of row minus information themselves. As mentioned previously, we adjust prediction horizon to 12 days. It was suggested in the table 1 that specific investors could lead information cascading about systematic shocks in equity market. According to table 1, if $NET_i$ in investors information flow $i$ is greater than zero, the investor $i$ tends to give information rather than receive it. On the contrary, if $NET_i$ is less than zero, the information flow occurs to the investor $i$ from the other. As we have seen above, individual investors have the most number of total directional information flow (51.8) in buy money. It is controversial issue that individuals seem to have a psychological bias and be considered the sort of noise trader in several studies [8]. Our paper also supports the similar view that individuals have a lot of information and that it can play a deteriorate role of financial market. As further evidence, individual investors also have a lot of information flow on sell money and net buy money. In Panel A of Table 1, insurance investor showed a directional information flow of 11.6, followed by the pension fund investor with 6.1. When investigating sell volume, investment, insurance, pension funds, financial investment investors actively give and take the amount of information excluding individual investors. Especially, since common information reflected in the market for selling stocks spreads more than other situations, average information flow in Panel B of Table 1 is highest among three databases. Additionally, degree of information flow has pairwise directional information flow, $C_{i\rightarrow j}$, which are the off-diagonal elements of the upper-left $9 \times 9$ submatrix. The highest observed pairwise information flow is from insurance to pension funds 16.1%. In return, the pairwise information flow from pension fund to insurance 15.2% is second-highest. The next largest pairwise directional information flow is from insurance to financial
investment 15%, and the pairwise information flow from financial investment to insurance 12.2%. As we have shown behind, several group of investors, which are the role of system source such as insurance, financial investment, and pension funds, are connected each other. As the Panel C of Table 1, the influence of individual and listed foreign investors on market viability will be led. The clear evidence is that individuals and listed foreign are investors who transmit their information to others. If there appear to be a tendency toward market stability, this factor should be incorporated into a contagion channel of exogenous shock and considered a factor of the capital asset pricing model (CAPM). Additional evidences are presented in Table 1 and some of them is included in Figure 1. In the next sub section, we consider 16.9 as average information flow which is the number of cascading information among whole investors in net buy money. Demirer et al (2018) presented the results form variance decomposition are closely related to recently proposed measures of systemic risk, such as marginal expected shortfall (Acharya et al. 2017) and CoVaR (Adrian and Brunnermeier, 2016).

Figure 1: Full-Sample Total Directional Information Flow. The figure plots the empirical survivor functions for total directional information flow to others and from others. The predictive horizon for the underlying variance decomposition is 12 days. (a), (b), and (c) represent directional information flow of Buy Money, Sell Money, and Net Buy Money database, respectively.
Consider a two range of information flow, shown in Figure 1(a), where the components are denoted by to (solid line) and by from (dotted line). The from column calculate the variability impact of the investors from the total variances of each investors forecast error. According to the definition, this is equal with value 100% except own total error variance. In the Figure 1(a), since its own effects are between 42% and 75%, the overall from column ranges from 25% to 58%. In Figure 1(b), the from column range is 28% to 63% and in Figure 1(c) it is 4% to 39%.

In a similar way, contributions to the others of each investor are not limited by 100%, therefore, the entry in the line to may exceed 100%. While the information delivered in the financial market is similar in terms of receiving information from other investors, the information delivered to other investors in highly differentiated. The difference between the distributions of the two types of information are shown in Figure 1. The survival function of the information to other investors is comparatively defined in flatter and boarder range than that of the information from other investors.

Since Figure 1(a) begins at least 24% for information flow from other corporate and ends at up to 57% for financial institution, the overall directional information flow from others is somewhat dense. On the other hand, overall information flows to others have a relatively flat distribution from 13% of other financial to 91% of individual investor. Especially, individual investors showed directional information flow to others of 91% for Panel A of Table 1, 76% for Panel B of Table 1 and 55% for Panel C of Table 1. In terms of the value of NET in Panel A of Table 1, individual(51%) is the investors who provide the most information to the market, followed by institution(11%), and pension fund(6%). The lowest sources are bank(-20%), other corporate (-17%), and other financial (-11%).

Finally, Panel A of Table 1 has 44.2 information flow, 50.5 for Panel B of Table 1 and 16.9 for Panel C of Table 1. The average information flow on Panel C of Table 1 is small because investors, except individuals and Investment investors, actively shared their own information. The information of individual investors who are free to trade in the stock market is reflected in the information in the financial market and delivered during the stock exchange process. It has the high value of average information flow, especially during the financial crisis, as we can see below. The reason for the increase in AIF is that every investor involved in this transaction systematically affect the KOSPI market. Specifically, the idiosyncratic volatility shock delivered to one investor is communicated to others through information flows.
3.2. Rolling Sample Results

First of all, this sub section presents a dynamic analysis through a rolling window and shows how the distribution of AIF varies during the financial crises. In addition, we calculate AIF each year and each investor, and provide which investors lead the movement of information flows in the financial market. In Figure 2 we plot AIF, defined as the mean of the sum of information flow from Table 1, estimated using a 250-day rolling window. We present the mean of average information flow during 20 days as one label. Figure 2 is illustrated the corresponding VDM, performed by considering the three databases such as buy, sell, and net purchase. Observe that the pairwise-directional approach was capable of detecting time-varying characteristics based on investor strategies. Blue round line is buy money database and red x line is sell money database, and green diamond line is net purchase database. respectively.

Average information flow plotted in Figure 2 has distinct patterns. It has tended to soaring during global financial crises. As information among investor is shared, it is plausible explanation that financial market is more
Figure 3: Rolling Distribution of Total Directional Information Flow. This figure plots rolling distribution of total directional information flow using (a), (b) Buy Money from and to (c), (d) Sell Money from and to (e), (f) Net Buy Money from and to. We plot the change of daily min, 25%, mean, 75%, and max of the distributions of to and from total directional connectedness. The rolling estimation window width is a 250-day, and the predictive horizon for the underlying variance decomposition is 12 days.
destabilized. It measures investor activity though information flow. First, looking at the features of the blue round line, average is 43.65 and drastically increase from 48.89 in February 2002 to 57.24 in March 2002. The reason for this is the vast use of credit cards in South Korea, which has caused a serious card impact on the economy. The most scale of Lehman brothers bankruptcy is propagated to financial market globalized in 2008. Average information flow is the lowest value (25.39) in July 2006 and is rising steadily by 50.18 in July 2007. It gradually gained from European debt crisis in 2010 and dwindle away from Greek debt crisis in 2012. The result indicates that the average information flow of KOSPI market is reflected from domestic crisis as well as global financial crisis. Green diamond and red diamond also have remarkably increased patterns during global financial crises. The green diamond line average is 48.34 and maximum is 62.81 in March 2002. Especially, the value climbed from 33.09 in November 2016 to 50.18 in July 2007. As we said before, Figure 2 embody that the amount of information flow increased (58.64) after decreased (51.77) during European debt crisis in sell money database. Moreover, the value is decreasing substantially from 59.67 at Greek debt crisis. Finally, in red cross line, although deviation is more small than other databases (average is 31.43 and maximum is 38.23 and minimum is 25.01), we found similar patterns with other databases during financial crisis.

Figure 3 shows the dynamic directional distribution of the AIF measured for buy money, sell money and net purchase, respectively. The solid line represents the rolling distribution of total directional information flow each year. The figures in left side such as (a), (c), (e) represent from and the figures in right side such as (b), (d), (f) represent to, using buy money, sell money, net buy money, respectively. The different colors represent the range of 25% and 75% or value of maximum and minimum of AIF. The reason for showing the distribution of total directional information flows is to describe how much information an investor sends and receives when a particular event occurs. During the financial crisis, we observed that the distribution of outflow among investors in the information flow network is wider than that of the inflow. This result shows that the propensity of investors to spread the risk when the market becomes unstable has changed. In order words, specific investors play a role of propagating information in the market. Also, Figure 3 shows the result that our results have similar patterns with Diebold and Yilmaz[26]. The overall amount of directional information flow also increase during global financial crises in this study.
4. Identifying the Source of Destabilization

This chapter shows that the results of dynamic AIF among investors through visualization such as the network diagram present relation between AIF and stability in financial market. In our study, unlikely the fact that Ozsoylev et al. [16] revealed whether the channel of information diffusion among investors is public or private arena, we sought the source of information flow within investors. Important finding of this study is that all investor shares their information through trading volume and individual investors and listed foreign investors have significant role of market uncertainty. Then, We use the variance of the domestic stock index across the same period as a robustness check.

We estimate NET value of average information flow each investor group and define investor who has the positive NET value as system source and has the negative NET value as system sink. Figure 4 indicates that the amount of information accounts for destabilizing financial market. Figure 4(a), (b), and (c) represent individual investors seem to detrimental role of market viability. The evidence is that individual investor tends to receive information to the other investors in the market as system source each year. Considering Figure 4(c), listed foreign investors also have a significant role of source in US subprime crisis as well as European debt crisis. In Figure 4(c) the amount of information by foreign investor increases before global financial crisis in 2000, 2001, and 2004, has had a role of source since 2007. It is likely that we focus on part for foreign investor as source of information. Also, in Figure 4(c) financial institution has the smallest amount of information in the sample period. There are not probable patterns in the other investors group. In Figure 4(d), individual investors have significant role of transmit information to equity market in all case. In net buy money database, which is well reflecting investor trading behavior, listed foreign investors have a role of source during global financial crises. In addition, listed foreign investors offer the low quality of information to other investors in the financial market. Consequently, individual and listed foreign investors could promote trading among investors and provide liquidity.

In order to complex networks display heterogeneous structures, we present weighted directed networks to show intuitively which investor is a deteriorate role of the system during global financial crisis. Note that investors connected if they gave and took information of forecast error. Node represents investor groups, and link among investors represents pair-wise directional information.
Figure 4: (Color online) Directional AIF of NET. (a), (b), and (c) show the directional AIF in buy money, sell money, and net purchase, respectively. (d) shows the number of source of each investor during 16 years (1999-2014).
Figure 5: (Color online) Investor Network Graph, 1999-2014. This figure plots network of pair-wise directional information flow. (a) Buy Money (b) Sell Money (c) Net Buy Money. The rolling window is a 250-day, and prediction horizon for underlying variance decomposition is 12 days. Node represents investor groups. ID is individual investors, OF is Other Financial, FI is Financial Investment, B is Bank, LF is listed foreign, IS is Insurance, OC is Other Corporate, PF is Pension Funds. Links between two investor groups represent pair-wise directional information flow. The link arrow thickness indicated the strength of the pair-wise directional information flow. We define the threshold of links is more than sum of mean and standard deviation.

A study by Ozsoylev et al. [16] found that the trading activity was active before transmitting event information from mainstream media due to information diffusion and information diffusion was caused from other channels than mainstream media. We have similar pattern that the amount of AIF caused from individual and listed foreign investor increase before
the global financial crises. As seen in Appendix: Figure 7-Figure 9, the relationship between AIF and volatility slightly have positive correlation. It seems that AIF among investor better reflects risks that exist in the real market than volatility known as measuring the existing market risk.

To examine the dynamic relationship between the AIF of trading volume of the market, the following regression from 2000 to 2014 is run:

\[
V O L_t = \beta_{0,t} + \beta_{k,t} \sum_{k=1}^{3} A I F_{k,t} + \epsilon_t
\]  

The results, shows in Table 2, document a significantly positive relationship between AIF and market risk during sample period. We also checked each year and got the similar results. It means that information flow among
Table 2: Regression of average information flow on market risk. This regression used equation nine. *, **, and *** denote statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
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<th>Vol(t)</th>
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<td>0.0065***</td>
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<tr>
<td></td>
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<td>(7.0536)</td>
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<td>SM</td>
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<tr>
<td></td>
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<td>(-5.6332)</td>
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</table>

The investor is statistically significant relation to instability of the KOSPI market.

5. Conclusion and Future Research

This paper investigates whether information transfer has an influence on the market risk in a financial market where investors are of a with bounded rationality, and each investor has access to different amounts of information. This paper makes two main contributions to the literature on financial networks. First, the ramification is caused by source of average information flow, such as individual and foreign investors. The listed foreign investor is most crucial role spending uncertainty to others during financial crisis. This result is to show with the study of previous researches [30,31]. Moreover, individual investor is an important role of creating market uncertainty during sample period. This results help us to understand the investor activity in the Korea stock market. Second, the results reveal systematic impact of dynamic relationship on of stock index volatility rather than the trading pattern of each investor. These relationship and associated results will allow us to understand that AIF captures market risk, although we cannot completely deal with additional variables related to market stability. Finally, the information flow among investors have a possibility that it can extend in explaining asset pricing theory because of positive relationships with return and risk [33,34].

The results shed light on the future research about anomaly of asset pricing and the complex network of market participants such as investor activity in terms of behavior finance. Overall, the results in the KOSPI market help
to explain which investor produce market instability. The findings of this study point to new for future research. We do not reveal the source of information flow at the individual stock level. Future researchers could prolong the results to investigate using network method with regard to the dynamic pattern of heterogeneous investors of specific stocks and the additional factor of price formation in Capital Asset Pricing Model.

References


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6. Appendix
Figure 7: (Color online) Correlation of Market Volatility and AIF (Buy Money). The figure plots relation between market volatility and average information flow of buy money. The rolling estimation window width is a 250-day, and the predictive horizon for the underlying variance decomposition is 12 days.
Figure 8: (Color online) Correlation of Market Volatility and AIF (Sell Money). The figure plots relation between market volatility and average information flow of sell money. The rolling estimation window width is a 250-day, and the predictive horizon for the underlying variance decomposition is 12 days.
Figure 9: (Color online) Correlation of Market Volatility and AIF (Net Buy Money). The figure plots relation between market volatility and average information flow of net buy money. The rolling estimation window width is a 250-day, and the predictive horizon for the underlying variance decomposition is 12 days.