PHD

Trading networks in Korean financial markets

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Award date:
2019

Awarding institution:
University of Bath

Trading networks in Korean financial markets

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A thesis presented for the degree of
Doctor of Philosophy

University of Bath

Department of Economics

November 2018

Contents

I Acknowledgments

First of all, I would like to say ”Thank you” to my best supervisor, Andreas Krause. Without him, I cannot even imagine to come to PhD program and, of course, to finish the degree. His questions have always sharpened my thoughts, which leads my PhD journey to the finish line finally. I am very much thankful for his advices and all of dialogues we had in his offices.

I express my sincere gratitude to Financial supervisory service in Korea, which supported my PhD financially for 2 years and gave me the chance to study abroad.

I am also very much grateful to my kind and clever colleagues in 3 East economics PhD rooms, Sunday, Maryam, Richard, Noha, VAN, Trinil, Yuexian, Yachao, Konstantinos, Magdalyn. And special thanks to Kook.

My beloved friends who Bath connected us, made my life unexpectedly fruitful and delighted. Chang's family, Kevin's family, all of my precious Korean community members in Beechencliff church, Dukgun's family, Jin's family, Haryun's family and devotional ladies in Hungary and English friends from Widcombe church, I thank you all.

My beautiful wife, Jieun and my invaluable son, Dael, we all are walking through this long journey of the life together. Like we did here in Bath, we will be happy together until the end of our breadths. And I thank unending supports from my parents and mother in law.

Finally I thank God who provided all the graces above.

Now I am standing in the starting line as an independent researcher. I hope my intellectual products from all of my efforts in my whole life to make a tiny contribution to develop this world a little better.

Jaehak Hwang

November 2018

II Thesis Abstract

In spite of tremendous research on the financial traders and markets, the connectedness of traders in financial markets have not been investigated by previous literature. However, the information of traders' inter-connectedness across the financial markets can be the key to understand how the financial market function and how the market volatility changes. In this thesis, the traders' connectedness across five different Korean financial markets is investigated with network theory.

In first paper, I investigates financial traders' network structures across different capital markets. The influential traders and markets are found within the network based on the network structures estimated with Granger causality and generalized variance decomposition. I also find strong connections between traders and particular conditions. Then, the contributions of traders' connectedness measures to the financial market volatility are examined. The result shows that traders' influence is shown to be not necessarily related to the financial market volatility.

In second paper, financial traders' network structures across different capital markets are studied with nonlinear Granger causality and nonlinear generalized variance decomposition methods. Traders with stronger influence to other traders and the conditions under which the changes of their influence occur, are found. I also investigate contributions of traders' connectedness measures to the financial market volatility. Several influential traders' connectedness measures contribute to the market volatility, whereas other traders' connectedness measures do not contribute. In addition, I also find sensitive traders to the shocks of influential traders' daily net trading volumes.

In third paper I study financial traders' network structure in particular with the expectation on other traders' trading on next day across different financial markets. As a proxy of the expectation, the forecasted values of traders' trading volumes on next day with machine learning technic are applied. I estimate financial traders' network structure utilising the expectation of a trader's trading volume on other traders. I find influen-

tial traders such as foreign investors within the network. Then, I implement 3-phased impulse response analysis in order to capture the connections between financial market volatility, traders' connectedness measures and traders' actual trading volumes. The result shows the evidences that traders' connectedness measures and their trading volume can be functioned as financial market volatility spill over channel.

III Introductory Remarks

Numerous previous research has investigated financial traders' characteristics in order to understand financial market movement. Tremendous research has shown the reasons of the behaviours of individual investors, institutional investors and foreign investors. Some of them had insightful findings on the relationship between a certain type of traders' behaviours and financial market movement. Other research has been attracted to study about the inter-connectedness of financial markets. That research was triggered by the Global financial crisis (GFC). The crisis which occurred in US prime mortgage market has spread out to all over the world. It was found how the global financial markets or local financial markets were inter-connected and how their connectedness changed. The methodologies which were developed and widely used in the network theory, have been utilised effectively. Although those research results expanded our understanding of financial traders and financial markets, there are still some research gaps on how the traders are inter-connected each other.

In this thesis, I investigate financial traders' network and analyse the network structure with different perspectives. The main focuses of this thesis are to find influential traders in financial markets, their influence changes, and the relationship between traders' connectedness and financial market volatility. Given the fact that financial market movement is the result of traders' trading behaviours in the market, traders' connectedness can be the key element to understand financial markets. In other words, if the mechanism of financial traders' can be identified, financial market movements can be more understood based on the information.

I investigate financial traders' network structures of the most representative five Korean financial markets and analyse them. I estimate the network structures with linear Granger causality method and linear generalized variance decomposition. The network structures are estimated over different time periods and under specific conditions of foreign investors' trading patterns. I analyse the network with the connectedness measures which captures a traders' influence to others and find influential traders and markets. Strong connections between traders are also found and the changes of influential traders' influence are also shown. In addition, each trader's contribution to the market volatility is also examined with adaptive LASSO technique.

In the second paper, I examine financial traders' network structures with the assumption that the relationship between traders is nonlinear. Since the first paper assumes linear relationship between traders, it is hard to capture the nonlinear relationship. Despite the findings of the first paper, the linear assumption can be a significant obstacle. Thus, I estimated financial traders' network structure with nonlinear Granger causality method and nonlinear generalized variance decomposition based on the framework of first paper. This approach has a few advantages in terms of the comparability. Furthermore I expand the scope of the research to the impulse response analysis on traders' daily net trading volume. Although the relation of the traders can be understood with the network structure, the impacts of an influential traders' trading shock to the other traders are not investigated. I find that a few traders at the shocks of influential traders response more sensitively than others.

Real trading circumstances are reflected at the estimation of financial traders' network structures in the third paper. Instead of estimating network structures with traditional econometric methodologies as first and second paper, Traders' expectation on other traders' trading behaviours on next day are included in the model. The forecast values with a machine learning technique are utilised as the proxy of the expectations, since it is almost impossible to collect the data of traders' expectation on other traders' trading volume in real financial markets. Then, I examine traders' connectedness and their actual trading behaviours as the spill-over channels of financial market volatility. The findings show that there are evidences of market volatility spillover channels, and that traders' connectedness and their actual trading behaviours can function as the spill over channels.

This thesis have a few contributions to previous literature and policy makers. First of all, traders' network structures in capital market are investigated with diverse perspectives. Influential traders and responsive traders are found, which is the essential information to understand the mechanism of financial markets. This approach has not been taken enough, although the attributes of certain types of traders and their relationships between them and financial markets have been studied. Second, various methodologies including linear (and nonlinear) Granger causality and generalized variance decomposition are applied to estimate network structures and the results of them are compared in first and second chapter. In particular, nonlinearity can be captured with novel nonlinear methodologies. Appropriate methodology is then suggested depending on the objective of the research. Third, market volatility spillover channels are investigated and I suggest traders' network structures can function as volatility spillover channels. This can fill the gap of network studies on financial markets' interconnectedness and risk contagions. Previous literature has focused on the phenomenon of interconnectedness itself, not much on how they are connected. At the same time, this is a kind of practical application of traders' network structure.

Policy makers can use the research results in this thesis for making their market stabilization policies. Influential traders can be their policy target as reducing the influence of them, and responsive traders' behaviours can be utilised as supplementary tools to check whether their policy works well. In addition, policy makers and financial regulators can make trader-tailored policies, instead of launching a market-wide policy, which can have probable side effects or unintended balloon effects.

IV

Paper 1:
Financial traders' network structure across capital markets

Statement of Authorship

This declaration concerns the article entitled:									
Financial traders' network structure across capital markets									
Publication status (tick one)									
draft manuscript	x	**Submitted**		**In review**		**Accepted**		**Published**	
Publication details (reference)									
Candidate's contribution to the paper (detailed, and also given as a percentage).	The candidate contributed to/ considerably contributed to/predominantly executed the… Formulation of ideas: 100% Design of methodology: 100% Experimental work: 100% Presentation of data in journal format: 100%								
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.								
Signed	Jaehak Hwang					**Date**	30/11/2018		

Financial traders' network structure across capital markets

Jaehak Hwang*

Abstract

This paper investigates financial traders' network structures across different capital markets. The network structure is estimated using Granger causality and generalized variance decomposition. I identify the influential traders and markets within the network structure. Strong connections between traders and the particular conditions under which the influence of particularly influential traders increases, are also found. I also examine the contributions of traders' connectedness measures to the financial market volatility. The influence of influential traders on other traders is shown to be not necessarily related to the financial market volatility. This paper contributes to the previous literature on the network studies in the field of finance, in terms of methodologies and traders' relations. In addition, policy implications for market stabilization policy are suggested.

1 Introduction

A great deal of research has tried to show the attributes of investors in financial markets and the relationship between the investors and the market movements. This research

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contributed to an understanding of the behaviours of certain types of traders in particular those classified as individual, institutional or foreign investors. This research has also become the corner stone in the debates concerning behaviours in the filed of finance (Muth, 1961; Shiller, 1990).

The majority of research (Joo and Durri, 2018; De Lellis et al., 2018; Barber and Odean, 2013) have shed light on individual investors. Unlike the institutional investors who have official investment objectives and risk management policies, the investment decision making by individual investors has been considered to be irrational and sentimental rather than rational. According to the common perception which takes it that individual investors might be more likely to manifest more irrational behaviours than institutional investors, a considerable numbers of studies (Foucault et al., 2011; Kim and Nofsinger, 2007; Veld and Veld-Merkoulova, 2008) have found that individual investors have made riskier decisions, which have contributed to the increase of market volatility.

Other strands of studies (Gabaix et al., 2006; Baik et al., 2010; Dennis and Strickland, 2002; Callen and Fang, 2013) focused on the institutional investors. The institutional investors who were keen to find short term absolute returns, such as fund managers, have been shown to have impacts on market volatility. A few studies (Bohl et al., 2009; Lakonishok et al., 1992; Dennis and Strickland, 2002; Callen and Fang, 2013) have shown that some particular types of institutional investors with long term investment objectives had slightly more stabilizing traits than others. These results appear reasonable because the concept of institutional investors is very broad. The specific goal and circumstances of investments vary substantially by the type of institutional investor involved. It is natural that the behaviours of hedge funds and public pension funds differ, which leads differences in their impacts on the market.

Foreign investors have been also an attractive research topic (Umutlu and Shackleton, 2015; Ebeke and Lu, 2014; Nguyen, 2016; Wang and Lee, 2015; Ebeke and Lu, 2014; Park et al., 2017) in this context particularly since global financial crisis (GFC) in 2008. Since GFC, due to the policy responses of many governments and central banks including quantitative easing of US Federal Reserve Bank (FRB) and European Central Bank (ECB), much investment has flowed into the emerging market Countries (EMCs). [1] However, these inflows are a double-edged sword. On the one hand, it has positive effects in that it can be a liquidity provider to the local markets, and that local government and companies reduce the burden of overseas financing particularly in the bond market. On the other hand, however, negative effects also exist at the same time in that foreign investors' substantial unidirectional trading can make the local market to fluctuate. In an extreme case, a sudden outflow of foreign investment from the local financial market can be disastrous for both the capital market and the foreign exchange market in that country, as a substantial withdrawal of foreign investment normally gives rise to a sharp decrease of financial asset prices and currency depreciation at the same time (IMF, 2014).

Foreign investors in domestic financial markets have some differentiated characteristics from local traders. They are more sensitive to currency risk, for their asset value can decrease when local currency value deteriorates. This is closely linked with the finding of IMF (IMF, 2014), which is that domestic macroeconomics conditions are important to foreign investors. Furthermore, the accessibility of information to foreign investors is a critical issue. It is difficult for foreign investors to acquire local investment information earlier than domestic traders although they tend to have more connections with which to acquire higher quality global investment information than domestic investors can obtain. Thus, foreign investors' reactions to a given piece of news can differ from those of domestic traders'.

Most of the previous literature, however, has only provided narrow points of views to see the market, although their contributions have greatly helped to understand the investors' behaviours. It is because they investigated the relationships between specific types of traders and market movement or the behaviours of a type of trader without considering the impacts of other traders. In this present paper, instead of focusing on specific types of traders, I investigate the relations among traders conditional on all other traders in the markets and their contribution to market volatility.

[1] IMF,"GLOBAL FINANCIAL STABILITY REPORT, Grappling with Crisis Legacies (September 2011)", http://www.imf.org/en/Publications/GFSR/Issues/2016/12/31/Grappling-with-Crisis-Legacies

With the broader perspectives, the inter-relations among traders matter more than the relationship between a single type of trader and the market. This is because the relationship between a type of trader and the market can vary depending on the conditions such as the other traders and the market. Although foreign investors have been doubted as the main driver of market fluctuation in emerging markets, if some local institutional traders sold more than foreign investors or foreign investors just followed those traders' trading strategy, foreign investors are not identified as the main driver of market fluctuation. In addition, the role of investors can vary depending on market and period, which means that the traits of investors are not independent from other traders' characteristics. Hence, in order to better understand a certain type of investors' role in the market, the analysis on the roles of all other traders needs to be implemented together.

Furthermore, it is also necessary to investigate the inter-relations of traders from different financial markets. In recent investment environments with developed financial derivatives and free entry to the market, complex and combined investment strategies across different financial markets have been utilized actively. The trading behaviours of foreign investors in the stock market possibly affect that of banks' in stock derivative market or the foreign exchange derivative market.

In this regard, I examine traders' relation including foreign investors and other local traders across different local financial markets using network theory. In order to obtain a better understanding and more meaningful results, I concentrate on the Korean case. The reason why I have selected Korea as a representative example is given below. First of all, foreign investors' participation is active. After the 1998 Asian financial crisis, the Korean authority has opened its domestic markets to foreign investors continually. Secondly, the financial market size is large among emerging market economies and economic fundamentals are relatively strong. That means that the Korean financial market is relatively stable, and that the possibility of the financial market's becoming volatile due to the unstable economic environment is considerably lower than other emerging market economies. Thirdly, despite the two conditions above, foreign investors are still sensitive to global bad news. When this type of news strikes, foreign investors often sell their securities and exit from the Korean market. That is why the Korean financial market has a shameful nickname: The global traders' ATM[2]

My research questions are composed of 4-parts. First, how are the traders inter-connected? The network structure of capital market provides a clue to understanding how the market mechanism operates across the traders. Some traders, such as institutional traders, have more investment information on markets and utilize that for their trading before the others obtain and take advantage of it in their trading. Some traders, such as individual traders, follow the traders with good investment records. The other traders (e.g. pension funds), however, do not follow the traders with more information and just adhere to their investment strategy regardless of other traders' behaviours. In this paper, traders' influence on each other is also examined based on the conditional pairwise causal relationship.

Second, how do the traders' relations change over time? The network structure in a capital market can change over time. It is highly likely that traders' behaviour under crisis compared with that during normal times will differ, since in a crisis, traders are more likely to react to the market movement more actively in order to reduce possible losses than during normal times. I divide the entire analyzed period into normal and crisis time periods, and estimate network structures of each one. The role of each trader's behaviour is also examined during each time period.

Third, who are the influential traders in financial markets? The greatest advantage of network analysis is to capture the influential traders' impact on the other traders. In this paper, influential traders, including foreign investors, are investigated in terms of whom they give impacts to. In addition, the changes of their influence as time varies and foreign investors' trading pattern changes, are also examined.

Lastly, does the connectedness of traders affect market volatility? The volatility of a financial market should match the trading activities since the price changes in financial

[2]Korean newspaper articles
http://news.mt.co.kr/mtview.php?no=2017081014154437270&outlink=1&ref=https%3A%2F%2Fsearch.naver.com
http://www.edaily.co.kr/news/news_detail.asp?newsId=01643286612877536&mediaCodeNo=257&OutLnkChk=Y

markets are the result of traders' trading activities. Thus, if the role of a central trader changes, it could impact on market volatility. In this paper, I investigate the contribution of trader's connectedness to market volatility with the adaptive LASSO technique.

I estimate the network structures with Granger causality and generalized variance decomposition methods. Based on the estimated network structures, I find influential traders and analyse the network. The strong connections among traders and the change of influential traders' influence during different time periods are also investigated. In addition, the contributions of traders' connectedness measures to market volatility are examined.

With the network analyses estimated with Granger causality and generalized variance decomposition methods, a few meaningful results are obtained. First of all, I find that foreign investors and stock, bond derivative and FX derivative markets are more influential than others, and that the particularly strong connections during specific time periods exist. In addition, the specific conditions which are the foreign investors' trading patterns and the time periods are shown to change influential traders' impact on others. For instance, individual investors lose their influence when foreign investors trade stocks during crisis period due to their strong influence during other time periods. Foreign investors are found not to increase financial market volatility, while other influential traders seem to contribute to increase market volatility. Consequently too cautious attitude to foreign investors' exit seems to lack the reasonable evidences.

This paper makes a number of contributions to the extant literature and to the deliberations policy makers. First of all, due to the recent methodology of network theory, the complex relationship among traders and the channels through which the influence of traders' influence on the market within the traders' network structure can be examined. To the best of my knowledge, this type of research, which includes the relationship between traders and the connection across different markets, has not been done yet. Secondly, if the influence of influential traders can be explained, the results can help policy makers stabilize local financial markets even during a period of crisis. Since the global financial crisis, many jurisdictions such as Brazil and Korea have legislated measures to alleviate the negative effects of foreign investors' cash flow.

In those circumstances, policy makers can launch the tailored policy for influential traders in order to stabilize the financial market based on the results of this research.

The organization of this paper is as follows. In Section 2, extant literature is reviewed by topic. Section 3 describes the methodology and Section 4 summarizes data analysed. In section 5 the results of analyses are described in detail and the robustness is checked in section 6. Finally a conclusion is given in Section 7.

2 Literature Review

In this section, related previous literature is reviewed by the following topics: individual and institutional investors, foreign investors, network study in finance and methodology of network studies. The extant research on investors' traits and impacts on the market did not elucidate the implication on the relations among investors despite their contribution to understanding of the financial markets. In order to overcome their limitations, network studies on finance, which investigated the relation between market and traders, are reviewed here. However, if network studies are used without sufficient econometric background, the economic implication between the relations cannot be easily achieved. Therefore, a complete understanding of the relations between traders presupposes an understanding of econometric backgrounds behind the connections within the network. The Previous literature on methodology have provided the theoretical backbone to this study.

2.1 The characteristics of individual and institutional investors

Some studies have shown that individual investors increased market volatility. Foucault et al. (2011) found that individual investors positively affected stock market volatility in the French stock market. Kim and Nofsinger (2007) showed the individual investors in the Japanese stock market had positive feedback in bull market. Positive feedback trading refers a trading pattern which makes a trader have more trading in the direction of market movement. With positive feedback a trader trades more when the market is good and less when it is bad, which accelerates market destabilization. Veld and Veld-Merkoulova (2008) proposed the causes of individual traders' positive feedback with questionnaires-based research.

Other research has suggested the psychological grounds of individual traders' irrational investment decisions. Joo and Durri (2018) tried to explain individual traders' deviation from rational price with survey data and found that a few psychological traits such as faith influenced their investment decision making. McInish (1982) approaches the drivers of individual traders' risk taking psychologically with a survey method.

Research on the institutional investors have been actively conducted. The evidence that institutional investors increased the financial market volatility has been suggested by numerous studies. Gabaix et al. (2006) suggested a theoretical model in which the large trader caused a sharp movement of price or volatility Baik et al. (2010) found that local investment advisors had more profitable trades, and that local institutional investors are more important to future returns than nonlocal institutional investors. Sias (1996) found that increases in institutional investors' interest induced the increases in volatility.

Some research, however, has shown the opposite pattern, which occurs mainly because of different investment objectives on the part of institutional investors. Bohl et al. (2009) showed that institutional investors stabilized index stock returns with the data from the Polish pension system. Using US data, Lakonishok et al. (1992) suggested the evidences that pension managers did not strongly pursue destabilizing practices. Dennis and Strickland (2002) presented the research result that the relations between institutional investors and market returns varied in terms of the type of investors such as fund managers and banks. Callen and Fang (2013) found that the attributes of institutional investors vary the impact on the market. Institutional investors with a long-term such as like pension fund managers were shown to have a negative relation with the market risk.

Another strand of studies compared individual and institutional investors. In the US market, institutional investors were thought to have more impact on the market than individual investors. Nofsinger and Sias (1999) investigated the stocks listed on NYSE (Newyork Stock Exchange) and suggested that the positive-feedback trading of institutional investors seemed more evident than individual investors, or that the impact of herding on prices also appeared to be more significant in institutional investors than in individual investors. Griffin et al. (2003) showed the results based on their research on the securities listed on Nasdaq. They found that strong daily patterns which were positively (negatively) following past intra-daily excess returns, could be explained by net institutional (individual) trading.

Other research found that herding behaviours were observed more in individual investors than in institutional investors. Goodfellow et al. (2009) suggested that individuals engage in herding during bear market periods while institutional investors does not appear to exhibit herd behaviour regardless of the market state. Bailey et al. (2009) found that common behaviours were more strongly shown for individual investors rather than institutional investors in the Shanghai stock exchange. Chuang and Susmel (2011) showed that in Taiwan individual investors invested more in riskier securities during downturn markets than institutional investors, and that individual investors traded more actively in highly volatile markets in order to obtain market gains.

2.2 Attributes of foreign investors

The role of foreign investors and their characteristics in local markets have been studied focusing on their impact on the return and volatility of the market. In addition, their contribution to price discovery and the existence of information asymmetry between foreign investors and domestic investors have also been researched.

One of the main research areas on foreign investors concerns the relation between foreign investors and market volatility. However, the results vary depending on the countries and period. Some studies (Umutlu and Shackleton, 2015; Ebeke and Lu, 2014) found that foreign investors increased market volatility in various emerging market countries. However, others found the opposite result. Nguyen (2016) showed that foreign investors' share of stock holdings decreased stock return volatility in Vietnam. Wang and Lee (2015) found that foreign investors short selling in the Korean stock market did not increase volatility. Wu et al. (2015) showed that foreign investment in Chinese local banks enhanced earnings smoothing.

The other essential study area of foreign investors concerns foreign investment and the market return. Ebeke and Lu (2014) showed that in twelve emerging markets increased foreign share of bonds reduced the level of local government bond yields. It is fairly plausible in emerging markets which lack systems for monitoring company management, that the active participation of foreign investors can enhance business performance. In contrast, other researchers have found that foreign investors passively increased their investment traders in local markets when the market was good, which is called positive feedback. Choe et al. (1999) and Kim and Wei (2002) showed that in the Korean stock market positive feedback of foreign investors was explicit before the Asian crisis. Arora (2016) found that foreign investors had positive feedback in India.

Given these incompatible research results, some of the literature has concentrated on the impact of foreign investors' on price discovery and their information asymmetry with local traders. Park et al. (2017) found that the active participation of foreign investors in the Korean treasury bond futures market significantly contributed to price discovery. The finding of Lim et al. (2016) was that foreign investors enhanced the efficiency of price discovery in the Malaysian stock market. Peranginangin et al. (2016) found that the aggressive trading of foreign investors helped price discovery in the Indonesian stock market using several price discovery measures such as component share (Gonzalo and Granger, 1995). Lee and Wang (2016) showed that in the Taiwan index options market underlying asset returns could be predicted significantly with the trading of foreign investors. Despite the positive contribution of foreign investors to price discovery, some research showed the opposite results. Chung et al. (2017) showed that more foreign investors in the Korean stock market aggravated information variation based on the bid-ask spread change. Although intuitively the participation of foreign investors in local markets seemed to have a positive role in price discovery, it was not an absolute phenomenon.

The comparative advantage of foreign investors in global investment information and their comparative disadvantage in local investment information have been also investigated considerably. Kang et al. (2016) found that in the Korean stock market, foreign investors had a greater advantages in global investment information than local traders did. Batten and Vo (2015) showed that foreign investors were inferior to local traders in the Vietnamese stock market, and that they preferred a buy and hold strategy reducing their domestic information asymmetry.

The studies on foreign investors suggest diverse results depending on the data analysed and the periods in which it was analysed. However, the approach to the analysis of the relation of foreign investors and local traders has not yet been implemented sufficiently.

2.3 Extant literature on network study in finance

A simple definition of network by Newman (2010) is a collection of points joined together in pairs by lines. Network theory has been used by the numerous researchers in various fields such as physics, chemistry, medical science, biology, and sociology. In economics and finance many studies have utilized the network theory and have shown many meaningful results. Based on the definition of network given above, the main objectives of network research in economics and finance are to investigate the network structure, the roles of points, and the change of network under endogenous and exogenous shocks.

Global financial crisis (GFC) became the catalyst for network studies in the financial area to estimate interconnectedness for investigating systemic risk (Kara et al., 2015). By the taxonomy suggested by (Kara et al., 2015) there are two types of network approaches to estimate interconnectedness. One is the direct method which has been much applied to interbank and CDS market. This method uses direct balance sheet data or a simulation method. The other is the indirect method using market price data, which has been implemented mainly in the capital markets.

One of the most representative examples of network analysis in economics concerns the interbank network. In this type of research, network topology is estimated by the exposure (lending) of a bank to others (Nier et al., 2007; Gai and Kapadia, n.d.; de Souza et al., 2016) or the settlements between two banks (Rotemberg, 2008; Kyriakopoulos et al., 2009). Once the network structure is investigated, the next step is to discover how the network structure changes under certain conditions such as the default of a few influential banks, critical credit events and serious decreases in asset values. This type of credit risk contagion has been examined deeply in particular after the global financial crisis in the process of studying the systemic risk. Although many studies (Allen and Gale, 2000; Bolton and Freixas, 2000) have provided theoretical grounds, empirical research is, however, challenging due to the difficulty involved in data collection. Interbank transaction data is not publicly available in general. Furthermore, balance sheet data is low-frequency and not appropriate for the determination of the change of credit risk. Hence, many studies have been carried out with simulation approaches.

The other strand of literature of network analysis concerns Credit default swap (CDS), which is a credit derivative in which the protection seller pays the protection buyer in case of a default. Since CDS is a bilateral contract with a payment amount, the network structure can be examined just as in the case of interbank lending if the data is available. Markose et al. (2012) analysed data of Federal Deposit Insurance Corporation (FDIC). In addition, in cases in which CDS is listed on exchanges, higher frequency data is publicly available, which makes the analysis easier (de Castro Miranda et al., 2012; Kaushik and Battiston, 2013).

The number of network analyses on capital market has also increased exponentially since the global financial crisis. Transaction datasets of financial products in capital markets are usually publicly available. In addition, due to the diverse financial products and players in the markets, the research topics are various and new methodologies have been developed.

Some research has attempted to find the network structures of asset returns. Chuang (2016) found that the centrality of brokerage firms explained the stock returns very strongly. Wang, Yan and Chen (2017) analysed Chinese interest rate and bond markets.

Their finding was that some short-term interest rates influenced to other interest rates, and that information flows between interest rates could explain the bond market segmentation in China. Caraiani (2017) studied the network with the US stock market index and utilised local properties which were average path length, diameter, cluster coefficients and average degree. They showed that local properties had the power of prediction.

Other research investigated the inter-relation of asset prices' volatilities. This research provided the clues to understand the contagions of market risk. Gao and Ren (2013) estimated the network structure with Chinese stock volatilities and showed that the stock with high centrality could play a pivotal role for systemic risk immunization. Song et al. (2016) investigated the network structure of Korean financial systems with GARCH-filtered risk premium of individual stock in Korea. They found an inter-linkage of financial events and the network structure. Wang et al. (2016) studied volatility spill-over across Chinese stock, bond, commodity futures and FX markets. Their finding was that the stock market was the most influential driver in volatility spill-over, and that the Global financial crisis and European sovereign debt crisis had impacted on the Chinese financial markets. Barigozzi and Hallin (2017) investigated the network topology with the volatilities of S&P 100 data. They shed light on the stocks in the financial sector which were important particularly during the global financial crisis. Creamer (2017) estimated the network structure with relevant topics of the news and examined the relationship of the network measures and the volatilities of stock of STOXX 50 including the top 50 European companies.

Research topics of network theory in economics and finance have been extended from the network within one market to the network across several markets or different countries. Bekiros et al. (2016) utilized network theory to investigate the relationship between US equity and commodity futures. Thapa et al. (2016) examined foreign exchange derivatives markets in forty countries and found a portfolio traders' wealth allocation strategy across these countries. Silva et al. (2016) showed the change of network topology for the global financial market.

Since the research of Brock and Hommes (1998), theoretical approaches to investigate the traders' (agents') behaviour with agent-based modelling have been implemented. Tedeschi et al. (2012) showed that theoretically, the agent can benefit from being imitated by others when he/she becomes the guru, and that the agent can acquire profit by following the strategy of the guru. Wang and Wang (2018) investigated the relation between herding behaviours of agents and market volatility. Based on their results, the more precise information of gurus can make other agents trade more, which leads to higher market volatility.

In spite of the recent development of network analysis in capital market like that described above, there have not been many empirical studies on the network between traders. A few studies attempted to examine the relationship between traders in network, but there were some limitations. Billio et al. (2012) investigated network structures of four financial sectors: hedge funds, banks, broker/dealers and, insurance companies. However, because their data was monthly returns, it is difficult to see the real relationship among those four sectors.

2.4 Extant literature on the methodology of network studies

At the initial stage, when network theory began to be applied to financial markets, the correlation between the market returns of two assets or volatilities has been utilized to investigate network topology (Bonanno et al., 2004; Garas et al., 2008; Peron et al., 2012). Earlier research focused on finding a network structure and applying network concepts to capital markets. However, with this approach, it has been challenging to fully understand the causal relationship between assets and the mechanism of systemic risk in the market.

In order to estimate the network structure with a causal relationship, various approaches have been tried. Among them, the methods which can be applied to time series data including asset price, are Granger causality and variance decomposition according to the taxonomy of Kara et al. (2015).

First of all, Granger causality which was introduced by Granger (1969) and Sims (1972) has been popular in economics and finance studies on the dynamic relationship between variables. In order to measure the pairwise causality with the Granger causality method, the extent to which the past of a variable (y) helps to forecast the other variable (x) over the degree to which the past of the variable (x) contributes to forecast itself (x), is quantified.

However, the simple unconditional Granger causality explained above has a critical drawback when capturing the pairwise causal relationship within a network structure. For example, when x Granger causes y under an unconditional setting, there could be a spurious causality. Although there is no causal relationship between x and y, if x and y respectively Granger causes z, a spurious causal relationships between x and y can be reported. To avoid this problem, the conditional Granger causality method needs to be applied (Barnett and Seth, 2014).

A number of studies estimated the network structures in diverse financial markets (Chuang, 2016; Gao and Ren, 2013; Wang, Yan and Chen, 2017; Song et al., 2016; Caraiani, 2017; Creamer, 2017). Recently the network size to estimate has been extended to high-dimensional cases with novel statistical approaches (Barigozzi and Brownlees, 2016; Dufour and Jian, 2016). Although even in those cases, pairwise causality relations are estimated by Granger causality measures.

The other method which has been popularly used in the network estimation is variance decomposition. This is the method to measures the contribution of one variable to the forecast error of the other variable under a VAR (Vector Autoregression) setting (Hamilton, 1994; Brooks, 2014). However, variance decomposition has a critical drawback in general, since it uses orthogonalized errors by Cholesky decomposition. When the order of variables in VAR model varies, the result can be different. In order to overcome this problem, Pesaran and Shin (1998) suggested generalized variance decomposition (GVD) from the idea of Koop et al. (1996). Their approach is that every node in a network shares forecast error variation of a certain node, and that the contribution of one node to the forecast error variation of that node is the connectedness.

GVD has a substantial advantage for network analysis which is invariant to ordering, whereas Cholesky-based variance decomposition is sensitive to ordering in vector autoregression (VAR) identification. Diebold and Yilmaz (2014) showed the connectedness with stock return volatilities of thirteen major US financial institutions and the result during global financial crisis was helpful to better understand the propagation of a crisis at each stage. Since the approach of Diebold and Yilmaz (2014), diverse studies have been implemented with the same methodology (Wang et al., 2016; Barigozzi and Hallin, 2017; Fernndez-Rodrguez et al., 2016; Chan-Lau, 2017). However, practically, their methodology would be difficult to use for high-dimensional network, which has many nodes.

Diverse connectedness measures have been suggested by many researchers, since it is still challenging to interpret the estimation results of matrix form network structures. The main objectives of these connectedness measures are to help to determine direct implications of the influence of each node on other nodes or on an entire network, and vice versa. Newman (2010) compiled most of the extant network concepts and theories. He suggested connectedness measures (or "centrality"), which has been popularly used. Among many centralities, the simplest and the most widely used one is degree centrality which sums the number of connected edges. Dufour and Jian (2016) suggested a slightly developed version of connectedness measure based on the Euclidean geometrical approach. They measured the influence of each node or sector with the geometrical distance to vector of the entire network. Wang, Xie, He and Stanley (2017) and Kenett et al. (2010) introduced entire, sectoral, and individual connectedness measures, which can capture the influence of not only the individual node, but also the sector or entire network.

In order to find which trader's connectedness measure affects the market volatility, a variable selection technique is needed. One of the most popularly used techniques for variable selection is LASSO (Least Absolute Shrinkage and Selection Operator) (Tibshirani, 1996). Although LASSO is not only very powerful but also widely used in various areas, the technique suggests inconsistent results under certain conditions (Zou, 2006). Zou (2006) suggested adaptive LASSO which fixed this problem. Here, I use adaptive LASSO to investigate the impact of traders' connectedness measures on the market volatility.

3 Methodology

3.1 Overview

The basic elements in a network are nodes and edges. A node is a point in an entire set and an edge is the connection between two nodes. If there is a direction in the connection between two nodes, the network is directed. Otherwise is it undirected. For example, if there is a causal relation between two nodes as is the case in this study, it is a directed network. In addition, the network can be divided into a weighted and an unweighted network depending on the weight of connection. Some connections may be stronger or weaker than others. In a weighted network, every edge (connection) has its unique value, while in an unweighted network, all edges are considered as having same weight. The relationship of traders in this paper is assumed to be directed and weighted.

This Section can be divided into two parts. One is the network estimation and the other is network analysis. In order to estimate the network, the nodes and edges should be defined. The node is the trader's daily net trading volume and the edge is the degree of causality between two nodes. The network can be represented in matrix form. The entry $c_{i,j}$ of causality matrix C means the degree of causality with which row entry i influences the column entry j.

Mathematical representation of this is given below. Network G can be represented with the set of nodes X and the edges C.

$$G = \{X, C\} \tag{1}$$

where $X = \{x_1, ..., x_n\}$ and $C = \{c_{i,j} : (i, j) \in X \times X\}$.[3]

I use eight types of traders in five different markets in Korea. Hence network nodes

[3]By the custom of network literature, nodes and edges are expressed with V (vertex) and E (edges). However, in this paper for the consistency of quotation, I use X and C.

processes are defined as $X_t = [x_{trader1,market1,t}, ..., x_{trader8,market5,t}]'$.

$x_{trader_{ii},market_{jj},t}$ is the daily net trading volume of trader ii in market jj on trading day t which is defined as in Table 1. The detailed explanation of daily net trading volumes are given below and represented in Equation 2. Firstly, the absolute values of all traders' daily net trading volumes are summed. Then, each type of trader's daily net trading volume is multiplied by two and divided by the sum of all traders' absolute daily net trading volumes. This is the daily net trading volume of each type of trader. In this way, daily net trading volumes of all traders are standardized to avoid the distortion of huge trades in large markets and to compare the impact of traders from different financial markets based on the same criteria. Descriptive statistics are given in Table 2. [4] Daily net trading volumes of all traders are stationary, as seen on Table 9. In addition, the detailed components of X are given in Table 10.

$$x_{n,t} = \frac{\text{trader n's daily trading volume} \times 2}{\sum |\text{trader n's daily trading volume}|} \tag{2}$$

Table 1: Definition of variables

	IND	BANK	FI	CIS	OTH	INS	GOV	FOR
Stock	$x_{ind,su}$	$x_{bank,su}$	$x_{fi,su}$	$x_{cis,su}$	$x_{oth,su}$	$x_{ins,su}$	$x_{gov,su}$	$x_{for,su}$
Stock Drv.	$x_{ind,sd}$	$x_{bank,sd}$	$x_{fi,sd}$	$x_{cis,sd}$	$x_{oth,sd}$	$x_{ins,sd}$	$x_{gov,sd}$	$x_{for,sd}$
Bond	$x_{ind,bu}$	$x_{bank,bu}$	$x_{fi,bu}$	$x_{cis,bu}$	$x_{oth,bu}$	$x_{ins,bu}$	$x_{gov,bu}$	$x_{for,bu}$
Bond Drv.	$x_{ind,bd}$	$x_{bank,bd}$	$x_{fi,bd}$	$x_{cis,bd}$	$x_{oth,bd}$	$x_{ins,bd}$	$x_{gov,bd}$	$x_{for,bd}$
FX Drv.	$x_{ind,fxd}$	$x_{bank,fxd}$	$x_{fi,fxd}$	$x_{cis,fxd}$	$x_{oth,fxd}$	$x_{ins,fxd}$	$x_{gov,fxd}$	$x_{for,fxd}$

[Note]
1. (Trader)
IND = Individual trader, BANK = Bank, FI = Financial investment(mainly securities companies)
CIS = Collective Investment Scheme, OTH = Others (small financial companies)
INS = Insurance companies, GOV = Government, FOR = Foreign Investors
2. (Market)
SU = Stock, SD = Stock derivative, BU = Bond, BD = Bond derivative
FXD = Foreign exchange derivative

Having defined the nodes, it is necessary to define the edges. As mentioned above, the degree of causality between two nodes is the edge. In this paper, I apply two methods

[4] Data source is Korean Exchange (KRX) and Korean Financial Investm.ent Association (KOFIA). Time period is from 2006 to 2015. KOFIA began to provide the data from 2006. During the investigated periods, there is no missing value.

Table 2: Descriptive statistics of daily trade

Stock		IND	BANK	FI	CIS	OTH	INS	GOV	FOR
	Mean	-0.01	-0.01	0.02	-0.08	0.00	0.02	0.09	-0.02
	Max	1.00	0.79	0.97	1.00	0.48	0.87	1.00	1.00
	Min	-1.00	-1.00	-0.94	-1.00	-0.67	-0.67	-1.00	-1.00
	Sted	0.60	0.11	0.23	0.44	0.04	0.13	0.30	0.61
	Skewness	-0.04	-2.51	-0.31	-0.01	-2.14	0.04	-0.20	-0.01
	Kurtosis	-1.28	24.70	2.47	-0.65	49.42	4.44	0.94	-1.30
Stock derivative									
	Mean	0.00	0.00	0.00	0.01	0.00	0.00	0.00	-0.02
	Max	1.00	0.67	1.00	1.00	0.41	0.88	0.94	1.00
	Min	-1.00	-0.59	-1.00	-1.00	-0.34	-0.64	-1.00	-1.00
	Sted	0.50	0.09	0.42	0.40	0.03	0.11	0.17	0.73
	Skewness	0.00	0.19	-0.02	0.00	1.23	0.54	-0.10	0.04
	Kurtosis	-0.98	8.49	-0.52	-0.17	44.44	8.39	4.90	-1.60
Bond									
	Mean	0.04	0.15	-0.85	0.28	0.02	0.11	0.16	0.09
	Max	0.44	0.91	0.97	1.00	0.51	0.66	0.88	0.86
	Min	-0.22	-1.00	-1.00	-0.74	-0.56	-1.00	-0.86	-1.00
	Sted	0.06	0.29	0.25	0.23	0.06	0.14	0.17	0.17
	Skewness	1.40	-0.76	2.87	-0.17	-0.33	-0.71	-0.02	-0.03
	Kurtosis	6.33	0.91	10.26	0.86	16.78	4.01	1.78	5.58
Bond derivative									
	Mean	0.00	-0.01	-0.01	0.00	0.00	0.00	0.00	0.03
	Max	0.89	1.00	1.00	0.90	0.33	0.96	0.66	1.00
	Min	-0.90	-1.00	-1.00	-0.93	-0.36	-0.87	-0.59	-1.00
	Sted	0.14	0.57	0.59	0.20	0.02	0.16	0.10	0.65
	Skewness	0.20	0.04	0.04	-0.10	0.31	0.17	-0.20	-0.05
	Kurtosis	7.20	-1.15	-1.29	2.25	70.36	6.02	4.07	-1.35
FX derivative									
	Mean	0.00	0.04	0.02	-0.06	0.00	0.00	0.00	0.00
	Max	1.00	1.00	1.00	1.00	0.70	0.75	0.34	1.00
	Min	-1.00	-1.00	-1.00	-1.00	-0.57	-0.61	-0.42	-1.00
	Sted	0.47	0.56	0.48	0.34	0.07	0.04	0.01	0.55
	Skewness	-0.01	-0.04	0.00	-0.11	0.31	-0.70	-7.65	0.01
	Kurtosis	-0.41	-1.04	-0.82	1.37	13.97	101.77	827.08	-1.01

[Note]
(Trader definition)
IND = Individual trader, BANK = Bank, FI = Financial investment(mainly securities companies)
CIS = Collective Investment Scheme, OTH = Others (small financial companies)
INS = Insurance companies, GOV = Government, FOR = Foreign investment

to estimate the causality. These are Granger causality method (GCM) and generalized variance decomposition (GVD). By comparing the differences of two estimation results, the strength and weakness of each method can be observed. In addition, the more appropriate method for a traders' network can be determined. To the best of my knowledge, this methodological comparison is the first trial in the extant literature although the comparison between linear and nonlinear GVD has been attempted by Chan-Lau (2017). For the efficiency of the quotation, the edge and the causality matrix are represented respectively as $c_{i,j}$ and C. One important point here is that in the causality Matrix C, row i is the source of influence and column j is the target of influence, which means i has an influence on j. The influence from trader i to trader j means that literally trader i has an influence to trader j on his/her trading behaviour. For more practical interpretations, trader j refers to trader i's trading behaviour when he/she decides how to trade.

3.2 Granger Causality Measure

Each node within the network is a trader's daily net trading volume at time t. In this section hereafter, for the sake of simplicity t is omitted. Within a network structure x_i is the source or influence and x_j is the target of influence conditional on the other components of X which are defined in Table 1. Both i and j mean the trader type and the market which a trader belongs to like table 1. $c_{i,j}$ is a pairwise causality measure and all causality measures among the traders can form a causality matrix.

The explanation given above can be also represented in a multivariate form. The unrestricted and restricted multivariate model processes can be respectively described as below. (Equation 3, 4)

$$X_t = \sum_{k=1}^{p} \beta_k \; X_{t-k} + \upsilon_t \tag{3}$$

where $X_t = [x_{trader1,market1,t}, ..., x_{trader8,market5,t}]'$ is a 40×1 vector. Coefficient matrix β_k is 40×40 matrix and error term $\upsilon_t \sim w.n.(0, \sum_{\upsilon})$ is 40×1 matrix. $\sum_{\upsilon}$ is assumed to be positive definite.

$$X_t = \sum_{k=1}^{p} \beta_k' \; J_i \; X_{t-k} + \upsilon_{i,t}' \tag{4}$$

where coefficient matrix β_k' is 40×39 matrix and this is different from β_k of an unrestricted model. Error term $\upsilon_t' \sim w.n.(0, \sum_{\upsilon'})$ are 40×1 matrix. $\sum_{\upsilon'}$ is also assumed to be positive definite. In restricted model, J_i plays an essential role and is a 39×40 matrix. J_i is made with the combination of 39×39 identity matrix and 39×1 zero column vector. Firstly, the identity matrix is divided into two matrices. One is the matrix from the identity matrix's column 1 to column $i - 1$, which is called "left matrix." The other one is the matrix from the identity matrix's column i to column 39 which is called "right matrix." Then, the matrices are combined by the order of left matrix, zero column vector, and right matrix. When i is one, no left matrix exists: and in case i is 39, no right matrix exists. For each i, a separate restricted model can be made and applied for Granger causality measure estimation.

Before the estimation, a proper model order needs to be determined. Here I use Akaike (AIC) and Bayesian information criteria (BIC). The optimal model order (p) is suggested as 1 in all restricted and unrestricted models.[5] All models with longer lag lengths are shown to have larger AIC and BIC statistics, which suggests they are not more appropriate than VAR(1). For the estimation of parameters, ordinary least squares (OLS) is applied. After the parameters estimation, Granger causality measures can be obtained with the forecast errors.

Besides the econometric appropriateness, which AIC and BIC suggests VAR(1) process, using VAR(1) process has a few implications here. Firstly, traders' decision making process can be reflected in the model, since trading data is daily. Traders are more likely to use the information extracted from the trading data of other traders on the previous day as their trading references rather than the data from a few days earlier. In particu-

[5]For estimation, MVGC Multivariate Granger Cusality Toolbox MATLAB toolbox(Barnett and Seth (2014)) is used. The toolbox shows the result of AIC and BIC.

lar, the information of all daily net trading volumes by trader types is publicly disclosed after 6 pm in Korea.[6] Furthermore, in the previous literature (Barigozzi and Brownlees, 2016; Dufour and Jian, 2016), the VAR(1) process was used. Thus, for the comparative objective VAR(1) can be helpful.

The lagged terms are not considered in this model. Although a few traders can monitor long term trends of the trading patterns of other traders and determine their trading in a real trading environment, the main focus of the investigation in this paper concerns each trader's daily reaction. In addition, all trading volumes are updated on a daily basis. The impact of lagged variables can be negligible after new information is announced. The result of AIC and BIC also suggests VAR(1). Thus, the possibility of a slower reaction after two days is not considered in the model.

Conditional Granger causality measure ($c_{x_i \to x_j | X}$) is defined to be as a log-likelihood ratio. The numerator is the forecast error of the restricted model and the denominator is the forecast error of the unrestricted model. Hence, the conditional Granger causality measure is assumed to be no less than zero.

$$c_{x_i \to x_j | X} \equiv ln\Big[\frac{det(Z_j \sum_{v_i'} Z_j')}{det(Z_j \sum_{v} Z_j')}\Big] (i, j = 1, ..., 40) \tag{5}$$

where Z_j is the identity row vector whose jth entry is 1 and whose other entries are all 0.

Statistical significance of estimated Granger causality measures can be tested against the null hypothesis of zero causality. $exp(c_{x_i \to x_j | X}) - 1$ scaled by d2/d1 follows asymptotically $F(d1, d2)$ distribution, where $d1 = pn$, ($n = 40$(variables number), $p = 1$(model order)) and $d2 = m - p(n+1)$, ($n = 40$(variables number), $p = 1$(model order), $m =$ sample numbers). Practically speaking, the estimation is implemented with the MVGC MATLAB toolbox (Barnett and Seth, 2014). In this paper, significance level is assumed to be 10%.

[6] KRX webpage, www.krx.co.kr

3.3 Generalized Variance Decomposition

Generalized variance decomposition (GVD) by Pesaran and Shin (1998) is the method which estimates pairwise network structure by one node's contribution to the forecast error of the other node. The most appealing point of GVD is order-invariance, while the traditional Cholesky-based variance decomposition has an ordering problem, in which the estimation results can be different depending on the order of the variables in the vector.

According to Diebold and Yilmaz (2014), GVD is estimated using the Vector Moving Average (VMA) representations given below. Firstly, it needs to suppose X_t to be stationary and error term υ_t to be a multivariate Gaussian process. X_t is actually stationary, as seen in Table 9. Then, X_t can be described as a VMA form.

$$X_t = \sum_{k=0}^{\infty} \Theta_k \; \upsilon_{t-k} \tag{6}$$

Generalized variance decomposition matrix(D)'s component(d_{ij}) is as

$$d_{ij}^h = \frac{\sigma_{jj}^{-1} \sum_{k=0}^{h-1} (e_i' \Theta_k \Sigma e_j)^2}{\sum_{k=0}^{h-1} (e_i' \Theta_k \Sigma \Theta_k' e_i)} \tag{7}$$

where σ_{jj} jth entry of diagonal of Σ. Σ is the covariance matrix of error term υ_t. e_i is a selection vector whose ith entry is 1 and 0 elsewhere. h is the predictive horizon. Here I use h=10 as Basel accord requires for market risk. Θ_h is the coefficient matrix in VMA representation.[7]

It is important to remember here is that one more operation is still needed after the estimation of the generalized variance decomposition matrix. Under the scheme of traditional variance decomposition, the sum of the forecast error variance decomposition of

[7] By the definition of Diebold and Yilmaz (2014), in generalized variance decomposition matrix(D) the entry d_{ij} means that jth column have impact on ith row which is opposite of Granger causality matrix in this paper. Hence I convert row and column in the analysis for keeping the consistency with Granger causality.

all variables is one. However, for the errors under generalized variance decomposition, variance is not orthogonal; the sum of generalized forecast error variance contributions on the variables cannot be one. In order to solve this problem, Diebold and Yilmaz (2014) convert d^g_{ij} into $\tilde{d}^g_{ij}$, where $\tilde{d}^g_{ij} = \frac{d^g_{ij}}{\sum_{j=1}^{N} d^g_{ij}}$. In this paper, same operator is applied.

3.4 Connectedness Measure

The objective of estimating the pairwise causality between two nodes conditional on the other nodes in the network is mainly to understand how the nodes interact in a network. However, once the network structure is obtained in matrix form, the degree of influence of a certain node on all other traders cannot be gauged without specific measures. To overcome this obstacle, the connectedness measures need to be defined.

Here, I use three types of Connectedness measures. These are OUT, IN, and RI (Relative Influence) measures. The OUT and IN measures respectively show each traders' influence on others and other traders' influence on that trader. Then, the RI can capture net influence of each trader within the network structure. The OUT measure can be acquired in Equation 8 adding a trader's influence to all others collectively. By contrast, the IN measure in Equation 9 is calculated with summing all influences from all other traders to one. These two measures are similar with the degree centrality, which is very commonly used in most of the network literature (Newman, 2010). While the OUT and IN measures investigates absolute unidirectional influence, the RI measure in Equation 10 (Kenett et al., 2010; Wang, Xie, He and Stanley, 2017) examines a trader's relative influence in a network. The value of RI is between -1 and 1. A positive RI means a trader is influential to others, but a negative RI means a trader is influenced by others. One important point here is that the "own causality" which is carried out by the same trader is not included in calculating these measures as Diebold and Yilmaz (2014) did. This is reasonable in that generally in a time series, the variable can be influenced by its own history to quite a high extent, although there is no evident autocorrelation.

$$OUT(i) = \sum_{j=1, j \neq i}^{N} c_{i \to j} \tag{8}$$

where $c_{i \to j}$ is the causality value from trader i to trader j which is the element (c_{ij}) of causality matrix (C).

$$IN(i) = \sum_{j=1, j \neq i}^{N} c_{j \to i} \tag{9}$$

where $c_{j \to i}$ is the causality value from trader j to trader i which is the element (c_{ji}) of causality matrix (C).

$$RI(i) = \frac{OUT(i) - IN(i)}{OUT(i) + IN(i)} \tag{10}$$

3.5 Network analyses frameworks

After estimating the network structures of traders with both GCM and GVD methods and calculating OUT/IN/RI connectedness measures, the frames for analyses must be built in order to better understand the relation of traders. In this present paper, I apply three types of analyses frames. They are the high-ranked connectedness measure, strong connections, and the dynamics of influential traders.

Firstly, I focus on the relative influence (RI) of each trader. The purpose of the analysis is to find the conditions which traders with high-ranked RI belong to. I concentrate on the traders whose ranks of RI are higher than 11th among 40 traders. Two different perspectives can be taken in this approach. One is to find the types of trader with higher relative influence and the other is to identify the market with high relative influence traders. This is a good first step to understand traders' network structure. However, since RI cannot capture the connections among traders, the analysis of OUT/IN measures is important.

The next step is analyzing OUT/IN measures to determine strong connections among traders which is defined below. To obtain strong connections, OUT and IN measures need to be analysed first. The OUT measure is the index of a trader's influence on other traders, and the IN measures are the values of the other traders' influence on that trader. Thus, OUT and IN measure can help to see the absolute influence of traders and the real connections between traders. Furthermore, if the components of OUT/IN measure are analysed, the main contributors can be found. The connections between main contributors of OUT/IN measures can provide a clue to see the operating mechanism within the network.

In this paper, the traders with Top 5 OUT and IN measure are mainly analysed for simplicity's sake. For each trader with the top 5 OUT measure value, three targets of the trader with the biggest causality measures are investigated. In the case of IN, in the same fashion, for each top 5 IN measure ranker, three sources of the trader with the greatest causality measures are examined. Within the network structure, it is highly probable that those connections overlap each other. I select the overlapped links and call them as "strong connections". If strong connections are found, they can be important clues to understand the network structure.

The last analysis frame is to analyse the RI/OUT connectedness measures of influential traders. Here, I choose influential traders as those with a high-ranked RI measure and foreign investors.[8] In this framework, the change of influential traders' RI/OUT connectedness measure is investigated as time periods (crisis and normal) and the trading patterns of foreign investors vary. To better understand the dynamics of impact of influential trader on the network when the trading pattern of foreign investors varies, I divide 6 sub-periods by foreign investors' trading patterns. Sub-periods are when foreign investors sell or buy stock(S), bonds(B), and stock and bonds together(SB).

[8]The reason why I choose foreign investors as influential traders, is based on the network estimation. They are shown more influential than others. The analysis on foreign investors' influence to local market can provide the view to see the role of foreign investors and the evidence to argue against the common conception on foreign investors, which foreign investors are the main reason of market fluctuation in emerging market countries.

Overall the analyses of the value of connectedness measure is not directly used, but instead the rank of connectedness measure is used. If the value of connectedness measure is used, a few problems can occur. Firstly, it is impossible to compare the result of GCM and GVD. Secondly, it is still difficult to ascertain a meaningful interpretation based on the value of connectedness measure. For instance, a double of the connectedness measure does not necessarily mean a double of the influence. However, by using the rank of connectedness measure, those problems can be solved.

In all three analyses frames, three different time sub-periods which are all, crisis and normal are applied. This approach can help to understand the effect of crisis periods by examining the differences between crisis and normal periods. The type of time division is different from previous studies. Many extant studies defined crisis times as 2008 and 2009, during which the global financial crisis began and financial markets fluctuated extremely. Some studies added 2011 when European fiscal crisis occurred. The other stream of studies used dummy variables. This is one if VIX (CBOE) is over trigger value, or zero otherwise. Compared to the former approach, the latter has a few advantages. In case of using daily data, the analysis based on the data during a whole year can distort the result, since the financial market was stable for some days during the whole year. On the contrary, with the latter approach the volatile period during a whole year can be analysed selectively, although whether VIX (CBOE) can explain the crisis of local financial market is still open to question. Fortunately, some previous literature has shown that VIX can explain the volatility of local financial markets. Hence, I choose the latter approach to define a crisis time. In this paper the crisis period is determined when VIX is over the historic mean plus one standard deviation based on the idea of Escolano et al. (2014).

3.6 Contribution of traders' connectedness measures to market volatility

The relation of traders' connectedness measures and financial market volatility is also investigated. In order to investigate the contribution of traders' connectedness measures to market volatility, daily market volatility and daily traders' connectedness measures need to be acquired above all. I calculate daily market volatility with the previous 200 days' market index data and make a market volatility time series with the 200 days moving window method, following the example of Fernndez-Rodrguez et al. (2016). The market indices I use are KOSPI (stock index) and KRW/USD futures which are the most representative indexes in Korean financial markets.

Next, I obtain traders' daily RI connectedness measures. Traders' daily RI measures are acquired with both GCM and GVD using previous 200 days data, which is consistent with daily financial market volatility. Time series of traders' daily RI are built with the same 200 moving window method. After that, daily market volatility and traders' connectedness measures can be obtained finally from 24/10/2006 to 30/12/2015 (2,276 observations).

In order to analyse the contribution of the traders' connectedness measure to the financial market index, the adaptive LASSO technique is applied. The primary benefit of this technique is that it minimizes the number of variables which have the significant relations. The other benefit is that it is easy to interpret. The greatest difference between adaptive LASSO and OLS is that adaptive LASSO makes the insignificant coefficients zeros, which helps to focus on significant variables for interpretation. In addition, this technique can be applied to the cases when the sample number is insufficient. Based on the research of Zou (2006), adaptive LASSO can be applied when the number of variables is greater than the number of observations. Thus, with adaptive LASSO technique, the contribution of a trader's connectedness measure to market volatility during an analysed period can be easily identified.

I take two approaches to investigate the contribution of traders' connectedness measures to market volatility. One is simply running adaptive LASSO regression during a full analysed period. In this way, the traders whose connectedness measures have positive, negative or zero coefficients during the period, can be found. However, with this approach it is difficult to investigate the change of traders' contributions during the different time periods.

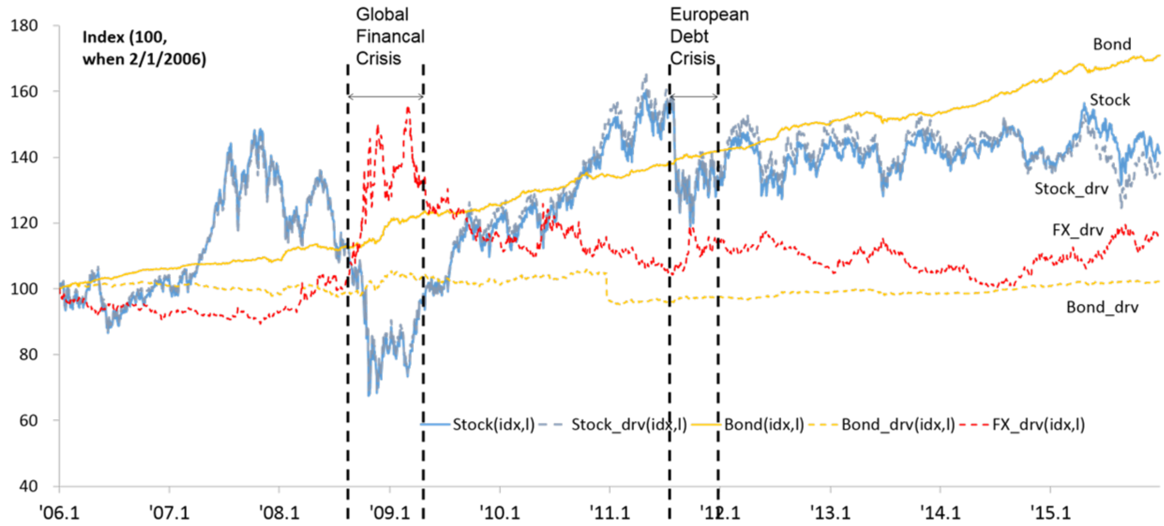
The other approach to overcome the simple approach above is running the adaptive LASSO regression daily with a narrower window and analyzing the coefficients. For this, I run a daily adaptive LASSO regression with previous 200 days data repeatedly for the entire analysed period applying the moving window method. After running daily adaptive LASSO regressions, daily coefficients of all traders can be acquired for all analysed periods. Then, each trader's daily contribution is divided into the positive or negative group based on the sign of the coefficient for all days. In the event that the coefficient is zero, the trader does not belong to any group on that day. In such a case, I count the days on which each trader belongs to the positive or negative group during the whole analysed period. Consequently the ratio of the number in the positive (or negative) group over the number of adaptive LASSO regressions run for the entire period, is each trader's positive (negative) contribution to market volatility. The positive (negative) contributing ratio of influential traders' is compared with the average ratio of all traders. That is one more merit of this approach. With the comparisons, it is possible to investigate whether or not there is a relation between the influence of a trader within the network structure and the contribution to market volatility.

4 Data

4.1 Korean financial market overview

Foreign investors have been considered to be de-stabilizers especially in the countries whose financial markets are open to the foreigners. Portfolio investments seeking short term high returns come to those markets and go out easily to re-balance their own portfolios. When global markets become volatile, there are two processes through which foreign investors impact on domestic financial markets. The first is the direct effect on the market. Sudden and huge selling trading volumes of foreign investors make a serious turmoil in the market. The next process occurs when the liquidity of foreign investors move out from the domestic market. Huge and sudden amounts of currency exchange lowers the

Figure 1: Korean financial market overview



[Notes]

1. During global financial crisis in 2008 and European fiscal crisis in 2011, there were sharp drops in stock market which is shown in blue line and sudden currency depreciation in FX market which is shown in dashed red line.
2. There were massive amount of foreign investors' investment outflow in Korean financial markets for those period. Due to that, over concern about foreign investors' money out has been formed in Korean financial markets.

value of local currency in the floating currency system in an open economy. Therefore, the influence of foreign investors is limited not only to financial markets, but also to the real economy through exchange rates.

The Korean financial market is one of the most representative examples. During the global crisis in 2008 and European fiscal crisis in 2011, stock price and local currency value decreased sharply as can be seen in Figure 1. Interestingly, during the very same periods, foreign investors reduced their net investment in the Korean stock and bond markets, which are shown in Figures 9 and 10. For during those periods, overall the Korean economy was not bad, at least it is very difficult to conclude the main reason why the exit of foreign investors' from the Korean financial market was economic fundamentals. If the domestic economy was not at risk and domestic traders did not sell much of their securities during those crisis periods, the reduction of foreign investors' net investment in the Korean financial market could be one of the most essential causes of the fluctuation of the domestic financial market.

In line with those events, whenever an item of bad news of from the global financial market was heard, the Korean mass media reported the trading trend of foreign investors and warned of the possibility of their exit from the Korean peninsula. Concurrently, Korean financial markets have been given a famous nickname "Global traders' ATM (Automated Teller Machine)", which refers to the way that global traders can easily take their money back when they need.

In this paper, I examine the credibility of common recognition on foreign investors' destabilizing role in the Korean financial market with network analysis. The biggest advantage of network analysis in this issue is to approach the problem with all the trading information of all traders acquired from financial markets, which can help to avoid the narrow view in which only the reduction of foreign investment and the plunge of market index are linked. In addition, I also investigate the contribution of trader's connectedness measures to market volatility. The real role of foreign investors in the Korean financial market can be determined with the combination of those analyses.

4.2 Data

For the analysis, daily net trading volumes of traders from January 2006 to December 2015 are used. I use the data of eight types of traders which are individuals (IND), banks (BANK), financial investment (FI), collective investment scheme (CIS), insurers (INS), government (GOV), foreign investors (FOR) and others (OTH). Individuals (IND) are individual or corporate traders. Banks (BANK) are commercial banks. Financial investment (FI) is the term defined by Korean law "*Financial investment services and capital markets act*" and are mainly securities companies. Collective investment schemes (CIS) are mutual funds. Insurers (INS) are life and nonlife insurance companies. Government (GOV) is the government and public funds including public foundations and public pensions. Foreign investors (FOR) are registered as foreign investors by the Korean financial authority. The details of traders are presented in Table 10. And Others is all other traders which do not belong to other criteria. Korea exchange(KRX) provides all trader types of traders' daily net trading volumes after the market closes on every working day.

The markets of stocks, stock derivatives, bonds, bond derivatives and foreign exchange derivatives are respectively KOSPI, KOSPI 200 futures, all bonds traded in the secondary market, 3-year Korea treasury bond futures and KRW/USD futures. The data source for stocks, stock derivatives, bond derivatives and foreign exchange derivatives is the Korea exchange.[9] Bond market data is provided from Korea financial investment association.[10]

In order to examine whether network structure changes by time period, I define a crisis period as one when the value of VIX index (CBOE) is over the historic mean plus one standard deviation. VIX index is the measure for market volatility in the US stock market which is known to reflect global financial market risk the most. As seen in Figure 2, VIX index represents crisis times appropriately.

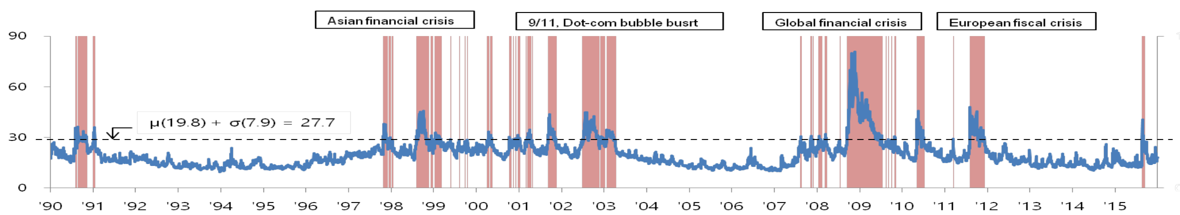


Figure 2: VIX index and crisis period

5 Results

Traders' network structures are estimated with GCM and GVD methods and each trader's RI/OUT/IN connectedness measure is calculated in this section. I analyse the network structures based on the connectedness measures. The objectives of analyses are to identify influential traders and markets, and to identify strong connections among traders,

[9] www.krx.co.kr
[10] www.kofia.or.kr

which can be the key clues to understanding the relations between traders. I then also investigate the changes in influential traders' connectedness measures and assess their influence within the network during different time periods. Finally, the contribution of traders' connectedness measures to market volatility is examined with adaptive LASSO technique.

5.1 Network estimation

Traders' pairwise conditional causal relationships are the elementary building blocks for network estimation. Causality matrices are built based on the causal relationship and are estimated using GCM or GVD. Each trader's connectedness measures which are relative influence (RI), OUT, and IN measures are obtained utilising causality matrices.

Firstly, I focus on Relative influence (RI) which can be interpreted as a trader's net influence on other traders within the network. RI is the difference of OUT and IN measures over the sum of OUT and IN measures in accordance with the definition. RI shows traders' roles within the network after offsetting their influence to others and the impacts of others on them, considering all traders can affect others and concurrently be influenced by others. However, since the scale of RI is different depending on the estimation methods (GCM or GVD), I use the ranks of traders' RI as I explained above. Influential traders and markets are identified based on the ranks of RI in this section. For the sake of simplicity of analyses, top 10 RI rankers are mainly investigated.

Then, strong connections within the network determined with OUT and IN measures are investigated. I define "strong connections"[11] as the overlapped connections of the targets of high OUT measure rankers and the sources of high IN measure rankers. The strong connections are found with both GCM or GVD and compared. The merits of strong connections complement the weakness of RI. Although a trader's influence on others can

[11] Technically, I concentrate on each top 5 OUT measure rankers and top 5 IN measure rankers. Then, I find respectively 3 most sensitive targets of top 5 OUT measure rankers (A) and 3 most influential sources to top 5 IN measure rankers (B). If there is overlapped connection between those two groups (A and B), it is called as "strong connections" in this paper.

Table 3: The number of top 10 Relative influence (RI) rankers' trader type

	IND	BANK	FI	CIS	OTH	INS	GOV	FOR
[GCM]								
All	-	1	2	-	1	1	1	4
Crisis	2	2	1	-	2	2	-	1
Normal	2	1	1	1	2	-	1	2
[GVD]								
All	2	1	2	1	-	-	-	4
Crisis	1	1	1	2	-	-	1	4
Normal	2	1	2	1	-	-	-	4

[Note]
1. The number of top 10 relative influence rankers in each trader type under certain methods (GCM, GVD) and time period (all, crisis and normal) is present.
2. (Trader type)
IND = Individual trader, BANK = Bank, FI = Financial investment(mainly securities companies)
CIS = Collective Investment Scheme, OTH = Others (small financial companies)
INS = Insurance companies, GOV = Government, FOR = Foreign Investors

Table 4: The number of top 10 Relative influence (RI) ranker's market

	Stock	Stock Drv.	Bond	Bond Drv.	FX Drv.
[GCM]					
All	1	2	1	3	3
Crisis	5	-	-	3	2
Normal	3	1	2	-	4
[GVD]					
All	2	1	1	3	3
Crisis	3	1	1	3	2
Normal	2	1	1	3	3

[Note]
The number of top 10 relative influence rankers in each market under certain methods (GCM, GVD) and time period (all, crisis and normal) is present.

be identified with RI, it is still difficult to find direct connections between traders. Yet, strong connections are the direct linkage between traders, so that the inter-connectedness between traders is captured. Strong connections can give an indication of financial market volatility spill over channels. Thus, I also concentrate on traders' OUT and IN measures.

5.1.1 Traders' relative influence

All traders' relative influence (RI) connectedness measures are estimated and presented in Figures 3 and 4. The estimation result of the top 10 RI rankers is summarised in Tables 3 and 4. [12] All estimations are executed for different time periods which are all, crisis and normal periods.

Most of the top 10 RI rankers are from foreign investors in general, as can be seen in Table 3. 4 foreign investors' RIs are in top 10 during all period, which is suggested by both GCM and GVD. However, only GVD estimates that most of top 10 RI rankers are from foreign investors during crisis and normal times, while respectively one and two foreign investors belong to the top 10 RI rankers during the same period with GCM. In addition, GCM and GVD suggest quite different results with some traders such as CIS, OTH and INS. CIS has the top 10 RI rankers mainly with GVD, but OTH and INS has top 10 RI rankers with only GCM.

The stock, bond derivative and FX derivative markets have more top 10 RI rankers than the stock derivative and bond markets (Table 4), although there is a slight difference between GCM and GVD. There are fewer top 10 RI rankers in the FX derivative market during crisis period than all and normal times based on the results of both GCM and GVD. By contrast, more top 10 RI rankers are found in the stock market during crisis time than all and normal periods.

The result provides several important implications. First, foreign investors can be more influential to other market participants than any other local traders. In addition, the influential foreign investors who are not from a specific market, but from most of markets, are shown to be substantially influential. Then, trading activities in the stock market and derivative markets can be the reference to other financial markets. During crisis time the stock market in particular plays a pivotal role as a signal to other financial markets rather than derivative markets.

[12] The result during all seems different from the ones during crisis and normal. This phenomenon is evidently seen on the result of GCM. As explained, the process of acquiring GCM matrix is different from GVD, in that each causality value can be obtained after statistical significant check. In case the value is not significant, that value is not considered for the analysis. In addition, the all period can have an independent traits, although it has the data during both crisis and normal.

Despite those meaningful implications, the different results depending on the use of GCM or GVD need to be examined further. The reason for different results, however, might result from the detailed process of each method. Although both GCM and GVD measure the causality with the forecast variance differences of investigating variables, only GCM tests the statistical significance of the causality. Thus, if the causality estimated by GCM is not statistically significant, the very entry of the causality matrix should be zero. On the contrary, all components of the causality matrix except self-causality entries on the diagonal line have non-zero values by GVD. Given the methodological difference, it is reasonable that the difference in results arises from the data, and not from an unexpected error.

A nonlinear relation among traders might be the reason for the difference at the same time. Linear methods, which are applied in this paper, cannot capture the nonlinear relations. Network analysis with nonlinear methods needs to be implemented as a further research topic.

5.1.2 Top 5 IN measures rankers' sources and OUT measure rankers' targets

The OUT connectedness measure captures a trader's influence on others and the IN connectedness measure gauges the impact of other traders on a trader. One important point here is that OUT and IN measures can offset each other. Every trader is influenced by from others and has an impact on others at the same time. Thus, the influence between two traders within a network is bidirectional and overall the net influence of a trader within the network is captured by the relative influence (RI) connectedness measure. However, OUT/IN measures are still important, since they show the absolute value of each trader's influence and play a key role in identifying strong connections among traders. Furthermore, in a case in which a type of trader's OUT/IN measure is high but his/her RI measure is low, the trader might not be influential, but he/she can be meaningful because the trader functions actively as a channel or a bridge for influence

Figure 3: Rank of traders' Relative influence (RI) by trader

[Notes]

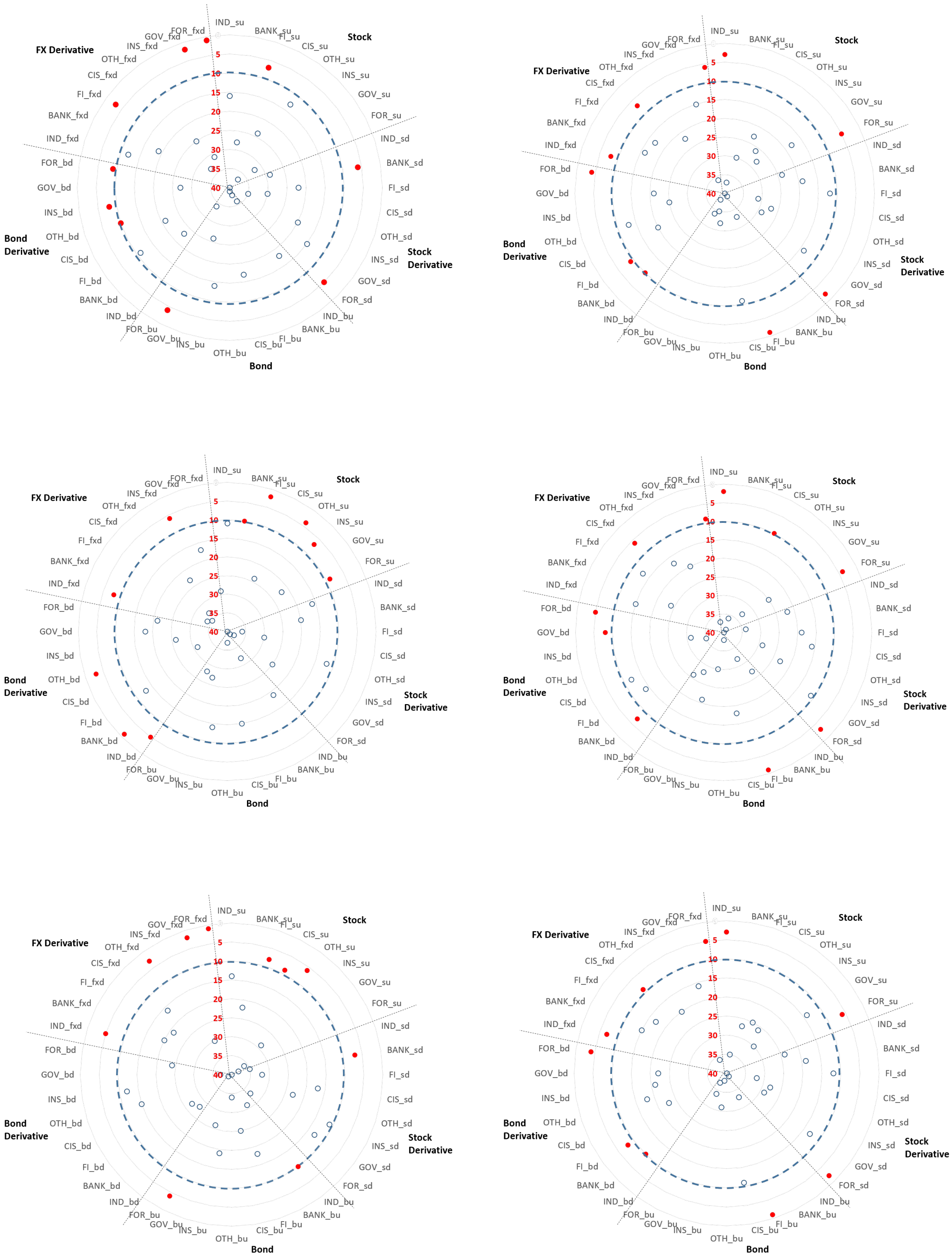
1. GCM / GVD (left / right), all / crisis / normal (1st / 2nd / 3rd line)

2. Trader's Relative influence (RI) rank is shown on each radar chart by the estimation method (GCM, GVD) and period (all, crisis, normal). If a trader's RI rank is higher than 10th, the circle is red. Otherwise the circle is white. The circles are arranged by trader type.

3. (Trader type) IND = Individual trader, BANK = Bank, FI = Financial investment, CIS = Collective Investment Scheme, OTH = Others, INS = Insurance companies, GOV = Government, FOR = Foreign Investors

4. (Market) su = stock, sd = stock drv., bu = bond, bd = bond drv. fxd = fx drv.

Figure 4: Rank of traders' Relative influence (RI) by market



[Notes]

1. GCM / GVD (left / right), all / crisis / normal (1st / 2nd / 3rd line)

2. Trader's Relative influence (RI) rank is shown on each radar chart by the estimation method (GCM, GVD) and period (all, crisis, normal). If a trader's RI rank is higher than 10th, the circle is red. Otherwise the circle is white. The circles are arranged by market.

3. (Trader type) IND = Individual trader, BANK = Bank, FI = Financial investment, CIS = Collective Investment Scheme, OTH = Others, INS = Insurance companies, GOV = Government, FOR = Foreign Investors

4. (Market) su = stock, sd = stock drv., bu = bond, bd = bond drv. fxd = fx drv.

Table 5: Top 5 IN/OUT measure rankers and their main sources and targets

	IN					OUT				
Top	1	2	3	4	5	1	2	3	4	5
[GCM]										
(all)										
trader	IND	FOR	OTH	FI	INS	INS	CIS	IND	FI	FOR
market	bd	su	bu	bu	su	bd	bd	bd	bd	bd
(crisis)										
trader	FI	FOR	BANK	GOV	CIS	FI	INS	CIS	BANK	OTH
market	bu	su	bu	bd	fxd	su	su	su	su	su
(normal)										
trader	IND	FOR	FI	INS	GOV	OTH	FI	INS	CIS	BANK
market	bd	su	bu	su	bd	su	su	su	su	su
[GVD]										
(all)										
trader	FOR	IND	CIS	CIS	FOR	FI	FOR	IND	FOR	FOR
market	sd	su	bu	su	su	bu	sd	su	su	bd
(crisis)										
trader	IND	CIS	BANK	FOR	CIS	FI	IND	FOR	CIS	FOR
market	su	bu	fxd	sd	su	bu	su	sd	fxd	su
(normal)										
trader	FOR	IND	CIS	CIS	FOR	FI	FOR	IND	FOR	FOR
market	bd	su	su	bu	su	bu	sd	su	bd	su

[Note]
1. The trader and the market with Top 5 IN and OUT connectedness measures are present under the method (GCM, GVD) and time period (all, crisis, normal)
2. (Traders)
IND = Individual trader, BANK = Bank, FI = Financial investment, CIS = Collective Investment Scheme
OTH = Others, INS = Insurance companies, GOV = Government, FOR = Foreign Investors
3. (Market)
su = stock, sd = stock drv., bu = bond, bd = bond drv., fxd = fx drv.

within the network.

The top 5 OUT and IN connectedness measure rankers estimated with both GCM and GVD and respectively the most three sensitive targets and the most three influential sources are presented in Table 5. All those connections and overlapped connections, which are called as "strong connections" here, are displayed in Figures 5 and 6. Strong connections are indicated with red dashed arrows.

As an influence giver which means a higher OUT measure ranker, financial investment (FI) in the bond market, Foreign investors (FOR) in stock and stock derivative markets, Individual investors (IND) in the stock market are found with GVD. In contrast, as an influence receiver which is a higher IN measure ranker, Collective investment scheme (CIS) in stock and bond markets, and Individual investors (IND) in the stock market are shown based on the results of GVD. In particular, GVD suggests that CIS in the FX derivative market becomes influential during crisis period, but Banks in same market becomes to be sensitive. Those results above are consistent with the general market conceptions and the extant literature.

The result of GCM, however, looks quite different from the one with GVD. It shows that the OUT measures of the traders in the stock market during crisis and normal periods and the traders in the bond derivative market, have significant impact on other traders. The IN measure of FI in the bond market and FOR in the stock market have higher ranks for all, crisis and normal periods. This might result from the difference in the methodological process or the data itself rather than an estimation error. As mentioned above, a statistically significant test for the causality in GCM can lead to a different result from GVD.

Next, I shed light on the strong connections between traders. GVD suggest several strong connections, which are the link from IND in the stock market to CIS and FOR in the stock market, the link from FOR in the stock market to IND in the stock market, and the link from FI to CIS in the bond market. Those strong connections are valid during all and normal periods.

However, several important changes are found during crisis period. IND's influence on FOR in the stock market disappears, while FOR's influence to IND still exists. This result provides supporting evidence that while foreign investors have a strong influence they nevertheless appear independent in their trading behaviours during a crisis, which is consistent with the previous literature. Furthermore, the link from CIS to the bank in FX derivative market newly appears. This can result from the reverse transactions of the currency hedge of overseas mutual funds and following transactions of banks.

GCM suggests strong connections which are slightly different from the result of GVD.

They are the links from OTH and INS in the stock market to FOR in the stock market, and the links from FI and OTH in the stock market to Government (GOV) in the bond derivative market during crisis and normal periods. There are strong connections from the traders in the bond derivative market to FI and OTH in the bond market during all period.

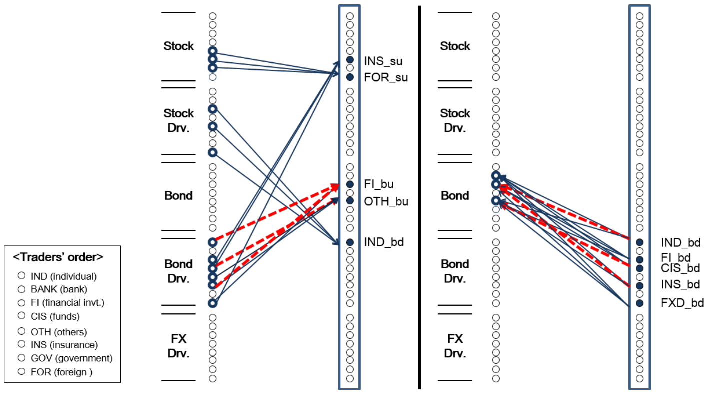
The analysis of OUT/IN connectedness measures and strong connections expand the scope of understanding of how the traders influence each other within the network structure. Given the results of the network analysis with RI measure, which are the influential traders such as FOR and IND and the influential markets such as stock and FX derivative markets, the way in which influential traders and markets are inter-connected with other traders is identified with the analysis.

The other practical merit of these analyses is that the information of the analysis results can be important resources for policy aims such as stabilizing financial markets. The policy makers can legislate an investors-tailored policy to restrict or incentivize a certain type of trader to trade.

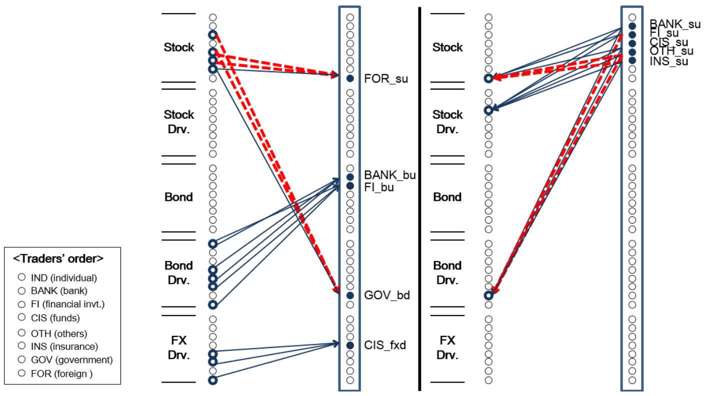
5.2 Change of influential traders's impact over different time period

I investigate the changes in the influence of influential traders by the time periods and foreign investors' trading patterns in this section. The change of relative influence of influential traders and comparative analysis according to the trading patterns of foreign investors can provide a deeper understanding of the dynamics of network structure, although the change of traders' RI, OUT and IN connectedness measures during all, crisis and normal times is examined. For instance, the influence of foreign investors can vary

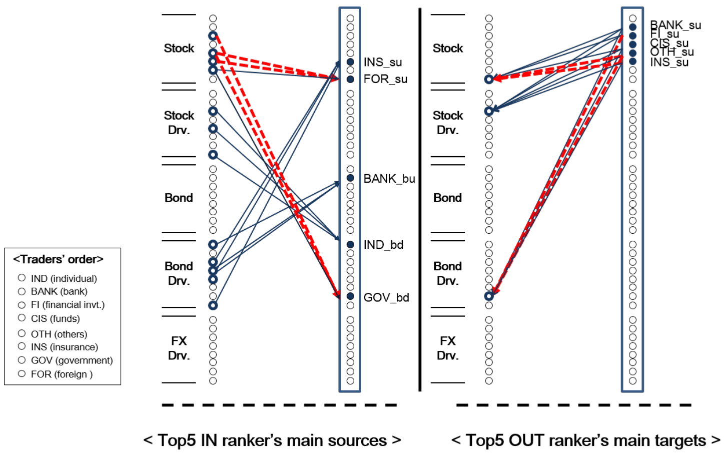
Figure 5: Relations between strong connection (GCM)



a. All



b. Crisis

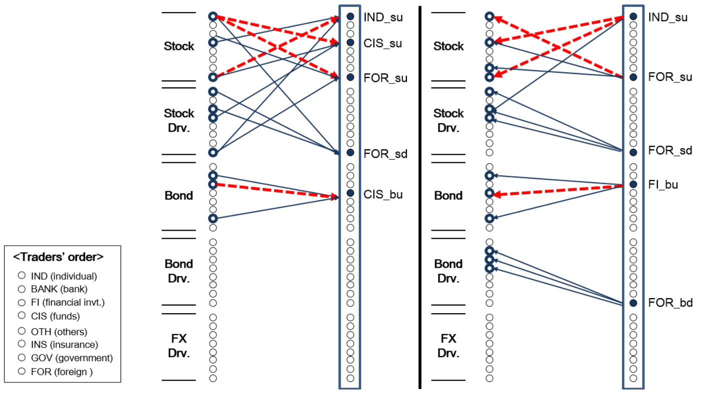


c. Normal

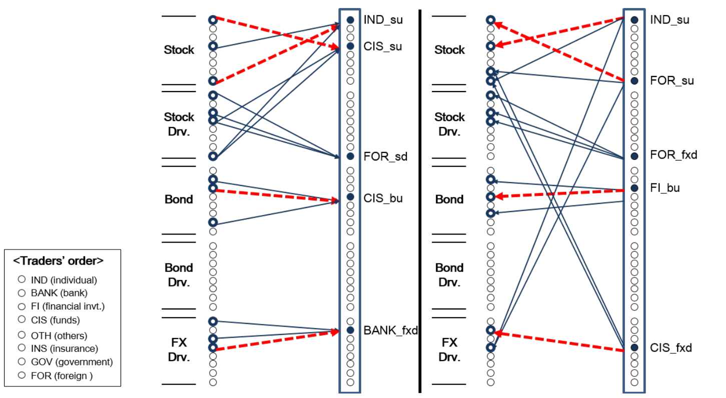
[Note]

1. Top 5 IN and OUT rankers' 3 main sources and targets are present during each time period (all, crisis, normal).
2. On left side, three main sources of top 5 IN rankers are shown. Colored circles are 5 IN rankers which are arrowed by 3 main sources.
3. On right side, three main targets of top 5 OUT rankers are described. Colored circles are 5 OUT rankers which are arrowing to 3 main targets.
4. Overlapped links on both sides are "strong connections" presented with red dashed line.

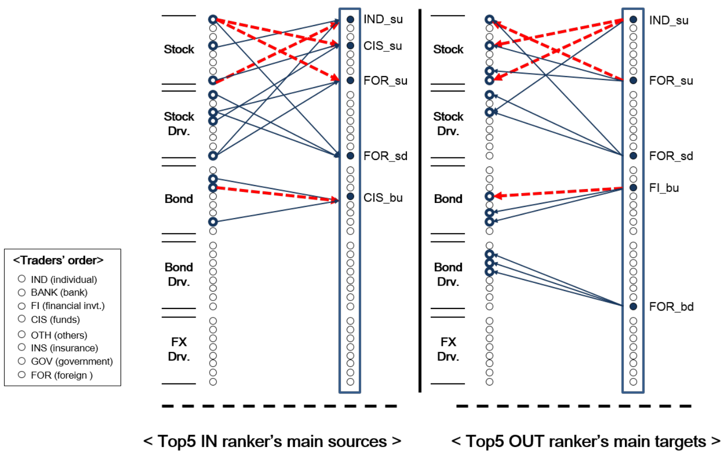
Figure 6: Relations between strong connection (GVD)



a. All



b. Crisis



c. Normal

[Note]
1. Top 5 IN and OUT rankers' 3 main sources and targets are present during each time period (all, crisis, normal).
2. On left side, three main sources of top 5 IN rankers are shown. Colored circles are 5 IN rankers which are arrowed by 3 main sources.
3. On right side, three main targets of top 5 OUT rankers are described. Colored circles are 5 OUT rankers which are arrowing to 3 main targets.
4. Overlapped links on both sides are "strong connections" presented with red dashed line.

between when they sell stocks and when they buy bonds. I divide the whole data set into six subsets when foreign investors sell (buy) stocks (bonds, or stocks and bonds together) for each time period.

I also choose other influential traders beside foreign investors according to the rank of RI. They are individual investors (IND) in the stock market, BANKs in the bond derivative market, financial investment (FI) in the bond market, and collective investment scheme (CIS) in the FX derivative market.

The influence ranks of influential traders, which is measured with RI and OUT connectedness measures are summarised on Tables 6 and 7. They are presented by the time period and the trading patterns of foreign investors. In addition, when their rank of connectedness measures is higher than 11, the cell is highlighted.

Foreign investors are present as highly influential mainly in the stock and derivative markets regardless of time and the trading patterns of foreign investors with GVD. In contrast, their influence on the bond market does not look significant with GVD. GCM, however, suggests that the foreign investors in the stock market can be influential when they sell stocks. Then they are influential in the FX derivative market during normal period with GCM. Despite the different results from both methods, it is in common with GCM and GVD that foreign investors in the stock market become more influential on stocks during a crisis, and that foreign investors in the FX derivative market are more influential during normal period. In addition, foreign investors in the FX derivative market are shown to be more influential during normal period with both methods when they buy than when they sell. This may be one of the items of contradicting evidence for the concern about the destabilizing role of foreign investors during a crisis period in an emerging market.

Other influential local traders are shown to have remarkable relations with the trading patterns of foreign investors. First, IND in the stock market loses their influence when foreign investors trade stocks during a crisis, while they are one of the most influential traders in the network during all, normal time. This is consistent with the previous result

Table 6: Ranks of foreign investors' connectedness measure

			SU		SD		BU		BD		FXD	
			OUT	RI	OUT	RI	OUT	RI	OUT	RI	OUT	RI
GCM												
All			40	40	36	5	27	4	5	9	11	1
Crisis			8	9	32	39	28	28	16	21	22	29
	Stock	S	8	7	38	38	27	19	16	8	3	15
		B	7	17	31	25	27	13	24	37	20	5
	Bond	S	17	6	21	40	35	26	7	18	25	27
		B	13	21	25	39	19	7	15	27	40	23
	Stock	S	23	28	16	34	25	5	7	23	33	38
	&Bond	B	4	8	25	17	10	9	23	38	35	31
Normal			8	38	37	33	12	4	32	24	18	1
	Stock	S	23	17	2	2	16	20	30	11	35	4
		B	32	29	18	18	37	37	13	10	5	3
	Bond	S	18	25	31	35	3	5	38	40	23	17
		B	8	33	37	25	10	14	23	26	29	1
	Stock	S	19	14	4	23	9	17	38	40	29	15
	&Bond	B	40	37	19	18	26	35	2	7	9	2
GVD												
All			4	5	2	2	25	34	5	4	7	6
Crisis			5	4	3	3	25	28	6	5	15	9
	Stock	S	10	33	2	3	23	21	11	5	13	6
		B	12	28	2	5	8	8	6	7	25	31
	Bond	S	5	5	19	19	37	39	15	13	7	8
		B	4	6	3	5	29	39	5	4	18	17
	Stock	S	23	23	21	21	32	32	22	22	34	34
	&Bond	B	4	11	6	8	30	35	2	2	24	31
Normal			5	6	2	2	24	34	4	4	7	5
	Stock	S	6	33	2	2	25	35	5	5	9	9
		B	18	39	2	2	21	22	4	5	5	4
	Bond	S	6	9	3	3	40	40	5	6	12	18
		B	6	7	2	2	27	40	5	4	7	5
	Stock	S	3	8	2	4	40	40	8	7	14	16
	&Bond	B	15	38	2	2	28	40	4	5	5	4

[Note]
1. The rank of foreign investors' OUT and RI in each market is present by period (all, crisis, normal) and their trading pattern (sell/buy stock/bond/stock&bond) estimated with GVD.
2. (Market) SU=Stock, SD=Stock Drv., BU=Bond, BD=Bond Drv., FXD=FX Drv.
3. (Trading pattern) S = sell, B = buy
4. The cell is shadowed when the rank is higher 10th.

in the case of strong connections, which is that the link from IND to FOR in the stock market disappears during a crisis. Second, BANKs in the bond derivative market have

Table 7: Ranks of other influential traders' connectedness measure

			IND_su OUT	IND_su RI	BANK_bd OUT	BANK_bd RI	FI_bu OUT	FI_bu RI	CIS_fxd OUT	CIS_fxd RI
GCM										
All			20	16	8	23	24	38	39	33
Crisis			10	11	1	1	38	40	24	33
	Stock	S	10	26	22	20	39	39	21	29
		B	4	14	12	10	35	36	21	33
	Bond	S	13	4	2	3	37	35	33	38
		B	11	14	1	1	23	19	37	24
	Stock	S	21	22	5	18	26	33	35	36
	&Bond	B	5	6	18	25	20	36	37	16
Normal			7	14	31	28	10	18	15	16
	Stock	S	12	7	29	16	20	22	40	24
		B	29	23	12	16	35	13	7	24
	Bond	S	12	13	39	33	2	2	24	20
		B	7	11	20	7	9	9	26	29
	Stock	S	18	26	40	34	12	8	32	32
	&Bond	B	38	27	4	17	25	13	16	34
GVD										
All			3	3	13	10	1	1	17	7
Crisis			2	2	10	7	1	1	4	6
	Stock	S	3	9	21	25	1	1	6	12
		B	7	12	9	6	1	1	11	21
	Bond	S	1	1	20	23	4	4	16	24
		B	2	3	8	7	1	1	7	11
	Stock	S	28	28	30	30	6	6	36	36
	&Bond	B	17	21	19	16	1	1	21	29
Normal			3	3	14	10	1	1	21	9
	Stock	S	3	4	15	12	1	1	17	6
		B	3	3	14	10	1	1	22	13
	Bond	S	4	4	18	19	1	2	22	17
		B	3	3	14	11	1	1	22	10
	Stock	S	5	5	13	13	1	1	20	17
	&Bond	B	3	3	14	12	1	1	22	16

[Note]
1. The rank of other influential traders' OUT and RI is present by period (all, crisis, normal) and foreign investors' trading pattern (sell/buy stock/bond/stock&bond) estimated with GVD.
2. (Trader) IND_su = Individual in stock market, BANK_sd = Bank in stock Drv. market
FI_bu = Finl. investment in bond market, CIS_fxd = Mutual funds in FX Drv. market
3. (Trading pattern) S = sell, B = buy
4. The cell is shadowed when the rank is over 10th.

an increased influence when foreign investors buy stocks or bonds during a crisis. Third, FI in the bond market is the more influential during normal periods with both methods when foreign investors trade bonds. The strong influence of FI in the bond market reflects their market making role in Korea. However, CIS in the FX derivative market does not seem to have particularly close relations with the trading patterns of foreign investors.

The influence of several influential traders on the other traders is shown to have close relations with time periods and the trading patterns of foreign investors. The dynamic inter-connectedness of traders can be understood with these analyses. Nonetheless, the different results by GCM and GVD needs to be researched further.

5.3 Traders' Contribution to the financial market volatility

The contribution of the connectedness measures of influential traders to the change in financial market volatility is examined in this section. In order to capture the relation of the connectedness of traders and financial market volatility, daily financial market volatility and measures of the connectedness measures of traders are estimated with 200 previous days' data applying a rolling window method as Fernndez-Rodrguez et al. (2016) did. As regards financial market volatility, stock index (KOSPI) and currency rate (KRW/USD) are chosen since they are the most volatile and the most representative indexes in Korean financial markets. Traders' RI are applied as a connectedness measures, for OUT and IN measures can offset each other.

There are two types of approach to assess the contribution of connectedness measures of traders to financial market volatility. One is a simple regression with adaptive LASSO technique. The dependent variable is daily volatility of financial market. Independent variables are the traders' connectedness measures. In Table 12, each trader's coefficient is present. However, the changes of traders' contribution to market volatility cannot be easily captured with this simple method, although the relation can be examined with the result.

I, thus, repeatedly run daily regression with the adaptive LASSO technique for the entire investigated period. Each trader's daily coefficients are divided into positive, zero and negative groups. After counting each trader's positive and negative coefficients, I comparatively analyse influential traders' positive (or negative) contribution day ratio with the average value of all traders' positive (or negative) contribution day ratio. The results are summarised in the Figures 7 and 8.

The contribution of foreign investors' to stock market volatility is shown to be decreasing in general. Their contributions over the average are found at negative contribution parts in the Figure 7 with a few exceptions in the bond derivative market during crisis period with GCM. This phenomenon looks more evident during a crisis with both methods. The result also contradicts the common conception that foreign investors destabilize the market during a crisis.

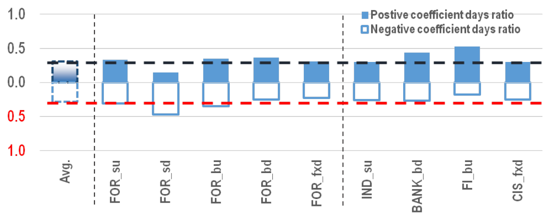
In contrast, other influential traders are more likely to increase stock market volatility, while FI in bond market seems to decrease market volatility with GVD. BANKs in the bond derivative market and CIS in the FX derivative, in particular, are found to increase market volatility, which are accelerated during a crisis. It is clear that influential traders can make a market more volatile, although this is not necessarily the case.

The contribution of foreign investors' connectedness measures to FX market looks more likely to decrease market volatility (Figure 8), although GCM and GVD suggest different results. All foreign investors except those in the FX derivative market, who increase market volatility, decrease market volatility with GVD. However, GCM suggests that foreign investors in the FX derivative market decrease market volatility. This requires further research.

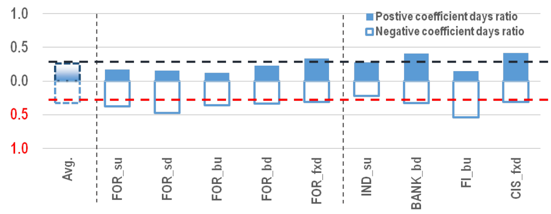
Other influential traders seem to increase the market volatility slightly over the average in general, in spite of the exception of BANKs in the bond derivative market and FI in the bond market with GVD. CIS in the FX derivative market, however, contribute to increase market volatility, which both methods suggests in common.

Most importantly, the implication of this result is that influential traders do not necessarily increase market volatility. The common conception on foreign investors may be false. Instead of increasing market volatility, foreign investors trader independently and rather decrease market volatility.

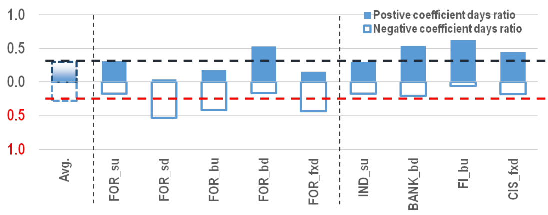
Figure 7: The contribution of traders' relative influence to stock market volatility



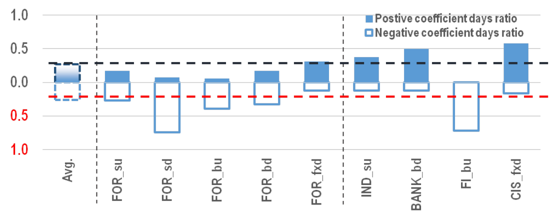
(a) All (GCM)



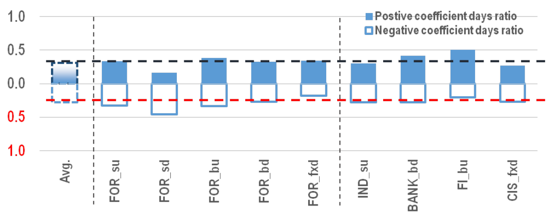
(b) All (GVD)



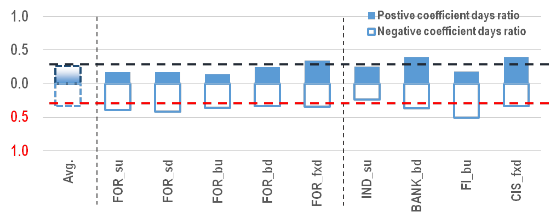
(c) Crisis (GCM)



(d) Crisis (GVD)



(e) Normal (GCM)



(f) Normal (GVD)

[Notes]

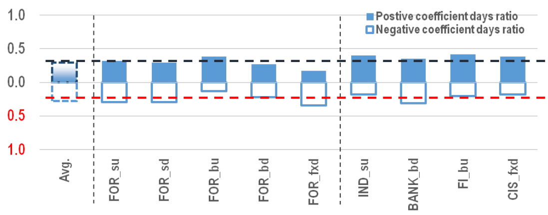
1. The ratio of influential traders' positive (negative) contribution days during analysed period are present compared to the average value of all 40 traders by time period (all, crisis, normal) and method (GCM, GVD).

2. Black dashed line in upper part of each figure is the average value of positive contribution day ratio and red dashed line in lower part of each figure is the average value of negative contribution day ratio. If a trader's positive (negative) coefficient day ratio is over the average value, it can be more contributing positively (negatively).

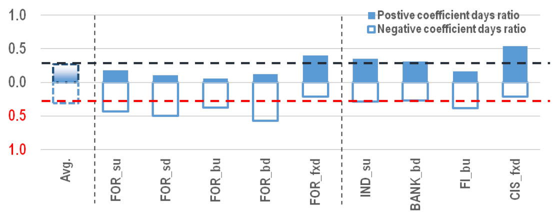
3. (Influential traders)

5 foreign Investors (FOR) from stock, stock derivative, bond, bond derivative and FX derivative market
Individual trader (IND) in stock market, BANK in bond derivative market,
Financial investment (FI) in bond market, Collective investment scheme (CIS) in FX derivative market

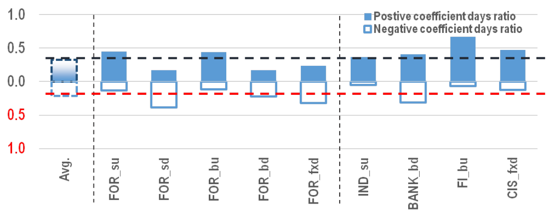
Figure 8: The contribution of traders' relative influence to FX market volatility



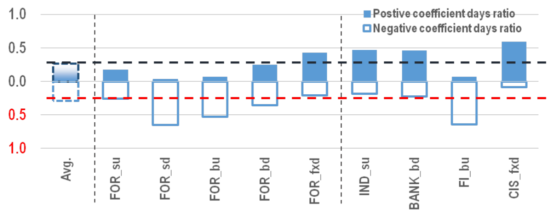
(a) All (GCM)



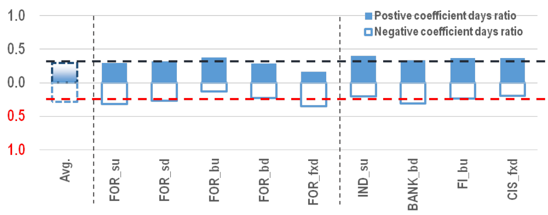
(b) All (GVD)



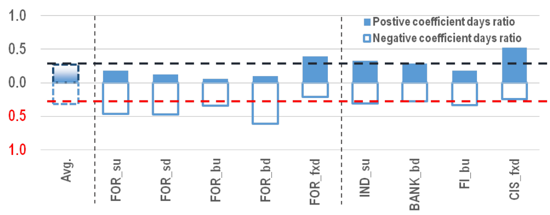
(c) Crisis (GCM)



(d) Crisis (GVD)



(e) Normal (GCM)



(f) Normal (GVD)

[Notes]

1. The ratio of influential traders' positive (negative) contribution days during analysed period are present compared to the average value of all 40 traders by time period (all, crisis, normal) and method (GCM, GVD).

2. Black dashed line in upper part of each figure is the average value of positive contribution day ratio and red dashed line in lower part of each figure is the average value of negative contribution day ratio. If a trader's positive (negative) coefficient day ratio is over the average value, it can be more contributing positively (negatively).

3. (Influential traders)

5 foreign Investors (FOR) from stock, stock derivative, bond, bond derivative and FX derivative market
Individual trader (IND) in stock market, BANK in bond derivative market,
Financial investment (FI) in bond market, Collective investment scheme (CIS) in FX derivative market

5.4 Discussion

So far, I have estimated traders' network structure, analysed the influence of influential traders and investigated the contribution of traders' connectedness measures to market volatility. By combining those results, a few meaningful insights on the mechanism of a capital market from the perspective of traders can be acquired and further research topic can be identified.

Foreign investors (FOR) and individual investors (IND) in the stock market are shown to have high relative influence (RI) in general. These two types of trader also play a pivotal role as a bridge within the network and the strong connection between FOR and IND is also found. However, during crisis period the critical changes of foreign investors are observed. The strong connection from IND to FOR disappears and the rank of RI of foreign investors reduces.

These results reflect that the investment decision process of foreign investors can be different from that of local traders, which is in accord with the extant literature which supports the claim that foreign investors trade with the negative feedback. Furthermore, the contribution of foreign investors to stock market volatility is close to the reduction of the volatility during crisis time. Thus, over-concern about the trading behaviour of foreign investors during crisis might be tackled by the evidence from this study.

There are more influential traders in the derivative markets. There are strong connections across the stock and stock derivative markets, and across the bond and bond derivative markets. The relative influence (RI) of foreign investors' are ranked high in derivative markets mainly during normal period.

These results may show that the trading strategies combined with derivative products are actively applied, and that foreign investors are the main agents. However, their contribution to market volatility seems to be negative, with the exception that foreign investors in the FX derivative market increase FX market volatility.

Based on the discussions so far, a few economic interpretations and policy implications can be obtained. The influence of foreign investors on other traders is shown to be significant in general. It reflects the fact that local traders are informed foreign investors and have experienced tremendous returns after opening Korean local financial markets to global investors since the Asian crisis in 1997. However, the trading strategies differ among traders. Individual traders look more sensitive to foreign investors. This can be explained with the theory of behaviours finance, which means that some traders are likely to copy the strategy of the trader who is likely to attain good profits. It is also consistent with the previous literature on individual traders.

The result of this paper can also be read from the perspective of information economics. The information advantage between foreign investors and local investors has been discussed by an enormous quantity of research. Some argue that foreign investors have more information on global markets, so they can obtain abnormal returns when the global market has strong influence on the local market. Kang et al.(2016) found that in the Korean stock market, foreign investors took greater advantage from global investment information than local traders. The investment information in global markets is not just about the public data such as global market indexes or the economic policies of important institutions (e.g. US Fed), but also concerns the strategic decision makings of important global financial companies or the investment interests of influential global investors which can be acquired only through insiders. Given that restriction of access to the investment information, the presumption that foreign investors' information is superior seems quite reasonable. In contrast, others insist that local investors can have better returns because they have more information about local financial markets. Batten & Vo (2015) showed that foreign investors were inferior to local traders in the Vietnam stock market, and that they preferred a buy and hold strategy, reducing their domestic information asymmetry. The result in this paper supports the notion that foreign investors have information superiority in global financial markets. They trade independently during a crisis, which can be seen in the fact that the strong connection between individual traders and foreign investors in the stock market disappears, and contributes to a decrease in market volatility. In other words, foreign investors can reduce their losses during a crisis with the global market information and trade differently from the way the local investors do, which finally results in a decrease in market volatility.

Some lessons about interconnectedness in capital markets can also be given from this paper. First of all, interconnectedness in capital markets can function a little differently from the way the interconnectedness in a lending market works. In a lending market, "too interconnected to fail" is valid, since a central borrower's bankruptcy can cause a series of credit events. Similarly in a capital market it is expected that an interconnected trader might influence on other traders, which will increase market volatility. However, influential (interconnected) traders in capital markets such as foreign investors from the stock derivative market in this paper are shown to even reduce the market volatility, while other influential traders such as mutual funds in the FX derivative market increase market volatility. Thus, the direction of influence can matter more than the influence itself in a capital market.

Second, a broader view needs to be taken to understand the relationship between traders and market volatility. With the approach taken by previous literature in order to investigate the attributes of certain types of traders focusing on a specific type of investor or market, The disappearance of the influence of foreign investors on individual traders during a crisis cannot be explained. In addition, the inter-linkage between stock and derivative markets through the influential traders cannot be found. Foreign investors in the stock derivative market and banks in the bond derivative market impact on stock market volatility. Even derivative markets have been shown to have more influential traders than the stock or bond market in this paper.

Policy makers may take advantage of the results of this paper. For their market stabilizing role, they can identify which traders are the main causes of market volatility increase and then prioritize the objectives of their policies, instead of making a policy based on the common conceptions. In this paper, mutual funds (CIS) in the FX derivative market seem to increase stock and FX market volatility. This is understandable based on their trading amount and their currency hedging demands. Thus, the minimization of unnecessary trading of mutual funds and the stabilization of mutual fund investors should be implemented during crisis.

They can also extend their approach to monitor market volatility. The main concern of policy makers is the stock or bond market, because the majority of investors and the majority of investments are involved there. However, because the origin of market volatility can be from derivative markets, the scope of effective market stabilization policies needs to be extended to derivative markets and the traders in them.

A challenge in this paper is the different results of GCM and GVD methods. It is highly probable that those differences result from the methodological process used.

In addition, the mechanism through which the influence is propagated has not been investigated. Although the contribution of the measure of traders' connectedness measure to market volatility is examined, what the result shows is the econometrical relation, not the mechanism of influence spill over. Thus, the way in which market volatility and the real trading activity of traders' inter-acts, is a further research topic.

6 Robustness

6.1 Definition of crisis

As seen in the previous section, the network structures and analyses results are dependent on the data and the time period analysed. Thus, diverse definitions of crisis can be helpful to understand the change of network structure. In this section, I apply a number of different crisis definitions for estimating the network structure of traders. Here I define the crisis as the time at which the volatility of financial market index is greater than the mean and one standard deviation. This method is the same as the way the crisis with VIX index is defined. Instead, here five different domestic financial indexes are used. These are stocks, stock derivatives, bonds, bond derivatives and FX derivatives.

In Table 12, GCM suggests that the top 10 relative influence rankers are the same regardless of the definition of crisis. Firstly, during a crisis time BANKs, foreign investors (FOR) and insurance (INS) among top 10 relative influence rankers are shown to have more than two traders. There are no significantly influential traders from individual investors (IND) and collective investment scheme (CIS). In contrast, during a normal period, the top 10 relative influence rankers are more dispersed than during a crisis. With the exception of financial investment (FI), every type of trader has at least one trader in the top 10 relative influence rankers. This finding might be meaningful and suggests that during a crisis, some types of trader trade with stronger relative influence, while during normal period, traders with strong relative influence (RI) can disperse.

As seen in Table 13, the results are the same under five different crisis definitions. However, the difference between crisis and normal periods appears evident. Three traders among the top ten relative influence rankers are from the stock market and no trader is from the FX derivative market during a crisis time, while three traders are from the FX derivative market and no trader is from the stock market during a normal time. Then, during a normal period there is one more top ten relative influence trader in the bond market and one less top ten relative influence trader in the bond derivative market. The contrast between the stock and bond markets according to time period can also be acceptable. During a risky time period, the traders with higher relative influence are found in the more risky stock market.

The result estimated with GVD is different from the previous result GCM suggests, but it seems similar to the result of VIX based crisis definition in Tables 3 and 4. Firstly, the result with different crisis definitions are slightly different, unlike the result with GCM. However, regardless of the definition of crisis used, foreign investors (FOR) have at least three traders in the top ten relative influence in Table 12. Secondly, the results between crisis and normal time periods are not clearly different. Although a slight change within one or two can be found in five different types of traders, it is hard to say there is a great change. Thirdly, the role of financial investment (FI) can change depending on the time and the definition of crisis used. Under the definition of crisis with the stock and stock derivative markets index (crisis 1,2), the numbers of the top ten having relative influence during a crisis are less than those during a normal period. In contrast, under the crisis with bond and bond derivative markets index (crisis 3,4), the opposite situation occurs.

In the Korean financial markets, by law financial investment (FI) plays a market making role in the bond market. Based on this fact, financial investment (FI) seems to become more influential during a crisis time than normal period.

As seen in Table 13, it is difficult to find significant patterns according to the time and crisis definitions. Compared to GCM, the results with GVD even seems to be more evenly distributed. During a crisis, however, in the stock and stock derivative markets more traders are found than in the bond and bond derivative market. In contrast, during normal times, the bond and bond derivative markets have more top ten relative influence traders. These finding can be linked to the common sense notion that during a crisis time, the risky stock market can be more activated than the less risky bond market.

6.2 Network estimation conditions variation

Network estimation results can vary depending on the conditions which are the VAR model order, VMA predictive horizon, the significance level for adjacency matrix, the kind of adjacency matrix(weighted/unweighted) and so on. However, the network estimation results do not need to be robust as Diebold and Yilmaz (2014) asserted. As the conditions mentioned above become looser, two nodes can be more connected, which leads to high connectedness measures. Thus, the objective of this part is to assess the extent to which the connectedness measures change and the availability of the connectedness measures estimated above.

For GCM, the network estimation can change as the significance level varies. In addition, the network structure estimated with GVD can change when the predictive horizon changes.

Thus, I estimate the network structure at the 5% and 1% significance level for Granger causality and the results of the network structure with 5 % is shown to be almost the same, but small changes are found at the 1 % significance level.

With diverse predictive horizons($h = 1, 2, ..., 10, 15, 20$), I also try to estimate the network structure . In the case of predictive horizon changes in GVD, the results after h are equal to two, and converge to the original estimation result with a predictive horizon of ten. In case of h = 15, 20, the estimation results are the same.

6.3 Contribution of traders' connectedness measures to market volatility

The influential traders' contributions to market volatility are investigated with the adaptive LASSO technique. In order to see whether they are contributing, their positive (negative) contributing days are compared with the average days of positive (negative) contribution. Despite of the meaningful results obtained using this analysis, other traders' contributions to market volatility are not captured. Thus, a broader point of view which allows us to see all traders' contributions to market volatility needs to be taken and an effective tool to analyse a big picture needs to be used. In addition, the analysis framework which compares the positive (negative) contributions to the average value of all traders was not sufficient to understand traders' connections to market volatility from a "big picture" standpoint.

In this part all traders' ranks of positive (negative) contributions to market volatility are extracted and are compared concurrently. For the sake of analytical simplicity, I focus on two cases. One is to find positively contributing traders and the other is to find negatively contributing traders. A positively contributing case is defined as when the trader's rank at positive contribution is higher than 10th, and the traders' rank at negative contribution is lower than 31st. Conversely, a negatively contributing case is one in which the trader's rank at positive contribution is lower than 31st, and in which the traders' rank at negative contribution is higher than 10th. It is highly probable that the former one can contribute to increase the market volatility, and that the latter can mitigate the volatility of financial variables. This approach might be adversely affected by the extreme cases in which all traders contribute to the market volatility. In these instance, even the trader with a lower rank can contribute enough to the market volatility. However, the main objective of this

Table 8: Summary of traders' contribution to market volatility

	Stock market				FX market			
	GCM		GVD		GCM		GVD	
	P	N	P	N	P	N	P	N
All	6	6	4	6	7	4	6	6
Crisis	6	6	4	7	7	3	5	8
Normal	4	7	3	4	6	5	6	7

[Note]
1. The number of (positive or negative) contributing traders to stock and FX market, is present by method (GCM, GVD) and period (all, crisis, normal).
2. P = the number of traders with positive contribution,
N = the number of traders with negative contribution

paper is to measure a trader's relative contribution compared to other traders. Thus, the analysis result can be meaningful in extreme cases.

The result is summarised in Table 8. The mode number of traders who have positive or negative contributions to each financial market is six, while GCM suggests more positive contributors and more negative contributors are estimated with GVD. More detailed results are present in Tables 16, 17, 18 and 19.

Table 16 shows the contribution to stock market with GCM, IND in stock derivative market, FI in bond market and INS in FX derivative market are shown to increase market volatility. FI in the FX derivative market, CIS in the stock derivative market and FOR in the stock derivative market seem to decrease market volatility. This result is consistent with that of the contribution of influential traders which includes FI in the bond market and FOR in the stock derivative market. GVD also suggests a consistent result with the analysis given in the previous section.

Traders' contributions to the FX market are also consistent with the previous analysis, as CIS in the FX derivative market increases market volatility and FOR in the FX derivative market reduces market volatility. In addition, a few traders such as IND in the stock market, Banks in the bond market, INS in the bond market are chosen as positive contributors and other traders including IND in the FX derivative market and GOV in the stock market are estimated as negative contributors. Regarding the FX market, GVD also suggests consistent result.

7 Conclusion

In this paper I estimate traders' financial networks with Granger causality and generalized variance decomposition methods and analysed the network structures. Connectedness measures are drawn from the estimated network structures. The influential trader types and markets are identified with the RI connectedness measures. The strong connections between traders are also found with OUT/IN connectedness measures. The changes of influential traders by time period and the trading patterns of foreign investors are examined. Following this, the contribution of influential traders' connectedness measures to market volatility is measured with the adaptive LASSO technique.

Within the network structure of the Korean financial market, foreign investors and other investors including individual investors and financial investment are shown to be influential. Foreign investors and individual traders have strong bidirectional connections, but the link from individual traders to foreign investors is disconnected during a crisis. The influence of foreign investors is realized mainly in derivative markets, whereas individual investors in the stock market and financial investment in the bond market are also influential. Most of foreign investors decrease the market volatility, whereas other influential traders seem to increase market volatility.

Foreign investors' cannot be blamed for fluctuations in the financial market despite their high influence based on the results. During a crisis, they seem to behave differently from local traders, which does not contribute to an increase in market volatility. Thus, over-concern about exits of foreign investors and Korean financial market fluctuation lacks reasonable evidence.

This paper has a number of contributions to the extant literature and the deliberations of policy makers. I apply network analysis tools to financial networks of traders which have not been investigated much so far. Granger causality and generalized variance decomposition methods which are the most popularly used in network analysis are applied for network estimation and the estimation results are compared. The conclusion of analyses can be helpful to better understand the role of foreign investors in local financial markets, which could contribute to the correction of the common belief that foreign investors can diminish market fluctuation. Finally, the deep investigation of traders' networks can help policy makers launch influential investor-tailored policies for stabilizing financial market volatility.

In spite of the findings in this paper, a few further research topics still exist. One of the greatest challenges in this paper is the nonlinearity. Although a few meaningful research results are drawn, nonlinear relation between traders cannot be captured. Besides, in order to better understand traders' networks and the impact on the real financial markets, the trading responses of traders at the shock of other traders' trading needs to be investigated.

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Table 9: ADF(Augmented Dickey-Fuller) test result

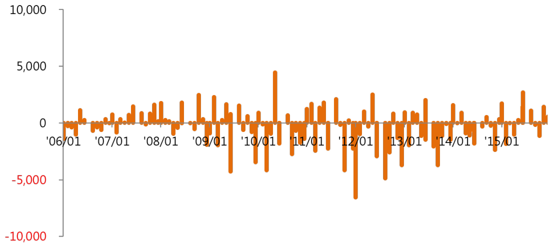
	IND	$BANK$	FI	CIS	OTH	INS	GOV	FOR
SU	-28.00	-20.02	-18.03	-14.70	-45.57	-23.66	-18.74	-13.80
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SD	-25.26	-39.02	-57.65	-24.72	-58.63	-40.19	-50.16	-51.76
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BU	-12.22	-29.94	-45.91	-16.16	-44.70	-30.58	-17.05	-13.75
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BD	-31.57	-49.93	-32.17	-48.99	-29.64	-40.31	-43.50	-51.76
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FXD	-47.07	-21.92	-41.16	-12.10	-48.52	-28.71	-49.99	-55.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

[Note] t-statistic (prob)
1. (Trader)
IND = Individual trader, BANK = Bank, FI = Financial investment(mainly securities companies)
CIS = Collective Investment Scheme, OTH = others (small financial companies)
INS = Insurance companies, GOV = Government, FOR = Foreign investment
2. (Market)
SD = Stock, SD = Stock Derivative, BU = Bond, BD = Bond Derivative, FXD = FX Derivative

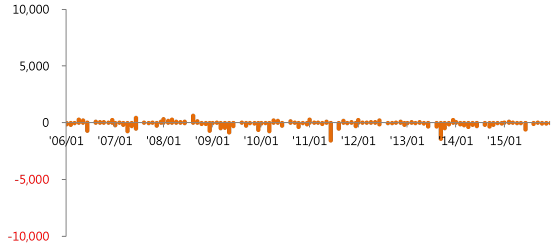
Table 10: Traders' detail

Trader	Detail
IND	Individual, general corporation
$BANK$	Banks
FI	Financial investments (securities companies, financial advisory firms, and etc)
CIS	Collective investment scheme. (public and private)
OTH	Other financial companies (mutual saving bank, credit union, and etx)
INS	Life insurance, nonlife insurance
GOV	Central(local) Government, Public pension fund
FOR	Foreign investors

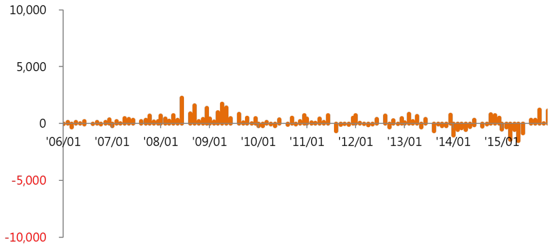
Figure 9: Each trader's monthly net trading volume in stock market



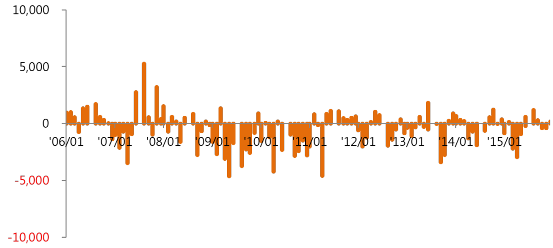
(a) Individual investors (IND)



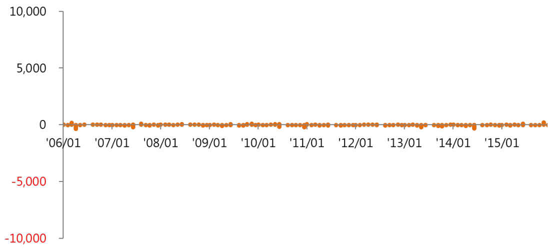
(b) Bank (BANK)



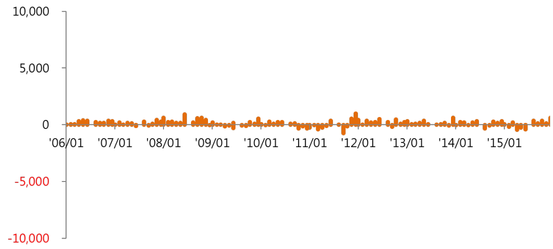
(c) Financial Investment (FI)



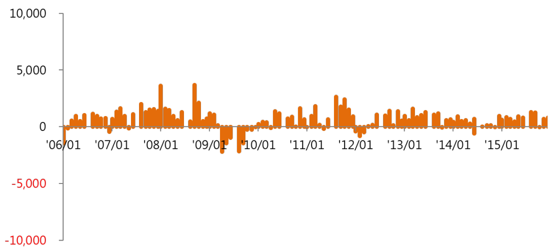
(d) Collective Investment Scheme (CIS)



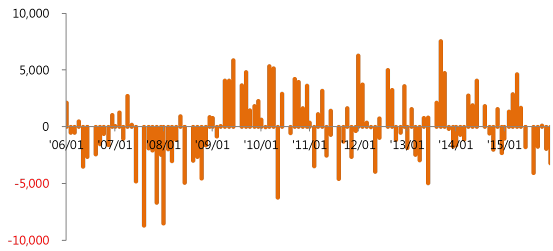
(e) Others (OTH)



(f) Insurance (INS)



(g) Government(GOV)

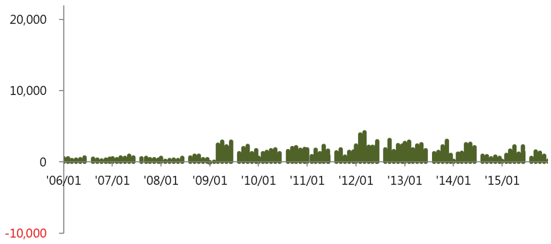


(h) Foreign investors (FOR)

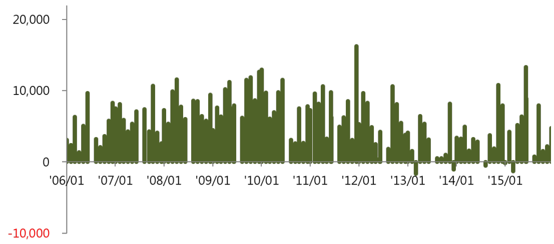
[Notes]

1. Monthly net trading volumes in stock market are present by trader types. Unit is billion KRW.
2. Foreign investors reduced their investment during crisis period, which are shown at figure(h).
3. Individual investors trading volumes looks volatile compared to other traders, shown at figure(a).
4. Collective investment schemes seem to trade with the opposite pattern of foreign investors shown at figure(d).

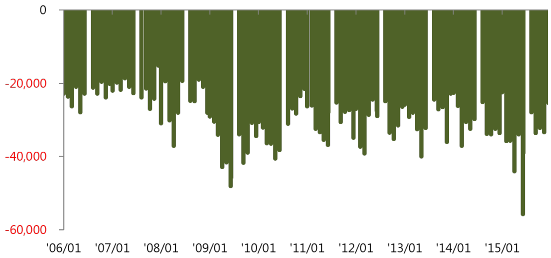
Figure 10: Each trader's monthly net trading volume in bond market



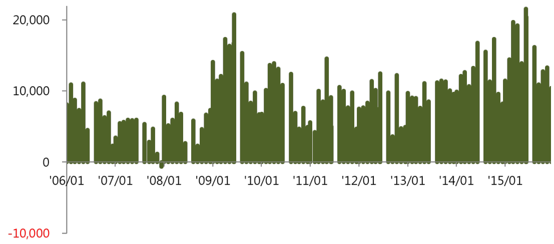
(a) Individual investors(IND)



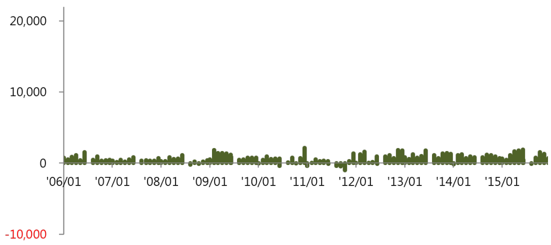
(b) Bank (BANK)



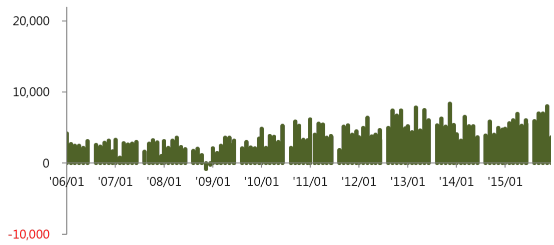
(c) Financial Investment (FI)



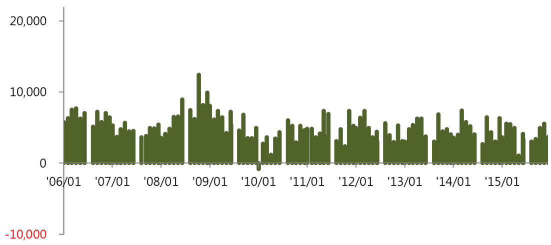
(d) Collective Investment Scheme (CIS)



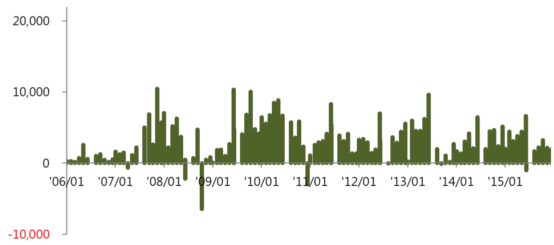
(e) Others (OTH)



(f) Insurance (INS)



(g) Government(GOV)



(h) Foreign investors (FOR)

[Notes]

1. Monthly net trading volume in bond market is present by trader type. Unit is billion KRW.
2. Foreign investors reduced their investment during crisis period, which are shown at figure(h).
3. FI plays a market-making role, so that their net investment is negative(figure(c)).
4. BANKS, CIS and GOV are shown to have large amounts of investments. (figure(b,d,g)).

Table 11: Adaptive LASSO regression result

	Stock						FXD					
	GCM			GVD			GCM			GVD		
	A	C	N	A	C	N	A	C	N	A	C	N
intercept	112.0	175.7	113.0	154.3	279.6	91.5	32.0	66.1	32.8	117.6	151.5	50.8
IND,su	16.6	37.6	-2.4	245.6	0.0	266.4	23.7	47.2	3.4	74.6	90.2	73.0
BANK,su	-19.4	18.5	-30.2	26.2	27.7	26.1	0.0	30.3	-9.5	0.0	19.0	-8.4
FI,su	0.0	14.9	10.3	-13.4	78.5	-36.9	-23.5	0.0	-13.1	-30.3	72.5	-17.2
CIS,su	15.1	17.3	17.1	105.3	107.5	30.6	6.3	0.0	6.8	58.9	50.2	0.0
OTH,su	-33.6	-3.1	-4.8	-103.8	30.8	-102.3	-17.6	-28.7	7.2	-5.9	79.2	-11.5
INS,su	6.7	27.3	16.1	113.9	144.2	72.5	-13.4	0.0	-16.2	34.3	8.5	34.0
GOV,su	4.1	-9.7	0.0	-58.1	0.0	-36.7	0.0	0.0	-3.4	-47.4	0.0	-58.2
FOR,su	6.3	5.5	26.3	-7.7	0.0	0.0	-16.4	0.0	2.9	0.0	35.9	0.0
IND,sd	-6.0	8.8	11.7	0.0	0.0	7.4	-19.4	-8.6	-5.0	0.0	58.1	0.0
BANK,sd	6.1	7.4	13.1	0.0	0.0	0.0	0.0	0.0	-4.0	0.0	37.8	0.0
FI,sd	0.0	0.0	-4.5	0.0	-111.6	0.0	12.8	17.0	4.8	108.5	17.1	70.8
CIS,sd	-13.9	0.0	-19.8	66.5	204.7	82.5	10.2	22.2	8.2	19.1	101.1	17.0
OTH,sd	37.7	32.7	28.3	0.0	21.6	0.0	14.1	11.3	7.7	0.0	25.5	0.0
INS,sd	4.1	27.0	-17.6	-80.2	0.0	-19.6	21.3	35.7	-6.9	-64.4	-14.8	0.0
GOV,sd	14.4	-2.9	24.3	-61.8	0.0	-70.9	0.0	0.0	9.2	0.0	35.2	0.0
FOR,sd	0.0	0.0	7.6	-294.9	-181.2	-271.0	-10.2	0.0	-8.4	-240.2	0.0	-162.5
IND,bu	-11.0	-34.0	4.3	0.0	0.0	13.4	-15.2	0.0	2.2	0.0	63.1	4.6
BANK,bu	23.3	57.5	8.3	0.0	42.6	0.0	26.3	43.1	9.0	9.5	117.7	0.0
FI,bu	46.6	0.0	39.4	-79.3	-45.6	0.0	13.1	0.0	2.5	-38.3	0.0	11.0
CIS,bu	0.0	0.0	0.0	0.0	69.7	-20.4	-11.4	0.0	-12.9	0.0	70.8	-26.9
OTH,bu	-35.6	0.0	0.0	77.4	140.3	61.2	-33.4	0.0	-10.8	0.0	44.7	-6.6
INS,bu	-4.5	9.0	-12.8	0.0	116.9	0.0	1.9	0.0	-1.8	0.0	43.9	0.0
GOV,bu	-47.9	0.0	-53.2	61.4	138.7	26.5	-1.2	0.0	-9.0	31.0	116.0	0.0
FOR,bu	0.0	7.8	0.0	0.0	20.7	-8.6	7.8	16.0	8.0	0.0	17.2	-25.6
IND,bd	-10.1	0.0	13.5	54.0	152.5	0.0	-36.3	0.0	-4.7	106.9	167.5	45.1
BANK,bd	0.0	25.6	-7.9	-23.1	45.2	45.0	-12.7	16.8	-20.7	-57.6	0.0	18.4
FI,bd	0.0	-26.8	0.0	0.0	75.3	0.0	9.4	0.0	0.0	64.1	196.3	0.0
CIS,bd	-33.0	0.0	-10.5	0.0	0.0	0.0	-21.6	-9.8	0.0	-41.0	0.0	-37.4
OTH,bd	0.0	6.7	17.9	9.9	23.2	0.0	-24.4	0.0	-4.2	22.5	62.7	15.8
INS,bd	0.0	0.0	4.2	-67.3	0.0	-80.9	7.0	0.0	11.6	23.3	33.0	0.0
GOV,bd	0.0	-47.6	6.5	-81.9	-25.7	-82.0	-6.3	-48.2	-4.6	8.9	115.7	13.6
FOR,bd	14.8	38.1	16.6	118.9	136.2	108.8	12.1	9.5	11.8	-92.7	97.9	-14.1
IND,fxd	17.1	11.8	12.9	0.0	77.6	23.0	0.0	10.7	0.0	-27.2	50.5	-36.5
BANK,fxd	4.3	5.2	11.3	-42.5	0.0	-85.2	0.0	9.9	7.8	0.0	76.4	-51.7
FI,fxd	-24.2	-11.3	0.0	209.6	88.2	129.5	-23.6	-25.8	4.4	176.2	142.5	114.0
CIS,fxd	0.0	18.7	-11.4	109.2	242.7	91.3	5.3	0.0	-3.8	101.8	202.7	49.5
OTH,fxd	0.0	-2.6	0.0	-43.1	11.9	-43.8	-7.0	-33.2	-3.5	6.2	69.7	-3.9
INS,fxd	-1.5	0.0	3.6	-29.2	47.4	-22.8	-9.1	0.0	0.0	-21.9	0.0	0.0
GOV,fxd	0.0	-11.6	11.3	0.0	0.0	0.0	11.0	18.1	14.9	12.2	55.1	-1.7
FOR,fxd	12.5	12.1	12.0	0.0	53.1	0.0	-2.8	16.6	-13.8	-17.2	77.4	29.3
R-squared	0.9	1.0	0.9	0.9	1.0	0.9	0.8	1.0	0.8	0.9	1.0	0.9
MSE	456.8	61.4	257.1	285.6	79.6	211.1	260.4	70.2	54.4	102.8	33.4	40.4

[Note]
1. Adaptive LASSO regression result is present by methods and periods.
2. (period) A : all, C : Crisis, N : Normal
3. All coefficients can be divided into positive, negative and zeros.

(Appendix A) : Adaptive LASSO

LASSO (Least Absolute Shrinkage and Selection Operator) is a popularly used regression technique with regularization for enhancing prediction accuracy and performing variable selection (Tibshirani, 1996). Unlike OLS, the coefficients are determined by the cost function composed with squared errors and regularization, which is also called "$\ell 1$ penalty."

$$\beta_{LASSO} = argmin \left\| y - \sum_{j=1}^{p} \hat{\beta}_j x_j \right\|^2 + \lambda \sum_{j=1}^{p} |\hat{\beta}_j| \tag{11}$$

where y is the market volatility and x is the vector of traders' connectedness measures (x_1, x_2, ..., $x_4 0$). $\hat{\beta}_j$ is the coefficient of x_j estimated by LASSO. λ is nonnegative regularization parameter. LASSO suggests shrank coefficients, which can be exact zero, as λ increases. In this way, the actual meaningful (nonzero coefficient) variables can be identified. The most appropriate value of λ can be acquired by Cross-Validation. LASSO has been supported by much theoretical research and applied by various fields of empirical works.

However, LASSO variable selection can be inconsistent (Zou, 2006), so that adaptive LASSO is developed. Adaptive LASSO is different from LASSO in a sense that the weight vector is included in regularization term like Equation 12.

$$\beta = \arg\min \left\| y - \sum_{j=1}^{p} \beta_j x_j \right\|^2 + \lambda \sum_{j=1}^{p} \omega |\beta_j| \tag{12}$$

where β_j is the coefficient of x_j estimated by adaptive LASSO. ω is the weight vector and data-dependent. In this paper, I use $\omega = \frac{1}{\beta_{LASSO}}$ and β_{LASSO} is simple LASSO estimator. This approach is taken by Dufour and Jian (2016). Then, actual estimation can be executed by LARS algorithm which Zou (2006) showed.

After estimation process, the coefficients can be divided into three groups, which are positive, negative and zeros.

(Appendix B) : Robustness check

A.1. Crisis definition

In order to investigate the effect of crisis definition, I newly define the crisis based on the market volatility. The crisis period is defined in case that the volatility of each financial market is bigger than historic mean and one standard deviation. From Crisis 1 to crisis 5 are respectively stock(1), stock derivative(2), bond(3), bond derivative(4) and FX derivative(5) market. Normal period is the period which does not belong to the crisis period during investigated time period. This definition is applied to table 12 and 13. The number of RI connectedness measures top 10 rankers are present by trader types on table 12 and 13.

Table 12: Top 10 Relative influence ranker under different crisis & normal

	IND	BANK	FI	CIS	OTH	INS	GOV	FOR
GCM								
Crisis1	-	3	1	-	1	2	1	2
Crisis2	-	3	1	-	1	2	1	2
Crisis3	-	3	1	-	1	2	1	2
Crisis4	-	3	1	-	1	2	1	2
Crisis5	-	3	1	-	1	2	1	2
Normal1	2	1	-	1	1	1	2	2
Normal2	2	1	-	1	1	1	2	2
Normal3	2	1	-	1	1	1	2	2
Normal4	2	1	-	1	1	1	2	2
Normal5	2	1	-	1	1	1	2	2
GVD								
Crisis1	2	1	2	2	-	-	-	3
Crisis2	2	-	1	3	-	-	-	4
Crisis3	1	1	3	1	-	-	-	4
Crisis4	3	-	4	-	-	-	-	3
Crisis5	2	1	2	1	-	-	-	4
Normal1	2	-	3	1	-	-	-	4
Normal2	2	-	3	1	-	-	-	4
Normal3	2	-	2	2	-	-	-	4
Normal4	2	1	2	1	-	-	-	4
Normal5	2	-	2	2	-	-	-	4

Table 13: Top 10 Relative influence ranker's market under different crisis and normal

	Stock	Stock Drv.	Bond	Bond Drv.	FX Drv.
GCM					
Crisis1	3	2	3	2	-
Crisis2	3	2	3	2	-
Crisis3	3	2	3	2	-
Crisis4	3	2	3	2	-
Crisis5	3	2	3	2	-
Normal1	-	2	4	1	3
Normal2	-	2	4	1	3
Normal3	-	2	4	1	3
Normal4	-	2	4	1	3
Normal5	-	2	4	1	3
GVD					
Crisis1	2	4	1	2	1
Crisis2	3	2	1	1	3
Crisis3	2	3	1	2	2
Crisis4	2	2	2	1	3
Crisis5	2	2	1	2	3
Normal1	2	2	2	2	2
Normal2	2	2	2	2	2
Normal3	2	1	2	2	3
Normal4	2	1	1	3	3
Normal5	2	1	2	2	3

A.2. Yearly analysis

In addition to the crisis definition, influential traders' trader types and the market which they belong to are investigated during specific time period. In this part, yearly network estimation is implemented. In particular, there was global financial crisis (GFC) in 2008 and 2009 and European fiscal crisis in 2011. If there is a significant phenomenon for those year, the impact of crisis on traders' network structure can be found. This analysis is applied to table 14 and 15. The number of RI connectedness measures top 10 rankers are present by trader types on table 14 and 15.

Table 14: Yearly top 10 Relative influence ranker

	IND	BANK	FI	CIS	OTH	INS	GOV	FOR
GCM								
2006	2	2	-	1	1	1	3	-
2007	-	1	1	1	1	1	3	2
2008	1	-	3	1	2	-	2	1
2009	-	3	1	2	-	1	2	1
2010	1	2	2	-	1	1	1	2
2011	2	-	-	2	2	2	1	1
2012	2	2	1	2	-	-	1	2
2013	1	1	2	2	3	1	-	-
2014	2	1	-	2	1	2	2	-
2015	1	3	2	-	1	2	1	-
GVD								
2006	1	-	1	2	1	-	1	4
2007	2	2	1	3	-	-	-	2
2008	1	-	3	3	-	-	-	3
2009	1	1	1	1	-	2	1	3
2010	2	-	1	-	1	2	1	3
2011	2	-	2	-	-	1	2	3
2012	2	-	3	-	-	-	1	4
2013	2	-	3	1	-	-	-	4
2014	1	1	2	-	1	1	1	3
2015	2	1	2	1	-	-	-	4

Table 15: Yearly top 10 Relative influence ranker's market (GCM)

	Stock	Stock Drv.	Bond	Bond Drv.	FX Drv.
GCM					
2006	4	2	-	2	2
2007	3	1	3	-	3
2008	2	1	2	3	2
2009	2	-	4	2	2
2010	2	3	-	-	5
2011	4	1	1	1	3
2012	3	-	3	3	1
2013	1	2	1	1	5
2014	4	1	2	2	1
2015	2	4	1	-	3
GVD					
2006	5	2	1	1	1
2007	3	3	1	2	1
2008	3	2	1	2	2
2009	2	2	2	1	3
2010	2	2	1	2	3
2011	3	3	1	2	1
2012	2	3	1	2	2
2013	2	2	2	2	2
2014	2	3	3	-	2
2015	2	2	2	1	3

A.3. Contribution of traders' connectedness to market volatility

In order to supplement influential traders' contribution to the market volatility, all traders' contribution to market volatility is summarised on table 16, 17, 18 and 19. 2,076 daily adaptive LASSO regression are run with all traders' connectedness measures and market volatility of previous 200 days. As daily adaptive LASSO results suggest, all traders' coefficients of a day can be divided into positive, negative or zero. For entire 2,076 days, the results of all traders' coefficients (positive, negative or zero) are counted and ranked. Same trader's contribution can be positive on a certain day and negative on the other day. Consequently, a certain trader can have more days with positive coefficients, while other trader may have more days with negative coefficients.

Here, I divide a trader's positive and negative contribution and define two groups. One is positive contributor which has higher rank than $10th$ in positive and lower rank in negative at the same time. The other is negative contributor which has lower rank $31st$ in positive and higher rank in negative than $10th$ in negative.

Table 16: Contribution ranks of traders' connectedness measures to stock volatility(GCM)

	IND		BANK		FI		CIS		OTH		INS		GOV		FOR	
	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N
[ALL]																
SU	24	24	23	16	7	28	***6***	***34***	37	18	32	32	***39***	***3***	16	15
SD	***1***	***37***	***34***	***8***	***4***	***40***	***40***	***2***	***9***	***39***	11	30	20	25	***38***	***1***
BU	14	19	17	10	***3***	***36***	15	33	***35***	***5***	30	14	18	17	12	9
BD	26	11	5	23	27	6	33	12	13	22	29	13	19	7	10	27
FXD	25	20	8	29	***36***	***4***	22	26	28	35	***2***	***38***	31	21	21	31
[CRISIS]																
SU	18	28	***8***	***34***	28	18	***2***	***38***	32	14	24	21	21	16	17	27
SD	***3***	***33***	13	25	16	30	***40***	***9***	14	31	9	24	***5***	***35***	***39***	***4***
BU	***34***	***5***	19	13	***4***	***39***	31	20	22	8	33	15	11	36	27	10
BD	20	23	6	22	***35***	***2***	***36***	***6***	26	12	37	11	30	3	7	29
FXD	15	32	12	37	23	19	10	26	25	17	***1***	***40***	***38***	***1***	29	7
[NORMAL]																
SU	21	22	27	12	5	29	13	32	37	20	33	30	***39***	***1***	17	10
SD	***1***	***36***	***36***	***6***	***2***	***40***	***40***	***2***	12	39	18	27	28	21	***34***	***3***
BU	8	26	16	9	***3***	***31***	11	37	***35***	***5***	26	16	20	11	9	8
BD	***31***	***7***	6	19	23	13	32	18	10	28	22	17	14	14	19	23
FXD	25	15	7	24	***38***	***4***	24	25	29	38	***4***	***34***	30	33	15	35

[Note]
1. The rank of each trader's positive(or negative) relation with stock market volatility is present by period. For instance, (24,24) of IND in stock market during all period means that the rank of individual investors in stock market in contributing to stock market volatility positively (negatively), is 24th (24th).
2. P = positive relation, N = negative relation
3. Blue pair (P,N) is that the rank in positive is higher than 10*th* and the rank in negative is lower than 31*st*. Blue pair can be positively contributing to stock market volatility.
4. Red pair (P,N) is that the rank in positive is lower than 31*st* and the rank in negative is higher than 10*th*. Red pair can be negatively contributing to stock market volatility.

Table 17: Contribution ranks of traders' connectedness measures to stock volatility(GVD)

	IND		BANK		FI		CIS		OTH		INS		GOV		FOR	
	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N
[ALL]																
SU	17	35	9	26	26	7	6	30	19	10	16	40	14	34	31	12
SD	28	18	34	11	27	25	13	17	29	29	***37***	***8***	39	21	***35***	***4***
BU	24	9	***2***	***37***	***36***	***1***	21	16	***7***	***36***	18	28	***1***	***39***	38	15
BD	30	14	5	20	23	5	***33***	***6***	25	32	***32***	***2***	10	27	22	19
FXD	8	23	20	38	15	13	4	24	***3***	***31***	12	33	***40***	***3***	11	22
[CRISIS]																
SU	***9***	***33***	4	20	21	8	***7***	***35***	32	13	12	40	31	24	27	14
SD	14	27	20	36	19	39	15	16	33	12	***38***	***3***	25	26	***36***	***1***
BU	***35***	***10***	18	7	***40***	***2***	17	23	11	38	29	21	***2***	***37***	***37***	***6***
BD	6	19	***5***	***32***	30	30	23	15	8	28	***34***	***5***	22	17	26	9
FXD	1	22	24	31	10	11	3	29	13	25	28	18	***39***	***4***	16	34
[NORMAL]																
SU	20	33	12	26	25	6	8	29	16	10	17	39	11	35	31	11
SD	29	15	***36***	***7***	27	20	14	19	26	34	34	17	40	21	***32***	***8***
BU	21	9	***1***	***38***	28	2	24	13	***5***	***32***	15	28	***2***	***40***	37	18
BD	39	12	6	16	23	1	***35***	***4***	33	31	30	3	4	27	22	24
FXD	10	25	19	37	18	14	7	23	3	30	13	36	***38***	***5***	9	22

[Note]
1. The rank of each trader's positive(or negative) relation with stock market volatility is present by period.
For instance, (17,35) of IND in stock market during all period means that the rank of individual investors in stock market in contributing to stock market volatility positively (negatively), is 17th (35th).
2. P = positive relation, N = negative relation
3. Blue pair (P,N) is that the rank in positive is higher than $10th$ and the rank in negative is lower than $31st$.
Blue pair can be positively contributing to stock market volatility.
4. Red pair (P,N) is that the rank in positive is lower than $31st$ and the rank in negative is higher than $10th$.
Red pair can be negatively contributing to stock market volatility.

Table 18: Contribution ranks of traders' connectedness measures to FXD volatility(GCM)

	IND		BANK		FI		CIS		OTH		INS		GOV		FOR	
	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N
[ALL]																
SU	4	38	18	15	10	9	1	20	25	6	26	2	40	7	16	18
SD	33	1	30	22	12	35	31	19	14	25	24	36	17	26	19	17
BU	5	31	8	39	2	33	27	34	23	4	32	14	15	11	7	40
BD	21	10	13	13	35	16	37	28	20	27	3	32	29	3	22	29
FXD	34	5	11	21	36	12	9	37	28	24	6	30	39	23	38	8
[CRISIS]																
SU	13	38	3	39	23	18	4	21	17	11	26	3	28	12	10	30
SD	22	9	19	35	5	40	34	20	20	29	16	15	6	28	35	2
BU	25	4	21	27	2	36	40	8	15	24	24	16	7	34	11	32
BD	39	6	12	7	38	17	30	26	36	23	29	10	32	1	33	19
FXD	18	25	1	37	14	14	9	31	37	22	8	33	31	13	27	5
[NORMAL]																
SU	4	33	30	11	6	8	1	21	29	6	27	4	40	7	18	14
SD	34	1	32	20	14	31	28	19	11	23	25	37	24	24	16	22
BU	3	38	5	39	8	28	19	36	26	2	31	15	21	5	7	40
BD	13	12	12	18	33	17	37	30	15	29	2	35	23	13	20	32
FXD	35	3	17	16	36	9	10	34	22	26	9	27	39	25	38	10

[Note]

1. The rank of each trader's positive(or negative) relation with stock market volatility is present by period. For instance, (4,38) of IND in stock market during all period means that the rank of individual investors in stock market in contributing to stock market volatility positively (negatively), is 4th (38th).
2. P = positive relation, N = negative relation
3. Blue pair (P,N) is that the rank in positive is higher than 10*th* and the rank in negative is lower than 31*st*. Blue pair can be positively contributing to stock market volatility.
4. Red pair (P,N) is that the rank in positive is lower than 31*st* and the rank in negative is higher than 10*th*. Red pair can be negatively contributing to stock market volatility.

Table 19: Contribution ranks of traders' connectedness measures to FXD volatility(GVD)

	IND		BANK		FI		CIS		OTH		INS		GOV		FOR	
	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N
[ALL]																
SU	9	22	27	10	23	17	29	9	12	31	22	18	***38***	***7***	28	8
SD	11	20	33	13	***6***	***36***	21	23	24	19	20	15	19	39	***39***	***3***
BU	17	29	14	28	31	12	***36***	***4***	8	30	18	35	16	25	40	14
BD	25	11	13	24	15	37	***37***	***6***	***10***	***34***	30	16	***4***	***38***	***35***	***1***
FXD	***32***	***2***	5	26	2	27	***1***	***32***	***3***	***40***	26	5	34	21	***7***	***33***
[CRISIS]																
SU	7	30	12	8	28	10	23	17	18	14	24	28	***39***	***9***	26	24
SD	15	16	38	11	17	38	14	31	29	12	***32***	***6***	22	35	***40***	***1***
BU	20	34	21	21	***37***	***2***	***35***	***5***	11	29	25	23	***5***	***32***	***34***	***4***
BD	2	25	8	26	13	39	***36***	***7***	***9***	***37***	27	18	***1***	***40***	19	13
FXD	16	19	***31***	***3***	4	22	***3***	***36***	***6***	***33***	33	15	30	20	10	27
[NORMAL]																
SU	12	22	28	11	22	18	30	8	***9***	***33***	21	14	***36***	***9***	27	5
SD	10	21	29	12	***5***	***36***	25	23	23	20	17	15	18	39	***38***	***3***
BU	15	26	11	30	26	17	***33***	***6***	8	29	14	35	20	24	40	16
BD	***34***	***10***	19	25	16	37	***35***	***7***	13	31	31	13	***6***	***38***	***39***	***1***
FXD	***37***	***2***	***2***	***34***	3	28	1	27	***4***	***40***	24	4	32	19	***7***	***32***

[Note]

1. The rank of each trader's positive(or negative) relation with stock market volatility is present by period. For instance, (9,22) of IND in stock market during all period means that the rank of individual investors in stock market in contributing to stock market volatility positively (negatively), is 9th (22nd).

2. P = positive relation, N = negative relation

3. Blue pair (P,N) is that the rank in positive is higher than $10th$ and the rank in negative is lower than $31st$. Blue pair can be positively contributing to stock market volatility.

4. Red pair (P,N) is that the rank in positive is lower than $31st$ and the rank in negative is higher than $10th$. Red pair can be negatively contributing to stock market volatility.

V

Paper 2: Nonlinear causality network structure of financial traders across capital markets

Statement of Authorship

This declaration concerns the article entitled:									
Nonlinear causality network structure of financial traders across capital markets									
Publication status (tick one)									
draft manuscript	x	**Submitted**		**In review**		**Accepted**		**Published**	
Publication details (reference)									
Candidate's contribution to the paper (detailed, and also given as a percentage).	The candidate contributed to/ considerably contributed to/predominantly executed the… Formulation of ideas: 100% Design of methodology: 100% Experimental work: 100% Presentation of data in journal format: 100%								
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.								
Signed	Jaehak Hwang					**Date**	30/11/2018		

Nonlinear causality network structure of financial traders across capital markets

Jaehak Hwang*

Abstract

This paper studies financial traders' network structures across different capital markets with nonlinear Granger causality and nonlinear generalized variance decomposition methods. I identify those traders with a particularly stronger influence on other traders and the changes in their influence under different conditions. The contribution of traders' connectedness measures to financial market volatility is also investigated. The analysis reveals that some influential traders' connectedness measures contribute to market volatility, while other influential traders' connectedness measures do not contribute. Traders sensitive to the shock of daily net trading volume of influential traders are also found. The contributions of this study can be applied to previous literature and a number of policy implications for market stabilization are given.

1 Introduction

The connectedness of agents in financial markets has been researched by numerous previous studies. However, unlike in banking in which the agents have a direct linkage through lending and borrowing, the agents in capital markets have been investigated using the

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indirect methods such as Granger causality or variance decomposition. Through results obtained through these methods, the understanding of capital markets has been enormously expanded. In particular, the linkage among the different capital markets and the interactions of different financial markets have been investigated thoroughly.

The global financial crisis (GFC) in 2008 ignited this research. The turmoil in the US financial markets spread to the other financial markets all over the world, although there were differences of degree. Some research (Yang and Zhou, 2016; Silva et al., 2016) found the linkage among the financial markets in different countries. Other research (Thapa et al., 2016; Wang et al., 2016) showed that foreign exchange markets were inter-connected. Literature in the field of network theories suggested having central markets among several other markets, which could function as the core to spread the risk to other markets.

A strand of research investigated the industries (or individual stocks) in stock markets and their inter-relations, instead of the market. Nevertheless, it is still difficult to see why the striking movement occurred in capital markets or who started to sell (or buy) in large volumes. Thus, other studies examined the investors in capital markets and their inter-relations. They showed certain types of investors had explicitly different behaviours compared to others.

The literature of behaviour finance (Shiller, 1990; Tedeschi et al., 2012) suggested the theoretical ground to the research on the traders' inter-relations. It is that some traders imitate potentially profitable investment behaviours of other traders, which contradicts the assumption of traditional economics, namely "rationality."

That research on the inter-relations of financial markets and traders, however, left some challenges to understanding the mechanism of capital markets, in spite of significant contributions. The sources of triggers which caused the movement of financial market indexes have not been suggested with the results of that research. In addition, the research on the sub-parts of capital markets or the investors in the markets were not sufficiently comprehensive to explain the market mechanism.

In this context, the study of Hwang (2018) suggested meaningful insights. Hwang (2018) estimated traders' network structures across five different representative Korean financial markets and analysed them. The network structure of traders was estimated using both linear Granger causality and linear generalized variance decomposition methods. Some influential traders such as foreign investors were shown to have significant impact on others despite small differences between the results of the two methods. Furthermore, strong connections between traders in financial markets were investigated and specific conditions under which the influence of influential investors increased, were also found. Finally the contributions of the connectedness measures of influential traders on market volatility were also examined.

His study has a few meaningful contributions to our understanding of the mechanism of financial markets. He suggested that the perspective from which to view financial markets within a single frame was the connectedness of traders within the network structures. Those traders with higher connectedness measures are shown to have the possibility to function as a trigger of financial market movement. If the policy makers are aware of these influential traders, it would be very much helpful in the development of a market stabilizing policy. The study is also meaningful in terms of methodology. He applied both Granger causality and variance decomposition which have been the most commonly used in this field. The comparison of the results of these two methods is the first to be attempted to the best of my knowledge.

Although the results of Hwang (2018) was impressive, there are a few research gaps. Firstly, he assumed the linear relationship between traders, so that linear Granger causality method and linear generalized variance decomposition method were applied. However, in case of the existence of a nonlinear relationship between traders, the network structure can differ from his results. Furthermore, in terms of traders' actual daily net trading volume, the responses of traders to the changes of influential traders were not investigated. Those might be the key to understand the mechanism of financial markets.

It is highly probable that the nonlinearity can be found in complicated relationships among traders. Eight different types of trader from five separate financial markets are concurrently investigated in econometric models. Some traders have influence on others and a few of them receive influence from others at the same time. In addition, the relationship between traders varies according to the period investigated. Some relationships are sometimes stronger during crisis, but weaker during normal period and vice versa. Extremely complex relationships between traders are not likely to be explained by simple linear models. Thus, econometric models with a more flexible form should be applied.

I, thus, apply two different nonlinear methodologies in this paper. With these the methodological scope of the research is extended from linear to nonlinear and the methodological restriction of linear assumptions, which was criticized by Koop et al. (1996) can be released. In addition, the attributes of forty different types of traders' daily net trading volumes can be explained.

Nonlinear causal relationships have been an important issue in macroeconomic and finance literature (Frank and Stengos, 1989; Hsieh, 1989; Scheinkman and LeBaron, 1989; Abhyankar et al., 1997). If significant relationships between the variables cannot be captured with linear methods, but that the relationship is found with nonlinear methods, nonlinearity is a critical factor. Some research (Rahimi et al., 2016; Choudhry et al., 2016; Chu et al., 2016; Rafiq and Bloch, 2016; Andreasson et al., 2016) investigated both linear and nonlinear causal relationship between various financial variables at the same time. In this paper, I follow the analysis framework Hwang (2018) to investigate traders' network structure instead of applying both linear and nonlinear methodologies.

However, a nonlinear method is not always better than a linear one, and vice versa. Some variables have more linear relationships and others have more nonlinear relationships. Thus, the research with nonlinear methods can be meaningful, although similar research with a linear approach has already acquired significant results. In this sense, this paper makes a contribution to the previous literature (Hwang, 2018), which showed the network structure of financial traders using linear method.

The other motivation of this paper is the nonlinear approach with generalized variance decomposition method. Earlier literature focused on the Granger type nonlinear causal relationships. However, the comparison analysis of linear and nonlinear generalized variance decomposition methods has not attempted to the best of my knowledge.

In the present paper, the impact of sudden selling by an influential trader is investigated. Although the network structure of traders in capital markets is a very effective tool for understanding the inter-relations of traders, the actual impact of influential traders on the trading behaviours of other traders cannot be investigated without a further analysis on the other traders responses to the change of the trading of influential traders. Thus, nonlinear impulse response analysis on the selling shock of influential traders is implemented.

The process of estimating the network structure of traders is based on the approach of Hwang (2018). One merit of nonlinear methodologies is that they capture both linear and nonlinear relations. If there are just linear relations among traders, the results of this paper may be similar to the conclusion of Hwang (2018). However, even in the case of a linear relationship, the process of nonlinear estimation is more computation-based and requires more time and resources. In addition, in order to investigate the impact of influential traders on traders' daily net trading volume, nonlinear impulse response analysis is implemented. Thus, with regard to the research questions, a question of traders' responses on the change of influential traders is added in this paper beyond the scope of Hwang (2018). The research questions of this study are presented below.

First, are there nonlinear relationships between traders' daily net trading volumes and how are the traders' net trading volumes inter-connected? Second, who are the strongly influential investors in the Korean capital markets based on the nonlinear relationship and how do their influences change? Third, does a trader's connectedness affect the volatility of financial markets? Lastly if there is a shock on daily net trading volume of the influential traders, which traders react more sensitively?

Based on the network structure estimated with nonlinear methods, I find that foreign investors and derivative markets are more influential than other traders and markets. These results are in accord with the linear results of Hwang (2018) despite some differences. Fewer strong connections are found than in linear methods, which seems to result from nonlinearity.

The traders' contribution to market volatility with positive and negative directions are also investigated. It is found that the most foreign investors tend to contribute to decrease market volatility, but that other influential traders seem to function to increase market volatility. These results are also in line with the linear results.

Furthermore, by nonlinear impulse response analyses, some traders such as foreign investors, collective investment schemes and individual traders are found to be linked closely. Although the trading directions (buying or selling) of traders depend on the sort of shock, the linkages of those traders are shown explicitly.

The main contribution of this paper is the development beyond the research of Hwang (2018) with nonlinear methodologies. Due to the characteristics of those methods of capturing the linearity as well as nonlinearity, the conclusion of this paper is more comprehensive. In addition, the result of the impulse response analysis in this paper suggests the potential channels through which influential traders' can have an impact on the actual trading behaviours of other traders. This supplements the network analyses which just shows influential traders or the particular conditions increasing the impact of influential traders. Those contributions can provide a few insights not only to the previous literature but also to policy makers who oversee financial markets.

The rest part of this paper is organized as follows. In Section 2, the extant literature focusing on nonlinear methodologies is examined. The methodology is covered in Section 3. In Section 4, the results of the estimation and analyses are discussed. The comprehensive discussion, including the result of linear methods is given in Section 5. In Section 6 conclusions are reached.

2 Literature review

This section is divided into three parts. In the first, I review the previous literature studied on the linkage of financial markets, sub parts of markets and the traders in markets. I, then, summarise the research results of Hwang (2018). Lastly, I focus on the nonlinear methodologies in order to estimate nonlinear relationships between traders, the development history and the advantages of those nonlinear techniques.

2.1 Linkage of financial markets, sub-parts of markets and traders in markets.

Some research has focused on the inter-relation between different financial markets. A few of these studies attempted to investigate financial markets from different jurisdictions. Bekiros et al. (2016) investigated the connectedness of the US equity and commodity futures markets. They showed that the inter-linkage between the commodity and equity markets became strong only during the recent crisis period, and that the commodity markets were strongly connected. Thapa et al. (2016) studied the inter-connections of the foreign exchange (FX) markets among 40 different countries, and suggested that the countries with more liquid and cost-effective markets attracted the investors. Silva et al. (2016) implemented a study on 26 countries' banks exposures and cross-border investments, and found that the fragility of global financial markets was addressed with the network structure. Wang et al. (2016) examined the volatility spill over of Chinese financial markets, and found that the stock market was the largest net sender and the FX and commodity futures markets were net recipients. Yang and Zhou (2016) identified the network structures of numerous financial volatility indexes global financial indexes including US, major European countries and major Asian countries. They showed that the US stock market was the core of global volatility spillover network.

Other researchers shed light on the sub-parts of financial markets such as individual stocks or the stocks of financial institutions or CDSs. Musmeci et al. (2017) investigated the network structures of 1004 US stocks and having analysed them using different network measures, found that the stocks of financial industries had explicitly more influence on others than the stocks of other industries. Song et al. (2016) studied the relations of the stocks of Korean financial companies and analysed the topology of financial companies. They showed that the leading risk spill-over sector could differ by the characteristics of the event. Huang et al. (2016) studied the network structure of Chinese financial institutions. Their findings showed that small and medium-sized commercial banks contributed to more systemic risk, and that insurance companies had a greater contribution than banks. Kaushik and Battiston (2013) analysed CDS spreads of top US and European financial institutions, and showed that the interconnectedness of CDS could be an indicator of the systemic risk.

With a little narrower point of views, traders's inter-connectedness attracted a few researchers. Pinheiro and Coelho (2016) analysed the network structure of Brazilian investment funds and found that the network structures were closely linked with financial contagion results. Chuang (2016) analysed brokers' trading information in Taiwan, and found that the connectedness of brokerage firms were correlated with the returns of stock. Billio et al. (2012) investigated four different types of traders' interconnectedness. They are hedge funds, banks, broker/dealers and insurance companies. They found that banking and insurance sectors became more important systematically.

2.2 Nonlinear methodology

Firstly, various kinds of nonlinear Granger causality test techniques have been proposed since Granger (1969) first introduced the concept of this test. The proposition of Baek and Brock (1992) is a nonparametric statistical method utilising a correlation integral, which is an estimator of spatial probabilities. They showed the nonlinear relations between money and income. However, their approach had two weak points which are the nuisance parameter problem and a finite sample size of which test they applied to.

Thus, Hiemstra and Jones (1994) suggested a nonlinear Granger causality method based on Baek and Brock (1992). However, the test of Hiemstra and Jones (1994) (HJ's test) is for the bivariate time series. Thus, Bai et al. (2010) extends HJ's method to a multivariate setting. Later, Diks and Panchenko (2005) and Diks and Panchenko (2006) showed that HJ's test can reject the null hypothesis overly, and proposed a nonparametric test. Nishiyama et al. (2011) also suggested a nonparametric test. The main focus of their approach concerned conditional moments, a focus which was different from the joint cumulative distribution of the variants of the test of Hiemstra and Jones (1994).

Although those methods mentioned above can test the nonlinear causality between the time series, it is still hard how strongly connected nonlinearly. If the strength of a nonlinear connection cannot be captured, the influence of a trader cannot be exactly identified. Song and Taamouti (2016) introduced the measure of nonlinear causality, which is model-free and nonparametric. Their measure is differentiated from the earlier measures introduced by Geweke (1984) and Dufour and Taamouti (2010), in a sense that those were estimated based on the parametric linear models. Therefore, in this paper I estimate traders' network structure with the nonlinear Granger causality method of Song and Taamouti (2016).

Some of the previous literature showed that there were nonlinear relations between economic variables based on the techniques mentioned above. Bal and Rath (2015) showed the significant nonlinear Granger causality relations between oil price and exchange rates of China and India with the Hiemstra and Jones nonlinear Granger causality test. Chu et al. (2016) found a strong bi-directional nonlinear causality relation between investor sentiment and stock returns using a nonlinear causality test based on a Taylor series approximation. Nonlinear causality between stock returns and volatility was also examined by Bekiros et al. (2016) who used the method of Nishiyama et al. (2011). Other studies attempted to examine the causal relations between the economic variables using both linear and nonlinear methods and found the nonlinear causality where linear causality had not been found and the linear causality where nonlinear relations had not been uncovered. Rahimi et al. (2016) found some evidence of this in the interest rates in US and Canada. Choudhry et al. (2016) examined the causal relations between stock market volatility and business cycles in US, Canada, Japan and UK. Their results showed that there were some cases in which linear causality were found, but that nonlinearity wes not uncovered. Andreasson et al. (2016) also found the other examples of the evidence of mixture of linear and nonlinear causal relations between exchange rates and equity indexes.

Secondly, a nonlinear generalized forecast error variance decomposition technique and nonlinear impulse response function techniques have been studied in order to capture nonlinear relations between economic variables. A traditional impulse response function and forecast error variance decomposition suggested by Sims (1972) and Sims (1980) have been developed by numerous researchers into the nonlinear multivariate impulse response function and forecast error variance decomposition. The initiative to develop nonlinear impulse response functions has been carried out by Potter (2000), who proposed a univariate form of nonlinear impulse response functions. He introduces the concept of a generalized impulse response function. This idea was extended to the case of a multivariate nonlinear impulse response function by Koop et al. (1996). They showed the computation with Monte Carlo techniques in order to implement generalized impulse response functions. Their approach is applicable to both linear and nonlinear cases. Based on the research of Koop et al. (1996) and Pesaran and Shin (1998) proposed a generalized impulse response function and generalized forecast error variance decomposition, although their suggestion was restricted to linear models. Lanne and Nyberg (2016) finally suggested generalized forecast error variance decomposition, which was applicable to both linear and nonlinear models. Their proposition was developed based on the approach of Koop et al. (1996) and Pesaran and Shin (1998).

Nonlinear generalized variance decomposition and a nonlinear impulse response function have been applied to various areas of economic research. Forero and Vega (2016) studied the nonlinear relation of inflation and exchanger rate in the Peruvian economy using a nonlinear impulse response function. Lanne and Nyberg (2016) applied nonlinear generalized forecast error variance decomposition to US GDP growth and term spread between short-term and long-term interest rates. Chan-Lau (2017) investigated the network structure of global financial companies with linear and nonlinear generalized forecast error variance decomposition methods.

In this present paper, nonlinear Granger causality method by Song and Taamouti (2016) and nonlinear generalized forecast error variance decomposition by Lanne and Nyberg (2016) are respectively applied to estimate traders' network structure. In addition, nonlinear impulse response function of Koop et al. (1996) is also applied to investigate the responses of traders at the shock of the trading of strongly influential traders.

3 Methodology

3.1 Overview

In this section nonlinear Granger causality method (GCM) by Song and Taamouti (2016) and nonlinear generalized forecast error variance decomposition (GVD) by Lanne and Nyberg (2016) are mainly discussed. In order to explain nonlinear generalized forecast error variance decomposition, the nonlinear generalized impulse response function (GIRF) suggested by Koop et al. (1996) and their simulation approach is also described. For all those methods, nonlinear regression model needs to be assumed. The detail of nonlinear regression is explained in the section of the baseline model. For the sake of consistency and the objective of comparison, the definition of variable and analysis frame are same as the ones in Hwang (2018) as in Table 1.

3.2 Baseline Model

I assume a VAR-form nonparametric regression as presented below. For consistency and simplicity, the lag period is assumed to be one, which helps the interpretation.[1] Daily net trading volumes of investors today can make an impact on tomorrow's daily net trading volumes. This is becuase traders in financial markets refer other traders' trading

[1]Practically, traders can refer other traders' trading behaviours during the day after 6PM. In addition, previous literature (Dufour and Jian, 2016; Barigozzi and Hallin, 2017) assumed VAR(1) process.

Table 1: Definition of variables

	IND	BANK	FI	CIS	OTH	INS	GOV	FOR
Stock	$x_{ind,su}$	$x_{bank,su}$	$x_{fi,su}$	$x_{cis,su}$	$x_{oth,su}$	$x_{ins,su}$	$x_{gov,su}$	$x_{for,su}$
Stock Drv.	$x_{ind,sd}$	$x_{bank,sd}$	$x_{fi,sd}$	$x_{cis,sd}$	$x_{oth,sd}$	$x_{ins,sd}$	$x_{gov,sd}$	$x_{for,sd}$
Bond	$x_{ind,bu}$	$x_{bank,bu}$	$x_{fi,bu}$	$x_{cis,bu}$	$x_{oth,bu}$	$x_{ins,bu}$	$x_{gov,bu}$	$x_{for,bu}$
Bond Drv.	$x_{ind,bd}$	$x_{bank,bd}$	$x_{fi,bd}$	$x_{cis,bd}$	$x_{oth,bd}$	$x_{ins,bd}$	$x_{gov,bd}$	$x_{for,bd}$
FX Drv.	$x_{ind,fxd}$	$x_{bank,fxd}$	$x_{fi,fxd}$	$x_{cis,fxd}$	$x_{oth,fxd}$	$x_{ins,fxd}$	$x_{gov,fxd}$	$x_{for,fxd}$

[Note]
(Trader)
IND = Individual trader, BANK = Bank, FI = Financial investment(mainly securities companies)
CIS = Collective Investment Scheme, OTH = Others (small financial companies)
INS = Insurance companies, GOV = Government, FOR = Foreign Investors
(Market)
SU = Stock, SD = Stock derivative, BU = Bond, BD = Bond derivative
FXD = Foreign exchange derivative

behaviours for their trading the following day.

$$X_{t+1} = \Phi(X_t) + \upsilon_t \tag{1}$$

where $X_t = (x_{1,t}, x_{2,t}, ..., x_{40,t})'$ is the vector of daily net trading volumes[2] of trader x_i. $\Phi(X_t)$ is an unknown nonlinear function. Error term $\upsilon_t = (\upsilon_{1,t}, ..., \upsilon_{40,t})'$ and $E[\upsilon_t|X_t] = 0$.

3.3 Estimation of nonparametric regression

A nonlinear regression model cannot be estimated using the traditional methods which can be applicable to linear models. In this section, the estimation method for nonparametric regression which was introduced by Song and Taamouti (2016) is described. For the sake of consistent estimation, Song and Taamouti (2016) suggested the well-studied Nadaraya-Watson estimator (Nadaraya, 1964; Watson, 1964). Here I follow their approach.

The basic idea of nonparametric estimation is that the output data is weighted-averaged with various smoothing methods resulting in the minimization of observed errors as in

[2] A trader's daily net trading volume is the ratio of a trader's net buying (or selling) over the sum of all traders' buying (or selling). For instance, bank sells 1 billion KRW after offsetting all selling and buying in stock market. And all traders in stock market buy 10 billion KRW and sell 10 billion KRW. Bank's daily net trading volume is 0.1.

Equation 2. In the process of weighted averaging, the nearer results (X_{t+1}) have greater weights W_{t+1}.

$$\bar{\Phi}(X) = \sum_{t=0}^{T-1} W_{t+1}(X, \bar{h}) X_{t+1} \tag{2}$$

The weight (W_{t+1}) can be described more in greater detail with kernels which were suggested Nadaraya (1964) and Watson (1964), as seen in Equation 3.

$$W_{t+1}(X, \bar{h}) = \frac{K\left(\frac{X-X_t}{h}\right)}{\sum_{s=0}^{T-1} K\left(\frac{X-X_s}{h}\right)} \tag{3}$$

where $K()$ is a kernel. h is a bandwidth. A kernel can be understood as a probability density function and is assumed to meet a few conditions. [3] Here I use the Gaussian Kernel which is one of the most representative forms for the computational simplicity, although there are other various kinds of kernels such as the Epanechnikov, and triangle types. The Gaussian Kernel function is given below (Silverman, 1986).

$$\kappa(x_i) = \frac{1}{h\sqrt{2\pi}} \exp(-\frac{1}{2} \cdot \frac{x_i^2}{h^2}) \tag{4}$$

where $\kappa(x_i)$ is a univariate Gaussian kernel function. One important point here is how to deal with the multivariate form of kernels. I follow the multivariate form of Fan (2005), which is called product kernel in the data analysis area (Shalizi, 2013). Song and Taamouti (2016) also followed the approach of Fan (2005) like Equation 5. For the daily net trading volume of all traders, each kernel is calculated first and the product kernel can be obtained.

[3] 1) $K(x) \geq 0$
2) $\int_{-\infty}^{\infty} K(u)du = 1$
3) $K(-x) = K(x), \forall x$

$$K(X) = \prod_{i=1}^{40} \kappa(x_i) \tag{5}$$

A second important factor in estimating nonparametric regression is the bandwidth. As seen in Equation 3, if the bandwidth(h) is too wide, the estimated results can be over-smoothed and too stable. In contrast, if the bandwidth(h) is too narrow, the estimation result can be under-smoothed and too volatile. Thus, the choice of optimal bandwidth is very important. Here as an optimal bandwidth, I compute the bandwidth h suggested by Silverman (1986) with Equation 6.

$$h = 4/(2d+1)^{1/(d+4)} n^{-1/(d+4)} \tag{6}$$

where d is the dimension. For each kernel, the bandwidth h is assumed to be same as Song and Taamouti (2016) did.

3.4 Granger causality

The fundamental concept of Granger causality for the nonlinear method is the same as the conditional Granger causality method introduced in Hwang (2018). Granger causality measures can be calculated as the logarithmic ratio of the forecasted error of the restricted model over the forecasted error of the unrestricted model as seen in Equation 7. The difference between the restricted and unrestricted models is the inclusion of a variable (x_i) as an independent variable.

$$c(x_{i,t} \to x_{j,t}) = ln\Big[\frac{\sigma^2[x_{j,t+1}|I_{X_{-x_i}}(t)]}{\sigma^2[x_{j,t+1}|I_X(t)]}\Big]. \tag{7}$$

where $i, j = 1, 2, ..., 40$, $I_X(t)$ is information set at time t. X_{-x_i} is X vector without x_i. $c(x_{i,t} \to x_{j,t})$ means that trader i's daily net trading volume at time t Granger causes trader j's daliy net trading volume at time t+1.

Table 2: Causality matrix

	$c_{,1}$	$c_{,2}$	..	$c_{,39}$	$c_{,40}$
$c_{1,}$	$c_{1,1}$	$c_{1,2}$	..	$c_{1,39}$	$c_{1,40}$
$c_{2,}$	$c_{2,1}$	$c_{2,2}$	..	$c_{2,39}$	$c_{2,40}$
..	..	..	..	..	..
$c_{39,}$	$c_{39,1}$	$c_{39,2}$	..	$c_{39,39}$	$c_{39,40}$
$c_{40,}$	$c_{40,1}$	$c_{40,2}$	..	$c_{40,39}$	$c_{40,40}$

After acquiring the Granger causality measure, it needs to be tested for statistical significance. For the test, I follow the bootstrapping method which Song and Taamouti (2016) suggested.[4] I test with a 10% significance level which is consistent with Hwang (2018).

Two important attributes of the Granger causality measure $c(x_i \to x_j)$ here are pairwise causality and conditional on the information set $I_X(t)$. A pairwise attribute can help to understand the relation between two traders directly, but the relation should be understood with the condition of historical information of the trading of all traders. In other words, the causal relation can be different depending on the scope of the analysed network. If individual traders have an impact on banks within a stock market, that influence can be insignificant within the entire financial market network. The network analysis within five different markets can provide a wider perspective on the financial market.

Pairwise Granger causality measure ($c(x_{i,t} \to x_{j,t})$, i,j = 1,...,40) can be summarized in matrix form as in Table 2. For the sake of simplicity from now on I call $c(x_{i,t} \to x_{j,t})$ as $c_{i,j}$. With all $c_{i,j}$ causality measures, matrix (C) can be made as in Table 2. In addition, for actual analysis self causality ($c_{i,i}$, i=1,..,40) is excluded, as the extant previous literature (Diebold and Yilmaz, 2014) did .

Once the causality matrix is obtained, it can be turned into the each trader's connectedness measures. The ith row sum means the sum of trader i's influence on others as in Equation 8 and the ith column sum is trader i's impact from other traders as in Equation 9. I call the former the OUT measure and the latter the IN measure hereafter.

[4]Song and Taamouti (2016) showed the test statistic using Granger causality measure asymptotically normal distributed. However, they also mentioned that in the case of finite sample the asymptotic property cannot work. Thus, in this paper I use bootstrapping method for statistical significance test.

$$OUT(i) = \sum_{j=1, j \neq i}^{N} c_{i \to j} \tag{8}$$

where $c_{i \to j}$ is the causality value from trader i to trader j which is the element $(c_{i,j})$ of causality matrix.

$$IN(i) = \sum_{j=1, j \neq i}^{N} c_{j \to i} \tag{9}$$

where $c_{j \to i}$ is the causality value from trader j to trader i which is the element $(c_{j,i})$ of causality matrix.

Nevertheless, a trader's net impact on other traders cannot be explained only using OUT and IN measures, for a trader can influence others and be influenced by others at the same time. OUT and IN measures of a trader can offset each other. In order to overcome this limit, relative influence (RI) measures is used which can capture the relative net influence of a trader within the network as seen in Equation 10.

$$RI(i) = \frac{OUT(i) - IN(i)}{OUT(i) + IN(i)} \tag{10}$$

3.5 Nonlinear generalized impulse response function

An impulse response function is the economic technique used to observe the response or the persistence of variables in cases of shock. Much economic knowledge has been acquired using this technique. Through the contributions of a great deal of previous research, this method has been greatly developed. One of the most important contributing ideas among these was the generalized impulse response function introduced by Koop et al. (1996). Generalized impulse response function can not only be applied to both linear and nonlinear models, but also helps to solve the composition effect, which means the results of the impulse response function can vary depending on the composition of a shock. In traditional impulse response functions, the covariance matrix of shocks needs to be a diagonal matrix to solve the problem. Here I follow the approach of Koop et al. (1996) and use a generalized impulse response function.

Generalized impulse response function (GIF) is defined in Equation 11.

$$GI(n, \nu_t, \omega_{t-1}) = E[X_{t+n}|\nu_t, \omega_{t-1}] - E[X_{t+n}|\omega_{t-1}] \tag{11}$$

where $n = 0, 1, ...$ is time horizon, ν_t is shock at time t, ω_{t-1} is the history at time $t-1$. If the shock occurs in x_i at time t, this impulse response function shows the reactions of traders at time $t+n$. Here the shock is defined as one standard deviation of all traders' error vectors.[5] Error vectors are the residuals of a baseline model as seen in Equation 1. The history is the information set which is the past trading data of all traders. A generalized impulse response function can be calculated by the simulation method.

The Time horizon of an analysis is 10 days. The Bank for International Settlement (BIS) suggested 10 days as a standard period to compute market risk. However, it is difficult to determine how many days the effect of a shock on traders' trading volume lasts. Although the reaction to daily trading shocks can be faded out very fast, careful traders can consider a trend of the trading patterns of certain types of traders as a real life reference at the same time. I try a few sample tests of 20 days, and find no significant effect after 5 days. Thus, 10 days is sufficient to see the reactions of market participants to the trading shock of a traders.

An actual impulse response analysis can be implemented with the simulation method suggested by Koop et al. (1996) and Lanne and Nyberg (2016). The simulation process can be executed with the steps below. For the calculation, two initial conditions which are the shock ν_t and the history ω_{t-1}, play an important role. Then, randomly sampled

[5]Koop et al. (1996) suggested various versions of generalized impulse response functions. Having a condition on a particular shock, a particular history or a particular subsets of the shock or the history could be applied. In this paper, I applied a particular shock and all history during the analyzed period in order to have the analysis result based on an extreme case and the real market data.

residuals which are "random shocks"[6] here, are utilised for the simulation.

1. Obtain the residuals ε_t in Equation 1 and define the shock.

   (a) Residuals ε_t can be acquired as given below.

   $$\varepsilon_t = X_t - \Phi(X_{t-1}) \tag{12}$$

   where nonlinear function $\Phi(\cdot)$ is estimated with nonparametric regression using Gaussian kernel. $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, ..\varepsilon_{40,t},)'$ is the vector whose components are the residuals of the traders' daily net trading volumes.

2. Define the shock vector ν_t with residuals.

   $$\nu_t = (\delta_{1,t}, \delta_{2,t}, ..\delta_{40,t},)' \tag{13}$$

   (a) Shock vector ν_t is one standard deviation of all residuals, which is calculated according to the trader. $\delta_{n,t}$ $(n = 1, 2, , 40)$ is the standard deviation of trader n's residuals.

   (b) the shock vector ν_t can be positive or negative according to the characteristic of shock. In the case of traders' trading shocks, negative shocks can be more meaningful in terms of the effect on the financial market.

3. Draw N vectors ("random shocks") from all residuals randomly.

   (a) N is the period of analysis time horizon. Here I use N=10.

4. Select a history ω_{t-1}, which is the information for computation of conditional expectation.

   (a) Lanne and Nyberg (2016) described ω_{t-1} as "p lags of X_t in the model." In this paper, the model order is 1. Thus, all daily data are used for the history.

[6]Koop et al. (1996) called them "innovation"

5. Select a component of shock at the shock vector ν_t and calculate the generalized impulse response function in Equation 11 for all histories.

   (a) Determine the trader who has the shock in his/her daily net trading volume. (In this paper, generalized impulse response functions of influential traders who are determined according to the RI (Relative Influence) connectedness measure, are analysed.)

   (b) Leave the entry of the trader in the shock vector and turn other entries into zero like $\nu_{j,t} = (0, 0, , \delta_{j,t}, ..0)'$

   (c) Reflecting shock and history, calculate $E[X_{t+n}|\nu_{j,t}, \omega_{t-1}]$[7]

   (d) Calculate $E[X_{t+n}|\omega_{t-1}]$ without ν_t. [8]

   (e) Compute a generalized impulse response function over the time horizon(h).

6. Repeat steps 3 to 5 for all histories.

7. Repeat step 6 1000 times and average them out.

It is still difficult to see how other traders react to influential investors' sudden selling, although with the results of network structure analysis the strength and direction of influences among traders are found. In that sense impulse response analysis is the investigation method to find the response of other traders given a trading shock of one trader. In addition, depending on the objective of the analysis and the distribution of data, the shock and history can vary. Lastly, the Generalized impulse response function plays an important role in nonlinear generalized variance decomposition by Lanne and Nyberg (2016). The nonlinear generalized variance decomposition technique is described in detail in next section.

[7]Expectation value of nonlinear model is calculated with standard multistep forecasting methods (Lanne and Nyberg, 2016; Terasvirta et al., 2010)

[8]The calculation is same with $E[X_{t+n}|\nu_t, \omega_{t-1}]$ except just one point which is one more random shock is used instead of shock vector. (Koop et al., 1996)

3.6 Nonlinear generalized forecast error variance decomposition

Forecast error variance decomposition is the method used to test the contribution of a variable to the variance of other variables given the vector. However, traditional variance decomposition had a critical problem: namely, the result of an analysis can be different depending on the order of a variable. Pesaran and Shin (1998) introduced generalized variance decomposition for linear models to overcome the problem based on the approach of Koop et al. (1996). Lanne and Nyberg (2016) extended the scope of generalized variance decomposition to nonlinear models.

The fundamental idea of Lanne and Nyberg (2016) is to compute the generalized impulse response functions of all entries and each entry's contribution to the sum of all entries over the predictive horizon as given in Equation 14.

$$\lambda_{ij,\omega_{t-1}}(k) = \frac{\sum_{n=0}^{k} GI(n, \nu_{j,t}, \omega_{t-1})_i^2}{\sum_{j=1}^{40} \sum_{n=0}^{k} GI(n, \nu_{j,t}, \omega_{t-1})_i^2} \tag{14}$$

where i is the variable of which variance is computed, j is the variable at which the shock occurs, n denotes time horizon, $\nu_{j,t}$ means the shock vector whose jth entry has nonzero value and ω_{t-1} refers to history. The denominator is the whole effect of all shocks, and the numerator measures the effect of jth shock cumulatively.

After the network structure is obtained, the connectedness measures need to be computed for the analysis objective. For the sake of consistency and the comparison aim, OUT, IN and RI measures which are introduced in the previous section of Granger causality are used. In addition, self causality is also excluded from the analysis as in Granger causality.

3.7 Analysis framework

The actual analysis is composed of four parts which are estimating network structures, analysing networks, investigating traders' contribution to market volatility and implementing a nonlinear impulse response analysis. Firstly, I estimate the traders' network structure with both the nonlinear Granger causality method (GCM) and nonlinear generalized forecast error variance decomposition (GVD).

Once the network structures are obtained, the strength of traders' influence can be identified. With various connectedness measures of influential traders over all, crisis and normal periods are investigated. Given the network structures estimated with two different methods, particulary strong relations can also be examined. The results of the analysis can be a foothold to understand the channel of market volatility contagion.

The extent of traders' contributions to the financial market volatility can be acquired using the adaptive LASSO technique. As Hwang (2018) did, those traders whose connectedness measures have relations with market volatility for the last 200 days, can be identified with the coefficients of adaptive LASSO regression. The first three of all four analyses mentioned above are implemented with the same frameworks as Hwang (2018) did for the sake of the aim of consistency.

However, nonlinear impulse response analysis is not covered in Hwang (2018). This method has a few advantages in analysis. It is a model-free method, which means that it does not need to assume any type of model regardless whether it is linear or nonlinear. In addition, it helps to extend the scope of network analysis to understand the actual responses of traders at the shock of the daily net trading volumes of significantly influential traders. This attribute can be more meaningful in the sense that it is difficult to see the influence of strongly connected traders on the trading of other traders with network analysis alone.

4 Results

In this section, I estimate financial traders' network structures with the nonlinear Granger causality method and the nonlinear generalized variance decomposition method. The influence of traders, is then, investigated with the connectedness measures. Influential traders who are chosen based on the connectedness measures, are assessed under different time periods and the trading patterns of foreign investors. The contributions of the connectedness measures of traders to market volatility are also examined. Finally, the sensitive traders at the trading shock of influential traders are identified with nonlinear impulse response analysis.

4.1 Network estimation

4.1.1 Traders' relative influence

Traders' relative influence (RI) which is estimated with nonlinear GCM and nonlinear GVD, is analyzed first. The top 10 rankers of RI are mainly investigated, in order to maintain consistency with Hwang (2018) and in order to focus on the high relative influence. Trader types and the markets which have the most top 10 rankers are identified. Then, I analyse the results comparatively with Hwang (2018), which helps to see whether there are nonlinear relations between traders in a separate section.

Foreign investors (FOR) are suggested influential traders by both nonlinear GCM and GVD in regard to the trader type, as present in Table 3. This is described in Figure 1 more precisely. The traders with the top 10 relative influence (RI) are displayed as red circles during each time period and with nonlinear GCM or GVD.

Evidently polarized, are the results of nonlinear GCM and GVD shown to be into influential and non-influential types of traders. Based on Table 3, IND, BANK and FI do not have top 10 rankers during at least two time periods with nonlinear GCM. Nonlinear GVD also suggests that CIS, OTH, INS and GOV don't have top 10 rankers during at least two time periods. [9]

Both nonlinear GCM and GVD show considerably contrasting results, which seems more

[9] The result during all seems quite different from during crisis and normal. However, the period "all" here is the period which includes both crisis and normal. The estimation process for all period is separated and independent. Thus the result can be seen a bit different.

Table 3: The number of top 10 Relative influence ranker's trader type

	IND	BANK	FI	CIS	OTH	INS	GOV	FOR
[GCM]								
All	-	1	-	-	4	1	2	2
Crisis	1	-	-	2	2	3	1	1
Normal	-	-	2	2	2	1	1	2
[GVD]								
All	3	2	1	-	-	-	-	4
Crisis	2	2	1	1	-	-	-	3
Normal	3	2	1	-	-	-	-	4

[Note]
1. The number of top 10 relative influence rankers in each trader type under certain methods (GCM, GVD) and time period (all, crisis and normal) is present.
2. (trader type)
IND = Individual trader, BANK = Bank, FI = Financial investment(mainly securities companies)
CIS = Collective Investment Scheme, OTH = Others (small financial companies)
INS = Insurance companies, GOV = Government, FOR = Foreign Investors

Table 4: The number of top 10 Relative influence ranker's market

	Stock	Stock Drv.	Bond	Bond Drv.	FX Drv.
[GCM]					
All	-	4	2	1	3
Crisis	1	3	2	3	1
Normal	-	-	2	4	4
[GVD]					
All	2	2	-	3	3
Crisis	3	2	-	3	2
Normal	2	2	-	3	3

[Note]
The number of top 10 relative influence rankers in each market under certain methods (GCM, GVD) and time period (all, crisis and normal) is present.

evident than in a linear case (Hwang, 2018). With nonlinear GVD IND and BANK are influential traders while nonlinear GCM suggests OTH and INS are influential. Hwang (2018) argues that these contrasting results do not arise because of an error in analysis, but because of the methodological difference.

Derivative markets are shown to have more influential traders with both nonlinear GCM and GVD (Table 4). This is also given in Figure 2. The significance of derivative markets is also suggested by linear methods (Hwang, 2018).

However, the bond market is influential only with nonlinear GCM and the stock mar-

Figure 1: Rank of traders' Relative influence (RI) by trader

[Notes]

1. GCM / GVD (left / right), all / crisis / normal (1st / 2nd / 3rd line)

2. Trader's Relative influence (RI) rank is shown on each radar chart by the estimation method (GCM, GVD) and period (all, crisis, normal). If a trader's RI rank is higher than 10th, the circle is red. Otherwise the circle is white. The circles are arranged by trader type.

3. (Trader type) IND = Individual trader, BANK = Bank, FI = Financial investment, CIS = Collective Investment Scheme, OTH = Others, INS = Insurance companies, GOV = Government, FOR = Foreign Investors

4. (Market) su = stock, sd = stock drv., bu = bond, bd = bond drv. fxd = fx drv.

Figure 2: Rank of traders' Relative influence (RI) by market

[Notes]

1. GCM / GVD (left / right), all / crisis / normal (1st / 2nd / 3rd line)

2. Trader's Relative influence (RI) rank is shown on each radar chart by the estimation method (GCM, GVD) and period (all, crisis, normal). If a trader's RI rank is higher than 10th, the circle is red. Otherwise the circle is white. The circles are arranged by market.

3. (Trader type) IND = Individual trader, BANK = Bank, FI = Financial investment, CIS = Collective Investment Scheme, OTH = Others, INS = Insurance companies, GOV = Government, FOR = Foreign Investors

4. (Market) su = stock, sd = stock drv., bu = bond, bd = bond drv. fxd = fx drv.

ket is of importance with nonlinear GVD. The influential traders in the stock market, nevertheless, are barely found with nonlinear GCM unlike linear GCM.

Common outcomes from two nonlinear methods are found, despite the dissimilar results. One is that foreign investors are influential within traders' financial network. However, their influence shrinks during crisis periods. The other is that derivative markets can play an important role in connecting the traders within the network structures.

4.1.2 Top 5 IN measures rankers' sources and OUT measures rankers' targets

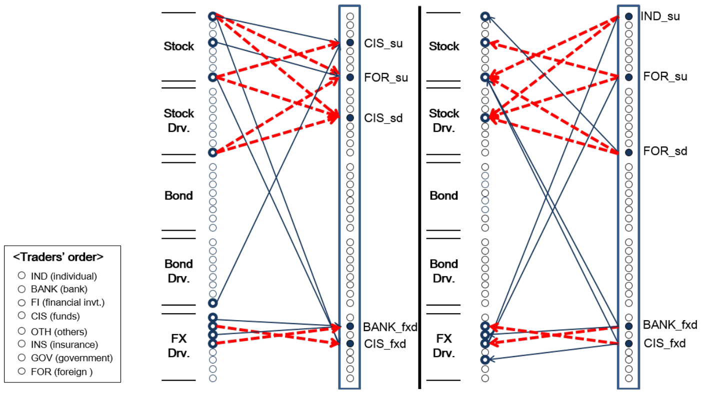
Traders' OUT and IN connectedness measures are analysed in this section. The OUT connectedness measure gauges a trader's influence on all other traders and the IN connectedness measure quantifies the influence of all other traders to a trader. The top five ranks of the OUT and IN measures are mainly focused on the analysis for the sake of consistency and the aim of simplicity. Table 5 shows the traders with the top five OUT/IN connectedness measures, the three most sensitive targets of each top five OUT measure ranker and the three most influential sources of each top five IN measure ranker.

"Strong connections" are also defined with the traders above to help the analysis.[10] Strong connections are the overlapped connections of the targets of the top five OUT measure rankers and the origins of the top five IN measure rankers. They are presented in Figure 3, and 4. If the strong connections are identified, it could be a clue to understanding the mechanism of market volatility propagation.

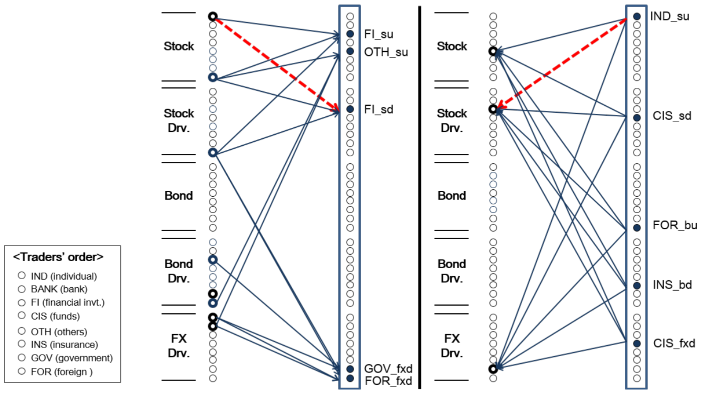
The way to find strong connections with the top five OUT and IN measures has an advantage over searching for the connections with the highest causality values. By definition, the strong connections should be the link between one of the top five OUT rankers and one of the top five IN rankers, which means the connections between the most influential and the most sensitive traders. However, the connection with the highest causality values cannot include the most influential or the most sensitive trader.

[10] The definition of "strong connection" is same with Hwang (2018).

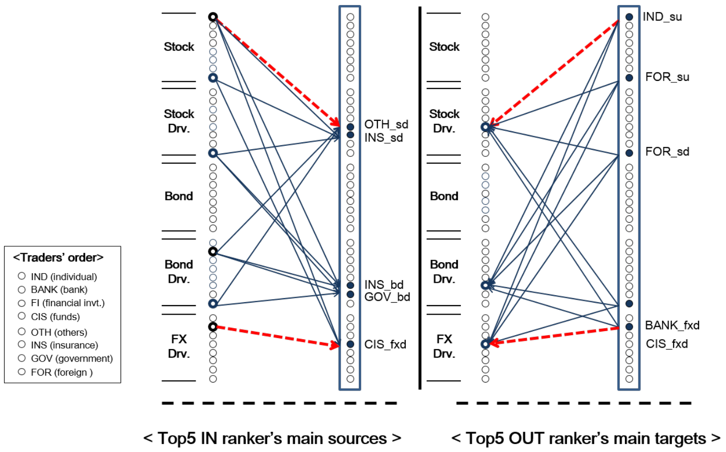
Figure 3: Relations between strong connection (GCM)



a. All



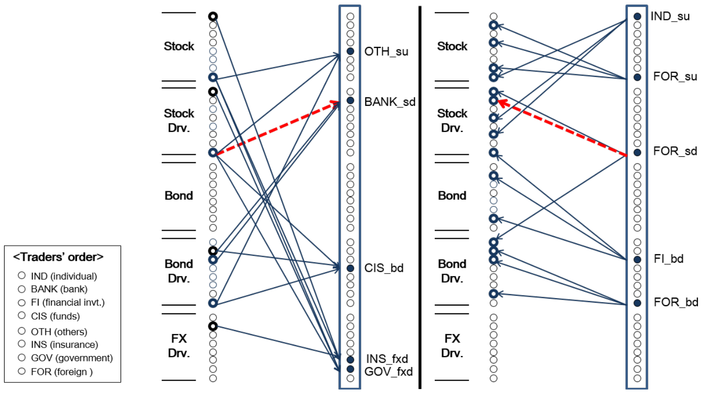
b. Crisis



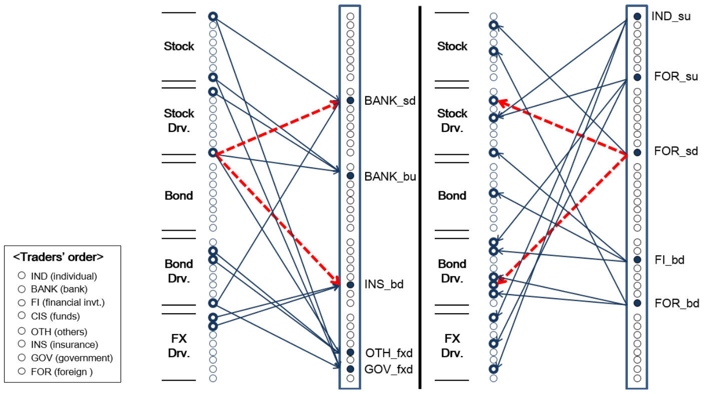
c. Normal

[Note]
1. Top 5 IN and OUT rankers' 3 main sources and targets are present during each time period (all, crisis, normal).
2. On left side, three main sources of top 5 IN rankers are shown. Colored circles are 5 IN rankers which are arrowed by 3 main sources.
3. On right side, three main targets of top 5 OUT rankers are described. Colored circles are 5 OUT rankers which are arrowing to 3 main targets.
4. Overlapped links on both sides are "strong connections" presented with red dashed line.

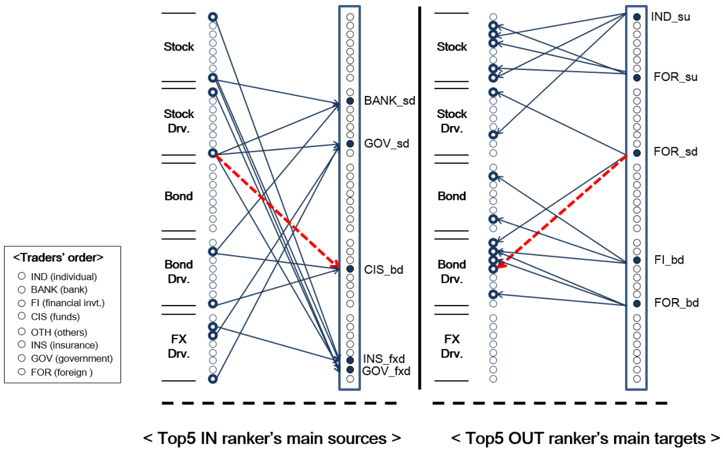
Figure 4: Relations between strong connection (GVD)



a. All



b. Crisis



c. Normal

[Note]

1. Top 5 IN and OUT rankers' 3 main sources and targets are present during each time period (all, crisis, normal).
2. On left side, three main sources of top 5 IN rankers are shown. Colored circles are 5 IN rankers which are arrowed by 3 main sources.
3. On right side, three main targets of top 5 OUT rankers are described. Colored circles are 5 OUT rankers which are arrowing to 3 main targets.
4. Overlapped links on both sides are "strong connections" presented with red dashed line.

Table 5: Top 5 IN/OUT measure ranker (GCM and GVD)

	IN					OUT				
Top	1	2	3	4	5	1	2	3	4	5
[GCM]										
(all)										
trader	FOR	CIS	CIS	BANK	CIS	FOR	IND	FOR	BANK	CIS
market	su	fxd	bd	fxd	su	su	su	sd	fxd	fxd
(crisis)										
trader	GOV	FI	OTH	FOR	FI	IND	CIS	CIS	FOR	INS
market	fxd	sd	su	fxd	su	su	fxd	sd	bu	bd
(normal)										
trader	OTH	CIS	INS	INS	GOV	FOR	FOR	IND	BANK	FOR
market	sd	fxd	bd	sd	bd	su	sd	su	fxd	bd
[GVD]										
(all)										
trader	BANK	CIS	GOV	INS	OTH	FOR	FOR	IND	FOR	FI
market	sd	bu	fxd	fxd	su	su	sd	su	bd	bd
(crisis)										
trader	INS	BANK	GOV	BANK	OTH	FOR	FOR	IND	FOR	FI
market	bd	bu	fxd	sd	fxd	sd	su	su	bd	bd
(normal)										
trader	BANK	INS	GOV	GOV	CIS	FOR	FOR	IND	FOR	FI
market	sd	fxd	sd	fxd	bu	sd	su	su	bd	bd

[Note]
1. The trader and the market with Top 5 IN and OUT connectedness measures are present under the method (GCM, GVD) and time period (all, crisis, normal)
2. (Traders)
IND = Individual trader, BANK = Bank, FI = Financial investment, CIS = Collective Investment Scheme
OTH = Others, INS = Insurance companies, GOV = Government, FOR = Foreign Investors
3. (Market)
su = stock, sd = stock drv., bu = bond, bd = bond drv., fxd = fx drv.

Table 6: The number of strong connections

	Linear			Nonlinear		
	All	Crisis	Normal	All	Crisis	Normal
GCM	3	4	4	8	1	2
GVD	4	4	4	1	2	1

[Note]
1. The number of strong connections is present under period (all, crisis, normal) and method (GCM, GVD).
2. Strong connection is the case which main sources of top 5 IN measure ranker and main targets of top 5 OUT ranker overlap each other.

Evidently both nonlinear GCM and GVD suggest similar traders as the top five OUT rankers (Table 5). FOR in the stock and stock derivative markets and IND in the stock market are also within the top five OUT measure rankers with nonlinear GCM during all and normal periods, while other traders including CIS in the FX derivative market are within the top five OUT measure rankers during crisis period. Foreign investors (FOR) in the stock, stock derivative and bond derivative markets, individual investors (IND) in stock market and financial investment (FI) in the bond derivative market are the Top five OUT measure rankers with nonlinear GVD, which does not vary depending on the time period. These consistent results are not found in the linear models (Hwang, 2018), in which linear GCM and GVD suggest the a different result.

In contrast, the result of the top five IN rankers is different according to the estimation method. It is also hard to find any patterns, although a few types of traders such as government (GOV) in the FX derivative market are repeatedly selected across different methods and time periods.

Another important finding is that the traders with the top five IN measures are barely overlapped with the top five OUT measure rankers. There were many overlapped top five OUT and IN rankers with the linear model (Hwang, 2018). The interpretation of the results with many overlapping cases of the top five OUT and IN rankers can be confusing, as the same trader can be influential and influenced at the same time. Relative influence (RI) of those traders is low, which means the net influence is not strong, although they function as a bridge of influence within the network structure. In this context, a nonlinear result shows the functions of traders (giving or receiving influence) within the network structure more clearly than linear methods.

There are eight pairs of strong connections found with nonlinear GCM during the all period (Figure 3). Half of them begin from foreign investors (FOR). FOR in the stock market influence CIS in the stock and stock derivative markets. FOR in the stock derivative market impact on FOR in the stock market and CIS in the stock derivative market. Individual investors (IND) have also two links to FOR in the stock market and CIS in the stock derivative market. Two residual pairs are found in the FX derivative market. However, during crisis period just one strong connection from IND in the stock market to FI in the stock derivative is found. During normal time, two strong connections which are IND in the stock market to OTH in the stock derivative market and BANK to CIS in the FX derivative market, are identified.

Strong connections with nonlinear GVD are begun from FOR in the stock derivative market regardless of time period (Figure 4). During all period, the strong connetion is toward to BANK in the stock derivative market, but points to CIS in the FX derivative market during the normal periods. Yet during crisis time, the strong connections are to BANK in stock derivative market and INS in bond market.

The difference in strong connections between linear and nonlinear methods can be summarised in two points. First, the number of strong connections with nonlinear methods are fewer than the ones of linear models as seen in Table 6. There are approximately four strong connections with linear methods during each time period. However, one or two strong connections exist with nonlinear methods except nonlinear GCM during the all period. Then, the connections are more related to the traders in the stock derivative market with nonlinear methods, while strong connections with linear models are more likely to be found in the stock market.

Fewer strong connections do not necessarily mean that there are fewer volatility spill-over channels, although strong connections can be evidence of "influence" : a give and take relation between traders. On the contrary, it means that the influence of a trader is not concentrated within the network under the nonlinear relations setup, and that the traders give and receive influence to and from each other in a more complex manners. In order to further investigate the relations of traders, a nonlinear impulse response analysis is implemented.

4.2 Influential traders' influence within the network structure

In this section the influence of influential traders including foreign investors and other traders with high relative influence (RI) is investigated over the time period as well as foreign investors' trading patterns. Other influential traders are individual investors (IND) in the stock market, BANK in the bond derivative market, financial investments (FI) in the bond derivative market and collective investment schemes (CIS) in the FX derivative market. I select FI in the bond derivative market based on the relative influence of nonlinear methods, while in linear models FI in the bond market is selected as an influential trader. I analyse the ranks of the influence of influential traders over time periods and the trading patterns of foreign investors, so that certain specific conditions under which influential traders function actively can be identified.

The influences of foreign investors are clear mainly in the derivative markets and during normal period, which are presented in Table 7. Nonlinear GVD suggests that their influence is high even in the stock market and during crisis period. This result is not much different from the one with linear models (Hwang, 2018). In addition, foreign investors in the stock market are shown to be more influential when they trade bonds rather than stocks. This might reflect the possibility that the trading strategy of foreign investors with the combination of stocks and bonds has an impact on the stock market.

Other influential traders' ranks of relative influence and OUT connectedness measures are shown to be relatively consistent over the time period and foreign investors' trading patterns. However, it is difficult to find an evident change of rank, as seen in Table 8. Furthermore, the results of nonlinear GCM and GVD seem to contrast. The other noteworthy finding is that CIS in the FX derivative market turns out to be strongly influential during crisis period with nonlinear GCM, which is in accord with the top five OUT measures with nonlinear GCM. Linear models of Hwang (2018) suggests similar results.

Importantly, the influence of foreign investors is re-identified mainly in the derivative markets, but it varies depending on the time period. This contradicts the influence of other influential traders which does not change much according to the time period. Foreign investors are remarkably influential rather during normal period than crisis time, which contradicts the common notion that foreign investors have strong influence during crisis time.

Table 7: Ranks of foreign investors' connectedness measure

			SU		SD		BU		BD		FXD	
			OUT	RI	OUT	RI	OUT	RI	OUT	RI	OUT	RI
GCM												
All			1	26	3	3	25	20	7	19	9	9
Crisis			25	28	24	26	4	5	28	30	37	37
	Stock	S	39	39	28	27	4	7	29	29	37	37
		B	38	38	16	19	2	4	22	24	33	34
	Bond	S	28	33	23	25	19	18	29	30	37	37
		B	20	23	23	22	31	30	24	24	34	34
	Stock	S	39	39	23	25	22	22	29	29	33	33
	&Bond	B	38	38	12	18	29	29	20	20	32	32
Normal			1	17	2	12	36	35	5	5	6	1
	Stock	S	39	39	1	18	30	30	2	3	18	24
		B	40	40	1	18	26	23	2	19	4	1
	Bond	S	5	24	1	13	39	39	8	15	20	20
		B	1	14	2	15	40	40	4	5	5	1
	Stock	S	38	38	7	13	37	37	14	14	22	24
	&Bond	B	40	40	1	19	39	39	6	22	2	1
GVD												
All			1	1	2	4	23	23	4	2	8	7
Crisis			2	1	1	2	25	25	4	4	13	13
	Stock	S	14	14	1	1	27	28	3	2	10	10
		B	13	13	1	1	17	17	2	2	10	11
	Bond	S	2	1	4	6	23	23	8	4	15	15
		B	5	5	2	3	28	28	3	2	11	11
	Stock	S	15	15	7	8	21	23	8	9	13	14
	&Bond	B	13	14	1	2	17	17	2	1	9	9
Normal			2	2	1	4	24	23	4	1	7	7
	Stock	S	9	8	2	4	26	25	1	1	6	7
		B	12	12	2	4	24	24	3	2	1	1
	Bond	S	4	3	1	4	25	25	2	1	7	7
		B	1	2	2	4	23	23	3	1	5	6
	Stock	S	14	14	1	2	26	26	3	3	7	7
	&Bond	B	11	11	3	3	23	23	1	1	2	2

[Note]
1. The rank of foreign investors' OUT and RI in each market is present by period (all, crisis, normal) and their trading pattern (sell/buy stock/bond/stock&bond) estimated with GVD.
2. (Market) SU=Stock, SD=Stock Drv., BU=Bond, BD=Bond Drv., FXD=FX Drv.
3. (Trading pattern) S = sell, B = buy
4. The cell is shadowed when the rank is higher 10th.

Table 8: Ranks of other influential traders' connectedness measure

			IND_su		BANK_bd		FI_bd		CIS_fxd	
			OUT	RI	OUT	RI	OUT	RI	OUT	RI
GCM										
All			2	17	14	16	13	15	5	38
Crisis			1	12	15	17	30	29	2	1
	Stock	S	33	33	20	19	26	26	1	2
		B	18	22	10	13	25	28	11	12
	Bond	S	10	14	9	10	26	28	1	1
		B	1	9	22	21	27	27	3	8
	Stock	S	31	32	14	14	26	26	9	9
	&Bond	B	18	19	15	15	21	21	24	25
Normal			3	29	10	19	7	8	34	38
	Stock	S	33	35	11	21	4	14	5	2
		B	35	38	7	17	3	15	39	39
	Bond	S	15	26	2	12	22	17	26	27
		B	3	21	11	23	7	6	36	37
	Stock	S	24	27	2	9	20	21	1	2
	&Bond	B	33	36	4	17	7	20	38	38
GVD										
All			3	3	7	8	5	6	14	14
Crisis			3	3	9	9	5	6	12	12
	Stock	S	8	8	5	6	2	3	15	15
		B	7	4	4	5	9	8	14	14
	Bond	S	5	3	1	2	3	7	13	12
		B	1	1	7	6	10	9	14	14
	Stock	S	11	10	1	3	4	6	14	13
	&Bond	B	8	8	4	4	5	5	14	13
Normal			3	3	6	8	5	6	15	15
	Stock	S	7	6	5	5	3	3	14	14
		B	8	7	6	6	5	5	16	16
	Bond	S	5	5	8	8	9	9	15	15
		B	4	3	8	9	6	7	15	15
	Stock	S	5	4	4	6	8	8	15	15
	&Bond	B	8	8	5	5	7	6	16	16

[Note]
1. The rank of other influential traders' OUT and RI is present by period (all, crisis, normal) and foreign investors' trading pattern (sell/buy stock/bond/stock&bond) estimated with GVD.
2. (Trader) IND_su = Individual in stock market, BANK_sd = Bank in stock Drv. market FI_bu = Finl. investment in bond market, CIS_fxd = Mutual funds in FX Drv. market
3. (Trading pattern) S = sell, B = buy
4. The cell is shadowed when the rank is higher 10th.

4.3 Contribution of traders' connectedness measures on the volatility of financial markets

The contributions of traders' connectedness measures (Relative Influence) to the market volatility are investigated to identify the relation between traders' networks and the volatility of the financial market in this section. As was done in Hwang (2018), the adaptive LASSO technique and the same framework of analysis are applied for the sake of consistency and the comparison objective. The stock market (KOSPI) and FX derivative market (KRW/USD futures) are used as the market volatility.

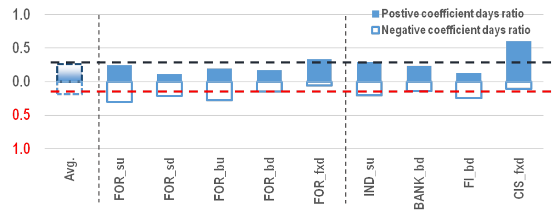
Briefly describing the framework, the contribution of a trader is determined depending on how many days a trader has positive (or negative) coefficients for all daily adaptive LASSO regression results. Adaptive LASSO regression provides the coefficients of regressors zero or nonzero values according to the relationship between regressors and the regressand. Then in a case in which the coefficients are nonzero values, a trader's contribution can be divided into the positive or negative group following the sign of the coefficient value. This classifying process is repeated for all days deducing 200 days during the period investigated, since the previous 200 days' data are used for running an adaptive LASSO regression. Finally, influential traders' positive (or negative) contributions are comparatively analysed with the average contributions.

Then, I expand the scope of this investigation further from influential traders to all traders. However, for the sake of the simplicity of the analysis I focus on two extreme cases. One is the trader with a high positive coefficient ratio and lower negative coefficient ratio, and the other is opposite case.[11]

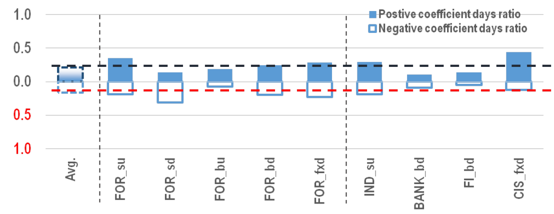
Foreign investors' contribution to stock market volatility is shown to generally decrease market volatility, although there are a few increasing instances depending on the market and the method, as seen in Figure 5. Nonlinear GCM suggests that FOR in the stock

[11]For the positive case, I choose the trader whose rank of positive contribution is higher than 10th, and whose rank of negative contribution is lower than 31th. Then I also select the negative case as the trader whose rank of positive contribution is lower than 31th, and whose rank of negative contribution is higher than 10th. I follow the strategy of Hwang (2018).

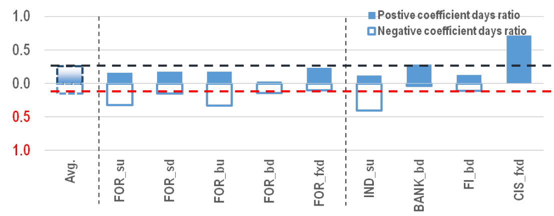
Figure 5: The contribution of traders' relative influence to stock market volatility



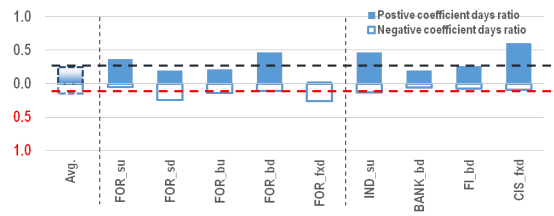
(a) All (GCM)



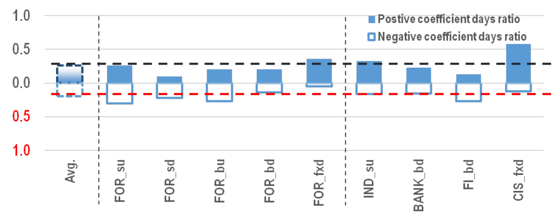
(b) All (GVD)



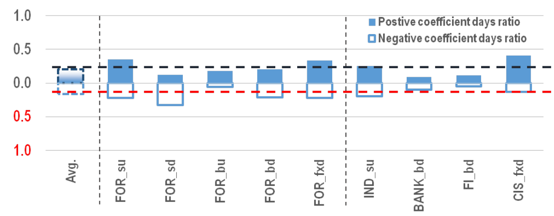
(c) Crisis (GCM)



(d) Crisis (GVD)



(e) Normal (GCM)



(f) Normal (GVD)

[Notes]

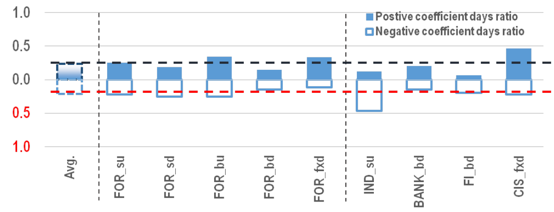
1. The ratio of influential traders' positive (negative) contribution days during analysed period are present compared to the average value of all 40 traders by time period (all, crisis, normal) and method (GCM, GVD).

2. Black dashed line in upper part of each figure is the average value of positive contribution day ratio and red dashed line in lower part of each figure is the average value of negative contribution day ratio. If a trader's positive (negative) coefficient day ratio is over the average value, it can be more contributing positively (negatively).

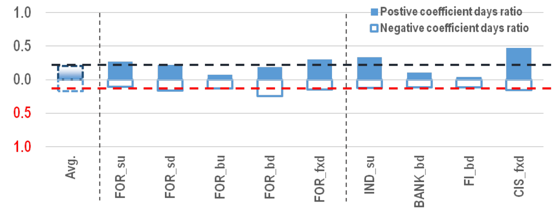
3. (Influential traders)

5 foreign Investors (FOR) from stock, stock derivative, bond, bond derivative and FX derivative market
Individual trader (IND) in stock market, BANK in bond derivative market,
Financial investment (FI) in bond market, Collective investment scheme (CIS) in FX derivative market

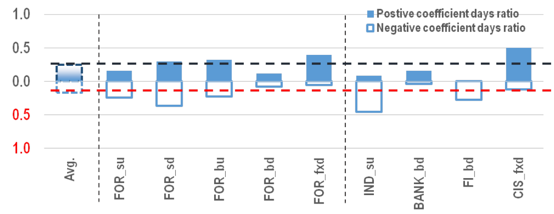
Figure 6: The contribution of traders' relative influence to FX market volatility



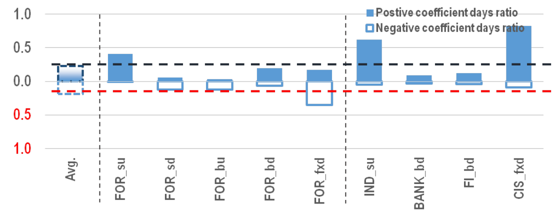
(a) All (GCM)



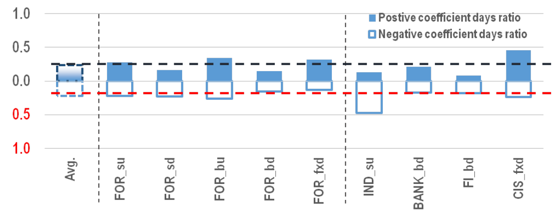
(b) All (GVD)



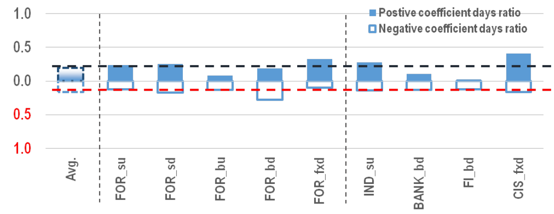
(c) Crisis (GCM)



(d) Crisis (GVD)



(e) Normal (GCM)



(f) Normal (GVD)

[Notes]

1. The ratio of influential traders' positive (negative) contribution days during analysed period are present compared to the average value of all 40 traders by time period (all, crisis, normal) and method (GCM, GVD).

2. Black dashed line in upper part of each figure is the average value of positive contribution day ratio and red dashed line in lower part of each figure is the average value of negative contribution day ratio. If a trader's positive (negative) coefficient day ratio is over the average value, it can be more contributing positively (negatively).

3. (Influential traders)

5 foreign Investors (FOR) from stock, stock derivative, bond, bond derivative and FX derivative market
Individual trader (IND) in stock market, BANK in bond derivative market,
Financial investment (FI) in bond market, Collective investment scheme (CIS) in FX derivative market

and bond markets decreases stock market volatility, and nonlinear GVD shows that FOR in the stock derivative market decreases stock market volatility. Yet, FOR in the stock market is likely to increase stock market volatility with nonlinear GVD.

The contribution of other influential traders to stock market volatility is revealed to be more consistent than those of foreign investors. In particular, CIS in the FX derivative market seems to increase stock market volatility. Yet IND in the stock market during crisis period is shown to have a different contribution which increases with nonlinear GVD but decreases with nonlinear GCM.

Overall nonlinear GVD suggests similar outcomes with linear models (Hwang, 2018). On the result of linear methods, FOR in the stock derivative market decreases market volatility and CIS in the FX derivative market evidently increases market volatility.

Remarkably, FOR and CIS in the FX derivative market are likely to increase FX market volatility only with the exception of FOR in the FX derivative market with nonlinear GVD during crisis period. (Figure 6) This is in accordance with the outcome of the linear GVD of Hwang (2018). Another evident finding regarding FX market volatility is that FOR in the bond market increases market volatility with nonlinear GCM and FOR in the bond derivative market decreases market volatility with nonlinear GVD.

Foreign investors and other influential traders appear to have different relations with market volatility despite several exceptions. This result means that influential traders within the network structures do not necessarily contribute to an increase in market volatility, and that in some cases they even decrease it. Therefore, it shows the need for more sophisticated research to develop a deeper understanding of financial traders and market volatility.

In addition, the contribution of all traders' connectedness measures to market volatility is summarised in Table 9. Detailed results are given in the Appendix (Tables 15, 17, 16, and 18).

The most remarkable finding in Table 9 is that the number of negative contributing traders

Table 9: Summary of traders' contribution to market volatility with nonlinear methods

	Stock market				FX market			
	GCM		GVD		GCM		GVD	
	P	N	P	N	P	N	P	N
All	5	4	2	3	3	5	4	2
Crisis	5	2	2	6	3	3	3	7
Normal	3	4	2	1	3	5	3	2

[Note]
1. The number of (positive or negative) contributing traders to stock and FX market, is present by method (GCM, GVD) and period (all, crisis, normal).
2. P = the number of traders with positive contribution,
N = the number of traders with negative contribution

to both stock and FX market volatility even increases respectively to six or seven during crisis period with nonlinear GVD, given the condition that all the numbers of positive (or negative) contributors are below five. Most of those increased contributors with nonlinear GVD during crisis period come from the bond and bond derivative markets, as seen in Table 17 and 18. This is in line with the fact that there are few positive contributors in the bond and bond derivative markets during crisis time with nonlinear GVD. Furthermore, positive contributors are hardly found during crisis time in the bond and bond derivative markets even with nonlinear GCM. Consequently, the increased market volatility may be result from the traders in the stock, stock derivative and FX derivative markets.

Finally, the contributors to stock and FX market volatility vary depending on the methods used. The contributors to stock market (FX market) volatility are shown to be mainly from the stock or stock derivative markets (FX derivative market) with nonlinear GCM, while the contributors to stock market (FX market) volatility do not belong to the stock market (FX derivative market) with nonlinear GVD. Further research is required to discover the real origin of stock and FX market volatility.

Table 10: The ratio of positive to negative reaction for first 3 days after shock

	SU	SD	BU	BD	FXD
Positive(A)	68	63	64	68	57
Negative(B)	52	57	56	52	63
A/B	1.3	1.1	1.1	1.3	0.9

[Note]
1. Traders' responses at foreign investors' selling shock from each market are divided into positive and negative.
2. Positive (negative) responses are counted among 120 responses which are 40 trader for 3 days.
3. The ratio is positive responses over negative responses.
4. (market) SU=Stock, SD=Stock Drv., BU=Bond, BD=Bond Drv., FXD=FX Drv.

4.4 Nonlinear impulse response analysis

Traders' responses in terms of daily net trading volumes at the shock of influential traders' selling are investigated in this section. The shock is divided from foreign investors and other influential traders and the analysis period (h) is 10 days. Practically speaking, the result of each investor's reaction means how much they trade in the market to which they belong at and after the shock. I concentrate on three the most responsive traders in respectively positive and negative directions.

4.4.1 Responses on foreign investors

Before the investigation, I observe all traders' responses to the selling shock of foreign investors for three days, which is summarised in Table 10. Traders are likely to react positively rather than negatively, to the shock of foreign investors' selling. This means that traders are more likely to buy for three days after foreign investors sell substantially. This phenomenon look more evident when foreign investors in the stock or bond derivative markets sell. The results are consistent with the results of connectedness measures, in which foreign investors' ranks of the OUT measure in the stock and derivative markets are higher than in the bond market.

However, opposite reactions occur in the FX derivative market. When foreign investors sell unexpectedly, local traders follow them instead. The influence of foreign investors on the FX derivative market can affect other traders in a slightly different way.

Table 11: The most sensitive traders to Influential traders' selling shock

Shock	Buy			Sell		
Foreign investors						
FOR,su	CIS,su	IND,su	CIS,sd	BANK,fxd	IND,sd	FI,sd
FOR,sd	IND,su	CIS,sd	CIS,su	FOR,su	IND,sd	IND,fxd
FOR,bu	CIS,bu	FOR,fxd	FI,bu	CIS,fxd	IND,sd	IND,su
FOR,bd	BANK,bd	FI,bd	IND,su	FOR,sd	BANK,fxd	CIS,su
FOR,fxd	FOR,su	IND,fxd	FI,bd	FI,fxd	IND,su	BANK,bd
Other influential traders						
IND,su	FOR,su	IND,fxd	IND,sd	IND,su	CIS,sd	CIS,su
IND,sd	IND,sd	CIS,su	IND,fxd	IND,su	FI,sd	BANK,fxd
Bank,bd	FOR,bd	IND,sd	FOR,su	FI,bd	CIS,fxd	INS,bd
FI,bd	FOR,bd	FOR,sd	CIS,su	BANK,bd	FI,bd	FOR,fxd
IND,fxd	BANK,fxd	IND,su	CIS,sd	FOR,su	FOR,fxd	IND,fxd
BANK,fxd	CIS,fxd	FI,fxd	BANK,bd	BANK,fxd	FOR,su	FI,bd

[Note]
1. The most three sensitive traders are present at influential traders' buying or selling shock.
2. Influential traders are 5 foreign investors and 6 other influential traders with high RI.
3. (trader) FOR=foreign investor, IND=individual, BANK=bank, FI=financial investment, CIS=mutual funds
4. (market) su = stock, sd = stock derivative, bu= bond, bd = bond derivative, fxd = FX derivative

CIS and IND are shown to be respectively main buyers and main sellers at foreign investors' selling shock, as described in Table 11. There are, in particular, other sensitive traders at foreign investors' selling shocks at the same time, who are FOR, FI and BANKs across different financial markets .

The other remarkable finding from impulse response analyses is the connection between stock, stock derivative and FX derivative market and the link between bond, bond derivative and FX derivative market. When there is a shock from the trader in stock or stock derivative market, there are sensitive traders mainly in stock, stock derivative and FX derivative market. This shows that there is a close relationship between the similar financial markets such as stock and stock derivative market, bond and bond derivative market, and that FX derivative market has its own role to connect other financial market.

Lastly, most of reactions occur at t+1 and they disappear at t+2, although just a few traders' reactions rebound slightly at t+3 (table 13). The impact of traders' daily trading is shown to last not long.

The result shows that other traders' actual reactions to the selling shock of foreign investors vary, and that the inter linkage between different financial markets, which are investigated in the previous sections, are reassured. In addition, the implication in this section has more practical meaning, for the result concerns the actual trading responses, not the causality.

4.4.2 Responses of other significantly influential traders

Noticeably, the greatest responses in both positive and negative directions come from the same market to which the origin of shock belongs, as seen in Table 11 and 14. The only one exception is foreign investors in the stock market at the shock from individual investors in the FX derivative market. It is reasonable that direct impact can be given on the same market. However, the second and third greatest responses are from the other markets at the same time. This result provides an evidence that all financial markets are inter-connected.

Reactions to their own shock can vary depending on the market to which they belong. Individual investors in the stock and FX derivative markets react negatively to the shock of their own trading, while individual investors in the stock derivative market are shown to respond in a positive way.

A particularly close relationship between BANKs and FI in the bond derivative market is also found. When one has a shock, the other reacts with the largest negative trading. This relation can be uniquely special because BANKs in the FX derivative market react to the shock at IND in the FX derivative market with the greatest positive response, but not vice versa.

The relationship between FOR and IND needs to be investigated with more attention. In the stock market, FOR's reacting positively (buy) to the selling shock of IND and vice versa is valid (as can be seen in Table 11). In contrast, FOR in the FX derivative market reacts negatively (sell) at the selling shock of IND in the FX derivative market, while

IND in the FX derivative market responds positively (buy) to the shock of FOR in the FX derivative market (Table 11).

Particularly close relationships are found with impulse response analyses, which complement the result of network analysis. Although connectedness measures of traders can show the inter-linkage between traders and influential traders, pairwise relationships in terms of actual daily net trading volumes are not investigated. In addition, the results of impulse response analyses can be utilised more practically.

5 Comprehensive discussion

In this section I discuss all results estimated with four different types of methods comprehensively. These are linear (nonlinear) GCM (GVD). Each method has its own strengths and weaknesses. In order to determine the most proper method for network estimation, comparative analysis can be helpful. Through the comparison between GCM and GVD and between linear and nonlinear, meaningful insights can be provided.

GCM (Granger Causality Method) is basically the test to capture the effect of a variables on another variable's variance without any condition on other variables, while GVD (Generalized Variance Decomposition) gauges the contribution of a variable on the forecast error of other variable with the condition that the sum of the contribution of all variables is one. Although the descriptions of the two methods seem similar, a critical difference becomes apparent on close examination of the procedures of the two methods. In GCM, the process of obtaining the causality measures which means the ratio of the variance of restricted model over unrestricted model, is directly pairwise. That means each causality measure of a variable A's causality to the other variable B needs to be tested independently of other causalities given in the VAR model. However, under the setting of GVD the main objective is to find the contribution of each variable to the variance of a particular variable. By definition, the sum of the contribution of all variables should be one, which means the contribution of a variable to the variance of another variable can be restricted to the contributions of the other variables to the variance of that variable. This difference between two methods can lead to the different values for traders' connectedness measures.

In addition, based on the financial network literature, the statistical significance of causality measures is considered with the GCM method (Wang et al., 2017; Song and Taamouti, 2016), while with GVD (Diebold and Yilmaz, 2014; Lanne and Nyberg, 2016) the statistical significance is not considered capable of estimating connectedness measures. That difference between these two methods can also give rise to a difference in estimation results. In particular, assuming an extreme case: with a statistically insignificant large causality value under GCM and GVD, GCM could suggest a low connectedness measure, but the connectedness measure estimated with GVD could be high.

Finally the other factor which gives rise to a difference between the methods is nonlinearity. Linear methods cannot capture the nonlinear relation between traders although a linear method has the advantages of methodological simplicity and ease of application. The notion that if there is a nonlinear relation between traders, the results of network estimation with nonlinear methods can be different from the one with linear methods, is straightforward. However, nonlinear methods are more time consuming and more expensive in terms of computation resources.

The summary of traders' network analyses is given in Table 12. The brief results of each category are summarised by the methods which are linear GCM, linear GVD, nonlinear GCM, and nonlinear GVD. Regardless of linear or nonlinear methods, the same methods have respectively similar results, although the detailed results vary. In addition, the consistent results over four different methods can be ascertained.

Influential traders are the trader type which have the most top ten relative influence traders. It is noticeable that foreign investors (FOR) are chosen in all periods and methods. In particular, with linear and nonlinear GVD, foreign investors show the highest relative influence except during normal period with nonlinear GVD. However, compared to linear and nonlinear GVD, GCM suggests more diverse trader types as influential

Table 12: Summary of results

		Linear		Nonlinear	
		GCM	GVD	GCM	GVD
Strong Trader	A	FOR	FOR	OTH	FOR
	C	even	FOR	INS	FOR
	N	even	FOR	FOR	even
Strong Market	A	FXD	BD, FXD	SD	BD, FXD
	C	SU	SU, BD	SD, BD	SU, BD
	N	FXD	BD, FXD	BD, FXD	BD, FXD
Strong Link	A	INS,bd→ FI,bu CIS,bd→ OTH,bu	FI,bu→ CIS,bu IND,su→ FOR,su FOR,su→ IND,su	FOR,su→ CIS,fxd IND,su→ FOR,su FOR,sd→ CIS,bd	FOR,sd→ BANK,sd
	C	FI,su→ FOR,su INS,su→ GOV,bd	FI,bu→ CIS,bu IND,su→ CIS,su CIS,fxd→ BANK,fxd	IND,su→ GOV,fxd CIS,fxd→ FI,sd CIS,sd→ OTH,su	FOR,sd→ INS,bd IND,su→ GOV,fxd
	N	OTH,su→ FOR,su FI,su→ GOV,bd	FI,bu→ CIS,bu FOR,sd→ CIS,su FOR,su→ IND,su	FOR,su→ OTH,sd FOR,sd→ CIS,fxd IND,su→ INS,bd	FOR,sd→ CIS,bu
Contribute to volatility (SU)	A	P(SD,3) N(SD,3)	P(BU,4) N(FXD,2)	P(FXD,4) N(SD,2)	P(SD,2) N(SU,1)
	C	P(SU,1) N(BD,2)	P(FXD,3) N(BD,2)	P(FXD,3) N(SD,1)	P(SD,1) N(FXD,2)
	N	P(SD,2) N(SD,3)	P(BU,3) N(SD,2)	P(FXD,2) N(SD,2)	P(SD,2) N(SU,1)
Contribute to volatility (FXD)	A	P(SD,3) N(SD,3)	P(BU,3) N(FXD,3)	P(FXD,1) N(BU,2)	P(FXD,2) N(SU,2)
	C	P(SU,2) N(BD,2)	P(FXD,3) N(BD,2)	P(FXD,1) N(SU,1)	P(SU,2) N(BU,4)
	N	P(SD,2) N(SD,3)	P(BU,3) N(FXD,3)	P(BD,2) N(SU,1)	P(FXD,3) N(SU,2)

[Note]
1. All results of linear and nonlinear analyses are summarised.
2. (Time)
A = all, C = Crisis, N = Normal
3. (Traders)
IND = Individual trader, BANK = Bank, FI = Financial investment(mainly securities companies)
CIS = Collective Investment Scheme, OTH = Others (small financial companies)
INS = Insurance companies, GOV = Government, FOR = Foreign Investors
4 (Market)
SU=Stock, SD=Stock Drv., BU=Bond, BD=Bond Drv., FXD=FX Drv.
5. (Contribution to market volatility)
P = positive relation, N = negative relation
P(SD,3) means that the most positively contributing market is stock derivative and the contributing traders are 3.

traders.

Influential markets show the market which has the most top ten relative influence traders during each time period. As seen in Table 12, the result varies depending on the time rather than the method. During all and normal period, the FX derivative market seems to have the most top ten relative influence traders with four different methods, although the bond derivative market is included with linear and nonlinear GVD. In contrast, the stock and bond derivative markets become influential markets during the crisis periods.

The strong link (connection) is chosen if there is a mutual connection between the traders of the top five OUT measures and the traders of the top five IN measures. The OUT measure is a trader's influence on other traders, and the IN measure is the other traders' influences on a trader. What matters in the OUT and IN measures is that the influence from and to others can be offset in the relative influence which is mentioned above. In many cases, the influence from the traders of the top five OUT measures can be given to the traders who have the top five IN measures. Although not all strong connections can be understood with these summarised results, a few implications drawn from them can be seen in Table 12. Foreign investors can be seen to be a source of influence during all and normal periods with linear GVD, nonlinear GCM and nonlinear GVD. However, during the crisis periods foreign investors are not found as a source of influence with linear GCM, linear GVD and nonlinear GCM.

Contribute to volatility shows the market which has the most traders whose contribution to market volatility is significant, and the number of significant contributing traders in that market. P and N mean respectively positive and negative relation with market volatility. The last row in Table 12 shows the result of traders' connectedness measures and FX derivative market volatility. The row above this is the result of traders' connectedness measures and stock market volatility. Although it is not clear in the summarized information in Table 12, there are a few meaningful implications. Firstly, the connectedness measures of the traders who belongs to different financial markets can affect market volatility. The traders' connectedness measures in the FX derivative market could have positive relations with the stock market volatility. At the same time, FX derivative market volatility can be affected by the traders' connectedness measure in the stock derivative market. The relations between traders' connectedness measures and market volatility suggested by linear methods and nonlinear methods differ. The results concerning contributions to stock market volatility and to FX derivative volatility appear similar with both linear GCM and linear GVD methods. However, it is difficult to find a similarity between those two results estimated with the nonlinear methods.

Linear and nonlinear GVD suggests respectively consistent results. Based on the results, foreign investors and bond derivative markets are shown to be influential to other traders and markets. Nonlinearity is not strongly found in GVD. Thus, GVD can be more strongly recommended where case that consistent result is needed and nonlinear relations can distort the research result. In contrast, in a case in which statistical significance can be critical, or in which a pairwise relation between agents is important, GCM can be a more appropriate method for the analysis. For instance, when the research objective is to find the most influential agent in a complex network structure, GVD can be recommended. If the main objective of research is to investigate the significant pairs among numerous links between agents, GCM would be the appropriate method.

Combining all results discussed above and the impulse response analysis, several important economic interpretation and policy implication can be acquired. Firstly, foreign investors are shown to be influential on other traders and derivative markets seem to function as an influence giver to other financial markets such as the stock and bond markets. Foreign investors' contributions to market volatility is closer to decreasing than increasing. This result is consistent with Hwang (2018).

The strong connections which show that specific patterns of influence giving and receiving in traders' networks are hardly found in nonlinear methods. It could be closer to the real trading environment, for traders' relations are extremely complex. Thus, impulse response analysis, which shows the actual responses to sudden changes in the trading of influential traders, can be an effective tool for understanding a traders' relation.

Given the results of impulse response analysis, individual traders are shown to be the main sellers at the shock of foreign investors' selling shocks. This suggests a consistent result with the previous literature on behaviour finance. Individual traders have been found to be inclined to copy the trading strategy of potentially beneficial traders. There are enough reasons for individual traders to copy the trading pattern of foreign investors given the fact that foreign investors in Korea have been acknowledged to have earned decent profits since the Asian crisis in 1997. In contrast, mutual funds (CIS) are found to be a main buyer at the point of the selling shocks of foreign investors' selling shock. This phenomenon can be interpreted as the need of institutional investors to follow their own trading strategy, which is includes officially announced investment objectives and risk appetite and which makes their trading behaviours more independent. This brings about a significant difference between the trading strategy of individual traders and institutional traders. At the same time, this point can also be understood with the perspective of the investment horizon. Mutual funds have relatively longer investment horizons, which can give room to absorb short term losses. In contrast, individual traders who have shorter investment horizons can be more adverse to short term losses, which leads them to sell at the point of foreign investors' selling shocks.

In addition, at the selling shocks of other influential traders in the stock and bond derivative markets, foreign investors are shown to be the largest buyers. This supports the different investment perspectives of foreign investors and local investors. At some specific point local traders may think that the market is not attractive enough to invest in, while foreign investors find reasons for profits such as currency appreciation or relative pricing strength compared to other countries.

This research result concerning influential traders and responsive traders in capital markets provides policy makers with a few "tips" for their market stabilizing policy making process. First, influential traders such as individual traders or mutual funds can be fundamental sources of information, since the market volatility spill-over process can be managed if their influence can be reduced. However, foreign investors who are influential but not contributing to an increase in market volatility cannot be an appropriate object for the policy. Then, the responsive traders at the point of the trading shock of influential traders such as individual traders and foreign investors can be the source of supplementary information for their policies. Close monitoring on the trading behaviours of those responsive traders can be used to check the effectiveness of the measure for influential traders.

More specifically, policy makers or financial regulators can adopt market stabilization policies which suit the market conditions. For instance, when foreign investors are in the selling positions during crisis, the policy giving incentives for mutual funds to buy more can be introduced. In contrast, where other influential traders such as individual investors or financial investment companies suddenly sell, giving incentives to foreign investors to buy local securities can be an appropriate policy response.

6 Conclusion

In this paper, traders' financial network structures in the Korean capital markets is estimated with the daily net trading volume of eight different traders across five different markets using two novel nonlinear methodologies which are nonlinear Granger causality and nonlinear generalized variance decomposition. The network structures estimated with two different nonlinear methods are analysed with RI/OUT/IN connectedness measures. The influence of foreign investors within those network structures is also investigated. In addition, the reactions of other traders at the point of selling shock of foreign investors and the other influential traders with high relative influence connectedness measures, are analysed with a nonlinear impulse response analysis which is implemented by a simulation method. Then the contributions of traders' connectedness measures to market volatility are investigated.

Based on the network structures estimated with nonlinear GCM and GVD methods, a few meaningful results are found. Nonlinear GCM suggests the traders with higher relative influence are distributed more evenly among the type of traders, while foreign investors are chosen as the trader type with higher relative influence based on the result of nonlinear GVD. Both nonlinear GCM and GVD suggests that derivative markets have more traders with higher relative influence than the stock or bond market.

Traders' influence and their relations are more deeply investigated with the OUT and

IN connectedness measures. The influence of traders within the network structure is not limited to the market to which the trader belongs, but extended to the other markets. Based on the results with both nonlinear GCM and GVD, the influence of foreign investors on others is identified in the top five OUT connectedness measure group. In addition, the strong connections between traders are also found.

The relative influence of foreign investors is also verified with two different nonlinear methods under different time and trading pattern settings. In particular, GVD suggests that foreign investors are one of the most influential traders in the stock derivative and bond derivative markets regardless of time and trading patterns. However, there are specific conditions under which foreign investors have a high relative influence with GCM method.

Nonlinear impulse response analysis is implemented. Traders' responses at the point of the selling shock of the trader with a higher relative influence are investigated. Those results can be a key factor to better understand the market volatility contagion.

The traders' contribution to market volatility with positive and negative directions are also investigated. It is found that the traders' connectedness in different markets can explain market volatility more than the traders inside the market. In addition, under specific conditions some traders are related to market volatility significantly and consistently.

This paper can contribute to the extant literature in a few perspectives. The traders' networks across financial markets are estimated with both nonlinear GCM and nonlinear GVD methods, which extends the scope of Hwang (2018) from linearity to nonlinearity and explains traders' interconnections in nonlinear settings. In addition, the strength and weakness of each methodology is analysed and the appropriate method for the achievement of the research objective is suggested. Then, the evidence for the way in which the influential traders impact on other traders is given with the nonlinear impulse response analysis. The most responsive traders when not only foreign investors but also other influential traders have a selling shock, are identified, which provides the ground for policy makers or financial regulators to develop a market stabilization policy. Finally, the contributions of traders' connectedness measures to market volatility are examined with adaptive LASSO techniques. The same result as Hwang (2018) is also found; namely that foreign investors are not contributing to the market volatility increase despite their strong influence.

The result of this paper can contribute to the earlier research (Hwang, 2018) in that nonlinear relationships among traders are captured with nonlinear methodologies, and that actual impacts of influential traders on other traders can be measured. Regarding the nonlinear relationship, it is found more with GCM than GVD. The result of nonlinear GVD is not much very different from the result of linear GVD. In addition, the actual impacts of influential traders on other traders are practically effective information. For it can give the policy makers and financial regulators information on the mechanism of the working of network structure in capital markets, although the network structures of traders provide the relations of traders.

In future, the traders' networks needs to be estimated with the condition that real trading procedures are reflected. In addition, the way in which the market risk spills over through the channels of traders' networks can be investigated.

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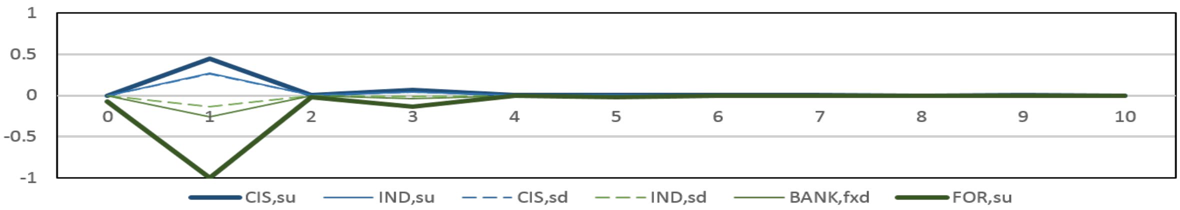
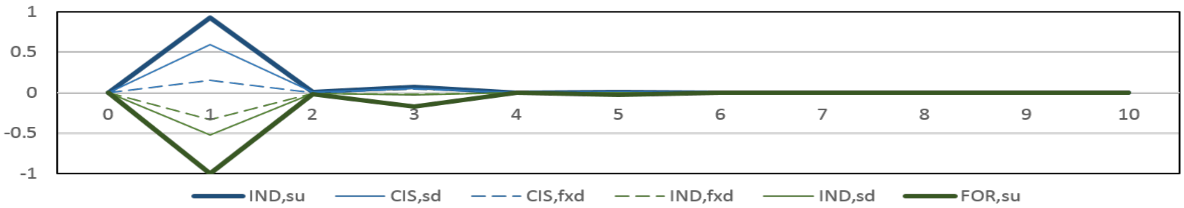
Table 13: Impulse response function

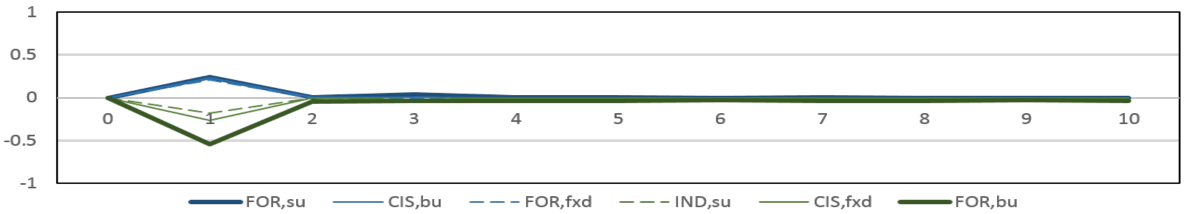
a. Impulse response function of the shock from foreign investors in stock market



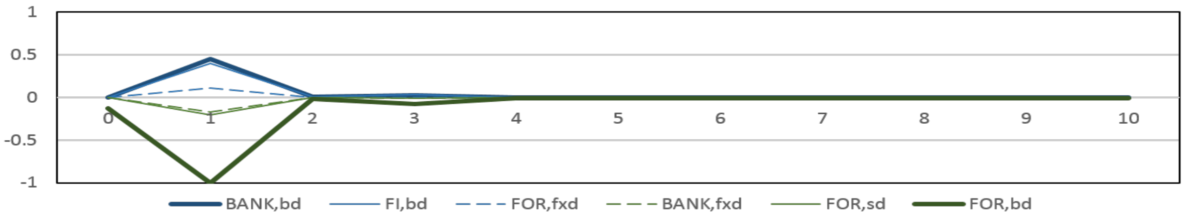
b. Impulse response function of the shock from foreign investors in stock derivative market



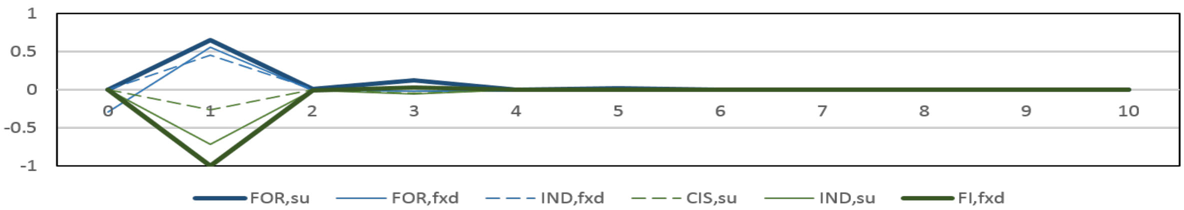
c. Impulse response function of the shock from foreign investors in bond market



d. Impulse response function of the shock from foreign investors in bond derivative market



e. Impulse response function of the shock from foreign investors in FX derivative market

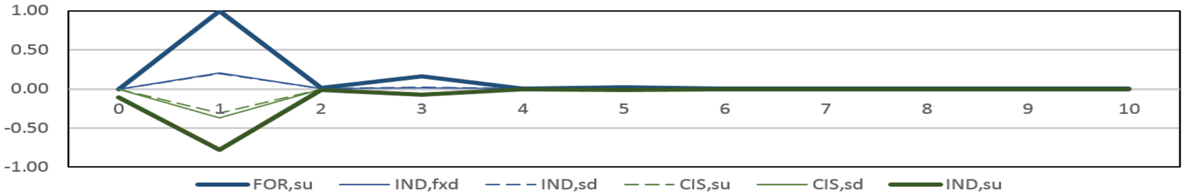


[Notes]

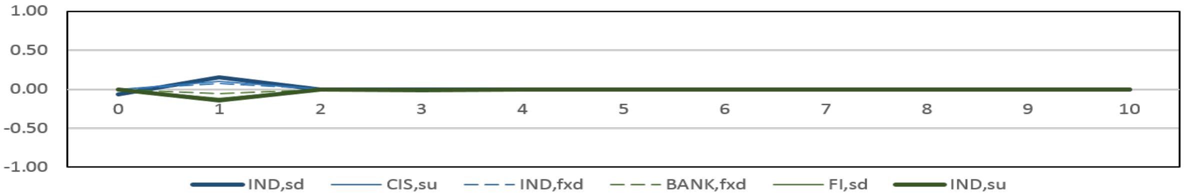
1. The three biggest (positive/negative) responses at foreign investors' selling shock in each market are present.
2. Blue (green) line is positive (negative) response.
3. Thick, thin and dashed line is respectively 1st, 2nd, and 3rd biggest response.

Table 14: Impulse response function

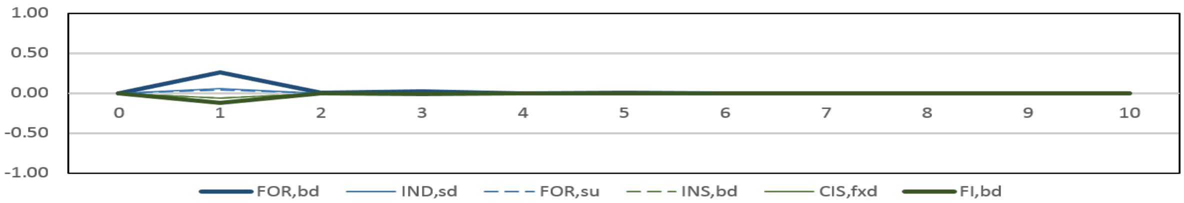
a. Impulse response function of the shock from Individual investors in stock market



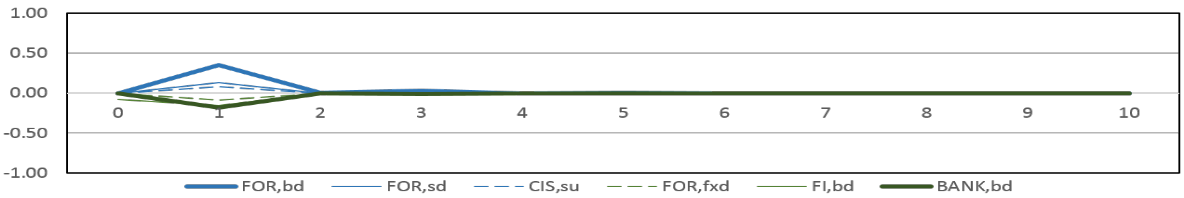
b. Impulse response function of the shock from Individual investors in stock derivative market



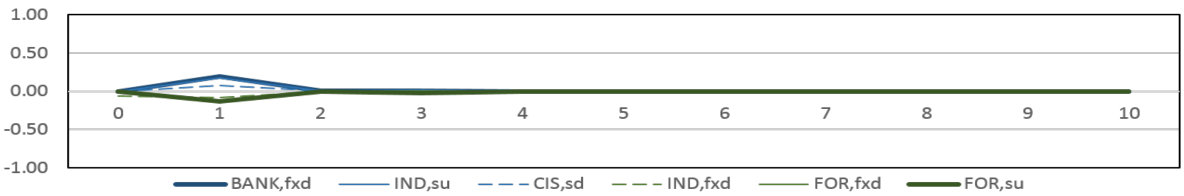
c. Impulse response function of the shock from bank in bond derivative market



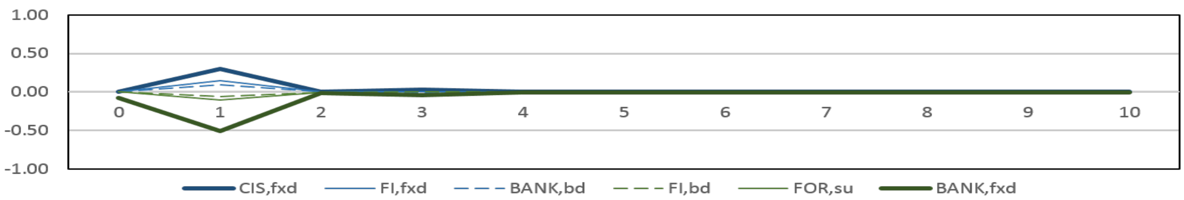
d. Impulse response function of the shock from financial investment in bond derivative market



e. Impulse response function of the shock from individual investors in FX derivative market



f. Impulse response function of the shock from bank in FX derivative market



[Notes] Same with table 13 with regard to other influential traders

(Appendix A) : Contribution of traders' connectedness to market volatility

Table 15: Ranks of contribution of foreign investors' centrality to stock market volatility (GCM)

	IND		BANK		FI		CIS		OTH		INS		GOV		FOR	
	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N
[ALL]																
su	16	18	11	7	2	19	17	5	32	16	19	23	27	31	22	6
sd	12	15	***5***	***39***	26	14	***40***	***3***	20	33	21	11	***39***	***8***	37	17
bu	***33***	***1***	10	40	14	25	36	28	3	22	18	35	28	21	30	9
bd	15	10	23	29	34	13	24	32	29	12	35	24	25	30	31	27
fxd	***7***	***36***	6	20	***38***	***4***	***1***	***34***	4	26	13	2	***9***	***37***	***8***	***38***
[CRISIS]																
su	29	2	11	20	***3***	***36***	14	18	36	19	12	33	32	13	24	8
sd	22	1	***6***	***38***	28	28	37	27	20	23	***35***	***7***	39	24	21	15
bu	10	9	13	35	16	31	30	17	17	11	26	21	33	10	23	6
bd	7	14	15	34	27	22	5	30	25	26	31	32	34	29	38	16
fxd	***2***	***39***	9	4	***40***	***5***	***1***	***40***	8	12	19	3	***4***	***37***	18	25
[NORMAL]																
su	11	23	13	6	2	16	16	4	31	15	22	18	26	34	21	8
sd	6	22	10	39	25	11	***40***	***2***	20	33	17	14	***39***	***5***	37	17
bu	***36***	***1***	***9***	***40***	14	21	35	29	3	25	12	36	24	20	29	12
bd	18	9	27	26	34	13	32	32	28	10	33	19	23	30	30	28
fxd	19	35	7	24	***38***	***7***	***1***	***31***	4	27	8	3	15	37	***5***	***38***

[Note]
1. The rank of each trader's positive(or negative) relation with stock market volatility is present by period. For instance, (16,18) of IND in stock market during all period means that the rank of individual investors in stock market in contributing to stock market volatility positively (negatively), is 16th (18th).
2. P = positive relation, N = negative relation
3. Blue pair (P,N) is that the rank in positive is higher than 10th and the rank in negative is lower than 31st. Blue pair can be positively contributing to stock market volatility.
4. Red pair (P,N) is that the rank in positive is lower than 31st and the rank in negative is higher than 10th. Red pair can be negatively contributing to stock market volatility.

Table 16: Ranks of contribution of foreign investors' centrality to FXD market volatility (GCM)

	IND		BANK		FI		CIS		OTH		INS		GOV		FOR	
	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N
[ALL]																
SU	***36***	***1***	28	3	***3***	***33***	12	4	22	14	***34***	***8***	30	11	17	18
SD	13	6	14	28	21	17	24	19	20	21	35	15	9	27	25	10
BU	***32***	***2***	27	36	19	26	40	23	2	16	31	30	***38***	***7***	7	9
BD	5	12	23	31	39	24	18	39	10	35	***37***	***5***	***4***	***38***	33	32
FXD	11	37	15	22	29	29	1	20	16	25	6	13	26	40	***8***	***34***
[CRISIS]																
SU	***37***	***1***	23	22	2	38	5	27	20	10	31	17	38	18	25	12
SD	16	6	***4***	***37***	30	20	24	39	29	11	***34***	***7***	36	30	14	5
BU	9	4	21	36	11	25	40	24	28	8	27	13	32	19	10	14
BD	***1***	***34***	26	33	***39***	***9***	13	21	18	40	19	15	12	26	33	28
FXD	***3***	***31***	7	3	35	32	6	23	22	2	15	16	17	35	8	29
[NORMAL]																
SU	***35***	***1***	27	3	8	30	15	4	23	16	***34***	***8***	24	12	13	19
SD	10	7	17	23	20	13	25	10	19	22	33	20	3	24	30	17
BU	***36***	***2***	28	36	22	26	40	18	2	21	31	32	***38***	***6***	6	11
BD	11	9	21	29	39	27	18	39	***7***	***33***	***37***	***5***	***4***	***38***	32	31
FXD	16	37	14	28	26	25	1	15	12	34	5	14	29	40	***9***	***35***

[Note]
1. The rank of each trader's positive(or negative) relation with stock market volatility is present by period. For instance, (36,1) of IND in stock market during all period means that the rank of individual investors in stock market in contributing to stock market volatility positively (negatively), is 36th (1st).
2. P = positive relation, N = negative relation
3. Blue pair (P,N) is that the rank in positive is higher than $10th$ and the rank in negative is lower than $31st$. Blue pair can be positively contributing to stock market volatility.
4. Red pair (P,N) is that the rank in positive is lower than $31st$ and the rank in negative is higher than $10th$. Red pair can be negatively contributing to stock market volatility.

Table 17: Ranks of contribution of foreign investors' centrality to stock market volatility (GVD)

	IND		BANK		FI		CIS		OTH		INS		GOV		FOR	
	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N
[ALL]																
SU	9	16	18	40	***33***	***4***	19	1	17	6	35	26	8	15	4	14
SD	***5***	***39***	40	19	12	11	6	20	16	25	***7***	***37***	21	34	***31***	***2***
BU	11	5	14	22	28	23	39	28	26	30	23	17	20	24	25	36
BD	***32***	***7***	37	33	29	38	22	12	34	29	2	8	13	32	15	13
FXD	3	3	30	18	36	10	1	27	24	31	38	35	27	21	10	9
[CRISIS]																
SU	7	19	11	40	17	21	10	28	13	36	4	24	27	1	12	32
SD	***3***	***39***	40	10	8	13	22	17	14	27	24	33	38	22	20	8
BU	9	7	23	12	***5***	***31***	***32***	***5***	37	34	33	14	***39***	***3***	19	16
BD	***35***	***9***	21	30	15	26	***34***	***2***	26	35	29	18	18	29	6	20
FXD	1	15	30	11	***31***	***4***	2	23	28	25	25	38	16	37	***36***	***6***
[NORMAL]																
SU	12	13	24	40	***34***	***3***	26	1	21	5	39	24	6	23	4	10
SD	***8***	***38***	40	22	19	12	3	20	18	21	***5***	***36***	14	33	30	4
BU	15	6	10	26	37	18	36	34	20	28	17	16	13	35	25	37
BD	28	8	35	31	31	39	16	19	33	27	1	7	11	30	22	11
FXD	9	2	29	17	32	14	2	25	23	32	38	29	27	15	7	9

[Note]
1. The rank of each trader's positive(or negative) relation with stock market volatility is present by period. For instance, (9,16) of IND in stock market during all period means that the rank of individual investors in stock market in contributing to stock market volatility positively (negatively), is 9th (16th).
2. P = positive relation, N = negative relation
3. Blue pair (P,N) is that the rank in positive is higher than 10*th* and the rank in negative is lower than 31*st*. Blue pair can be positively contributing to stock market volatility.
4. Red pair (P,N) is that the rank in positive is lower than 31*st* and the rank in negative is higher than 10*th*. Red pair can be negatively contributing to stock market volatility.

Table 18: Ranks of contribution of foreign investors' centrality to FXD market volatility (GVD)

	IND		BANK		FI		CIS		OTH		INS		GOV		FOR	
	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N
								[ALL]								
SU	3	27	31	24	11	20	*36*	*2*	30	12	*34*	*8*	22	4	10	32
SD	15	19	39	14	18	7	2	18	24	13	13	5	17	31	19	16
BU	35	15	28	11	*8*	*39*	38	23	20	36	32	33	23	37	37	25
BD	27	10	33	29	40	30	26	6	12	38	25	3	*9*	*34*	21	9
FXD	4	1	*7*	*40*	16	22	1	17	*5*	*35*	29	26	14	28	6	21
								[CRISIS]								
SU	*3*	*33*	19	17	17	31	14	18	31	15	8	14	*40*	*1*	*7*	*37*
SD	16	23	28	12	5	20	15	29	9	27	13	10	27	26	30	22
BU	24	24	*37*	*7*	*2*	*40*	*39*	*3*	29	32	*34*	*8*	*36*	*4*	35	21
BD	33	13	26	35	25	34	*38*	*2*	11	36	*32*	*6*	6	19	20	30
FXD	4	9	23	16	21	11	1	25	12	28	18	39	10	38	22	5
								[NORMAL]								
SU	6	23	33	28	8	19	*37*	*2*	29	13	*39*	*7*	17	8	12	27
SD	13	20	38	18	27	6	2	16	28	10	16	4	9	29	10	14
BU	36	11	26	15	21	37	34	34	19	35	30	38	20	39	35	24
BD	25	12	32	25	40	26	23	9	15	33	22	3	14	36	24	5
FXD	7	1	*4*	*40*	11	30	1	17	*3*	*32*	31	21	18	22	*5*	*31*

[Note]
1. The rank of each trader's positive(or negative) relation with stock market volatility is present by period. For instance, (3,27) of IND in stock market during all period means that the rank of individual investors in stock market in contributing to stock market volatility positively (negatively), is 3rd (27th).
2. P = positive relation, N = negative relation
3. Blue pair (P,N) is that the rank in positive is higher than $10th$ and the rank in negative is lower than $31st$. Blue pair can be positively contributing to stock market volatility.
4. Red pair (P,N) is that the rank in positive is lower than $31st$ and the rank in negative is higher than $10th$. Red pair can be negatively contributing to stock market volatility.

VI

Paper 3:
Financial traders' network structure and market volatility spillover channels

Statement of Authorship

This declaration concerns the article entitled:									
Financial traders' network structure and market volatility spillover channels									
Publication status (tick one)									
draft manuscript	x	**Submitted**		**In review**		**Accepted**		**Published**	
Publication details (reference)									
Candidate's contribution to the paper (detailed, and also given as a percentage).	The candidate contributed to/ considerably contributed to/predominantly executed the… Formulation of ideas: 100% Design of methodology: 100% Experimental work: 100% Presentation of data in journal format: 100%								
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.								
Signed	Jaehak Hwang					**Date**	30/11/2018		

Financial traders' network structure and market volatility spillover channels

Jaehak Hwang*

Abstract

This paper investigates financial traders' network structure across different financial markets. As a proxy of traders' expectations on a trader's trading volume, I forecast a trader's trading volume on the next day with a machine learning technique. I estimate the network structure with the impact of the expectation of a trader's trading volume on other traders. I identify certain influential traders, such as foreign investors within the network. Then, a three-phased impulse response analysis is also implemented to capture the connections between financial market volatility, traders' connectedness measures and traders' actual trading volumes. I find evidence that traders' connectedness measures and their trading volume can function as a spillover channel of financial market volatility.

1 Introduction

Since Global Financial Crisis (GFC) in 2008, the interconnections of financial markets have been researched actively. In particular, some studies (Gao and Ren, 2013; Song et al., 2016; Wang et al., 2016; Barigozzi and Hallin, 2017; Creamer, 2017) focused on the

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spillover of volatilities across different financial markets. However, the mechanism with which the market volatility spilled over has not investigated sufficiently, in spite of their meaningful contributions, as their focus was mainly on the relationship between markets.

The mechanism which means the channel through which the market volatility spills over, may be more important than the interconnections of markets themselves in the perspective of policy makers or financial regulators. Their main policy target during crisis periods is to stabilize extremely volatile financial markets. If they have the information of concerning the inter-connection of financial markets, their main goal in that situation is to insulate their market from central financial markets, or at least to reduce their connections with the central financial markets. Yet this might be very difficult, since the financial and economic connections over different jurisdictions are very complicatedly inter-mingled with enormous contracts and trades. Instead, assuming that the policy makers have the information of the channels through which the market volatility spills over, they might readily control those channels, which is a more feasible and effective policy option than disconnecting their market from central financial markets.

In addition, the most essential event for relevant to the investigation of the volatility channel which should be accompanied by an increase in market volatility. That is a trader's trading behaviour, because market volatility is the result of trading behaviours. Thus, in this paper traders' trading behaviours and their network structure as the channel of market volatility spillover are investigated .

I estimate the network structure of eight types of financial traders in five different financial markets [1] in Korea and calculate each trader's connectedness measure. Then, The relationships between the shock of financial market volatility (and macro economic variables) on the one hand and the traders' connectedness measures (and their trading behaviours), on the other, are investigated.

[1]Traders : Individual (IND), BANK, Financial investment (FI), Collective Investment Scheme (CIS), Insurance (INS), Government (GOV), Foreign (FOR), Others (OTH)
Financial markets : Stock (KOSPI), Stock derivative (KOSPI 200 futures), Bond (All listed bonds), Bond derivative (KTB 3 years futures), Foreign exchange derivative (KRW/USD futures)

The reason why I have chose the Korean financial market as the subject of analysis is that it is the most representative financial market among emerging market economies. During the Global Financial Crisis the financial markets in emerging economies experienced extremely serious fluctuations which spilled over from the US subprime mortgage market. The Korean market also went through the same problem, but there is no evident macro economic problem, which helps the analysis undistorted by macro economic impact. In addition, the size of the market is relatively large among emerging economies and it is widely open to foreign investors.

The research question is how financial traders' connectedness measures and their trading behaviours are related to financial market (or macro economic variables) volatility. I choose both foreign and domestic financial markets at the same time to differentiate the origin of market volatility and also select macro economic variables, which provide the implications of macroeconomic impact on financial traders. These analyses can give the policy makers the evidence to required to justify different approaches to the shock of financial markets and macro economic environments.

In modern financial markets, incalculable numbers of transactions are executed even in a single day, which makes understanding traders' trading behaviours challenging. However, their inter-relations can be expressed using a matrix form network structure, showing the pairwise causal relations of traders. For the actual analysis financial traders' network structures must first be estimated. A nonlinear Granger causality method is applied to capture traders' pairwise causal relationships, which is the element of a matrix form network structure. I develop our understanding a little further than that acquired through the approaches of previous studies (Dufour and Jian, 2016; Song and Taamouti, 2016) which are based on traditional econometric methods, since they do not appropriately reflect the real trading process. [2]

[2] Traders in actual trading processes have generally the expectations of not only asset prices but also influential traders' trading behaviours on next day, and they decide their trading of next day based on their utmost expectations on the price and influential traders' trading behaviours. In that process, some traders who have much influence on others are more often utilised by other traders but others whose impacts are little, are less referred.

The model used to reflect the real trading processes utilized the forecasted values of influential traders' trading volumes on next day using a machine learning technique, LSTM (Long short term memory). Expectation values of influential traders cannot be observed in a real trading environment. Thus, instead of these, the forecasted value is used. Machine learning techniques have been rapidly developed recently and have been applied to a wide range of financial sectors. [3]

The expectation forecast on a trader's trading on the next day is utilised for the network structure estimation. In the event that the expectation forecast for a trader (A) has a significant impact on a certain trader (B), it means that trader (B)'s daily net trading volume is influenced by the expectation forecast for trader (A). Based on all connections among traders, a network structure in a matrix form can be built and analysed using the connectedness measures. A few traders such as foreign investors and individual investors are shown to have a stronger influence to on other traders within the network structure.

The linkage of financial (or macro economic) indexes, traders' connectedness measures and actual trading with nonlinear impulse response analysis is, then, also investigated. Due to the frequency of data, monthly and daily analyses are implemented separately. [4]

I find in the monthly analysis that, if the shock is given at financial indexes, a few traders such as BANK in the FX derivative market, and individual investors in the stock market transform to be central, and that foreign investors in the stock and stock derivative markets and individual investors in the FX derivative market react negatively. Given

[3]Machine learning can be defined as computer programming to have an optimized performance with past data. (Alpaydin, 2014) Machine learning technology has been already widely applied in financial industry.("Machine-learning promises to shake up large swathes of finance", *The economist*) Unusual title like "head of machine learning" can be found in named financial companies. Machine learning are used in not only so-called front office jobs such as trading, but also middle or back office jobs such as compliance or risk management which needs to deal with heavy written documents rather than number crunching jobs. Besides the jobs such as fraud finding, credit assessment, insurance policy selling and claims management are gradually taken by machine learning techniques. It shows the best forecast performance among other forecasting techniques (ARMA/ARIMA and ANN (Artificial Neural Network)).

[4]Macro economic variables are normally announced with monthly basis so that the relationship between macro economic variables and monthly traders' connectedness measures are investigated. Traders' daily net trading volume cannot be linked with those two variables. Thus, in case of daily frequency, financial market volatility, daily traders' connectedness measures and traders' daily net trading volume can be investigated altogether.

the shock of macro variables, the reactions of traders are different depending on the kind of shock. While foreign investors and individual investors respond actively to the shock on balance of payment, BANK reacts to the shock of the unemployment rate and base interest rate.

Several further investigations are carried out in daily analysis with a three-phased structure which is composed of financial indexes, daily connectedness measures and traders' net trading volumes in addition to the meaningful findings of monthly analyses. The aim of this approach is to investigate how the volatility of financial markets transfers through traders' connectedness measures to their actual net trading volumes. Given the shock in a financial index, a few traders' connectedness measures react more sensitively than others. And given the shock in those network measures, some traders trade more or less actively. Finally at the point of certain traders' over-shot trading, a few other traders trade more or less. Three consecutive impulse response analyses are done to investigate the system risk transfer framework.

At the first phase, the top three positively (negatively) responding connectedness measures to the shock of financial indexes, converge to three particular traders who are individual investors in the stock and FX derivative markets, collective investment schemes in the stock and FX derivative markets, and foreign investors in the stock and bond derivative markets. This result is the same as the different shocks from five different financial markets. Given the shocks on the connectedness measures of six traders who are the most responsive in the first phase, the most sensitive responses are found in the other markets, which are different from the sources of shocks. The shocks converge to certain traders in the first phase, but diverge to different markets in the second phase. Finally, it is found that there is an autocorrelation at the point of the shock of traders' net trading volumes in the third phase. The largest responses to the shocks of those six traders who are the most sensitive in the second phase, are shown in the same traders. Comprehensively based on those results, it is evident that market volatility spillover channels in capital markets exist, and that some particular traders' connectedness measures and the daily net trading volumes of other specific traders may be the channels.

Several important contributions to earlier relevant literature are presented in this paper. Firstly, the systemic risk spillover channels are investigated under the three-phased framework and the evidence which shows that traders' connectedness measures can be the market volatility spillover channels, is provided. The results of this paper have a few benefits not only to other researchers in the field, but to policy makers and financial regulators. Information on the channel of market volatility spillover will allow policy makers and regulators to increase their understanding of the origins of market risk and to prepare for these extremely risky situations. Furthermore, investor-tailored policy can be launched for stabilizing the market volatility. This is the first time forecasting the daily net trading volume of traders in econometric research and even in the machine learning literature to the best of my knowledge. Those values are utilised for a proxy of traders' expectations on influential traders' trading, which helps to understand the real trading behaviour of traders and to estimate the network structure of traders. In addition, this paper fills the gap in our understanding of traders' network structures in capital markets through the impulse response analysis on financial (macro economic) variables, traders' connectedness measures and their actual trading volumes.

The structure of this paper is as follows: in Section 2, I discuss related previous literature. In Section 3, I present the methodologies. In Section 4 the explanation about the data analysed is provided. The monthly result is given in Section 5. Section 6 is about market volatility spillover channels with daily result. Section 7 describes conclusion and final remarks. In addition, detailed information on expectation forecasts is provided in Appendix A.

2 Literature review

This section is divided into several sub sections. Firstly, the theoretical and empirical studies on expectation formation are reviewed. Through that research, the backbone of the model in this paper is provided. Forecasting methodologies and the applications are also broadly covered afterwards. Traditional econometric methods and machine learning methods are compared and the method with the best performance is used for the analysis. Lastly, the literature on market volatility or risk spillover is reviewed.

2.1 Expectation building

In numerous previous studies in finance and economics, an agent's expectation has been studied from diverse perspectives. One of the most representative examples was to investigate the oscillation of market price or the price bubbles, which included not only the stock price bubble, but also classical bubbles like the Dutch Tulipmania or the Mississippi bubble. They saw the agent's expectation as the cause of the bubble. There have been active debates on why those bubble were formed and how traders' expectations functioned in financial markets, although there is no explicit consensus.

On one side of that debate the research has stressed on traders' rationality which was based on the rational expectation hypotheses since Muth (1961). They interpreted the price fluctuation as a process in which traders' rational expectations converged to the equilibrium price level. Even the bubble was interpreted as the result of speculative investors' rational expectations. Recently, rational expectation has developed into bounded rationality (Sargent, 1993) and adaptive learning (Bullard, 2006).

On the other side, there have been those studies which admitted the existence of noise traders, who acted irrationally. In their studies, the mass uniform behaviours of noise traders were the so-called "herding" and also called "animal spirits" by Keynes (1936) and Akerlof and Shiller (2010). Their approach to the expectation was not based on the rationality, which caused market fluctuations.

Regardless of the approaches to expectations, an agent's expectations has a dynamic attribute, which means that traders coordinate their expectations according to market conditions. Thus, economic outcomes vary according to the traders' attitudes on their expectations. This phenomenon has been generally considered to be an expectation feedback system.

There are two types of expectation feedback system: these are positive and negative feedback systems. Heemeijer et al. (2009) explained the expectation feedback system using the concept of strategic substitutability (complementarity). Strategic substitutability (complementarity) exists when an increase in trader i's actions gives an incentive for trader j to decrease (increase) his actions. Through explanation, strategic substitutes (complements) constitute negative (positive) expectation feedback. Tedeschi et al. (2012) provided an intuition on how the noise trader's positive feedback worked. Let us suppose that there are noise traders with pessimistic expectations and also rational traders planning to buy an asset. Due to the noise traders' selling, rational traders coordinate their expectation not to buy, which drives the asset price down. If in the opposite case, those noise traders have positive expectations and rational traders plan to sell the asset, then, noise traders buy more assets and rational traders revise their opinion not to sell. Finally the price is not likely to converge to the equilibrium level.

The expectation, however, is difficult to measure and to be acquired in the market, since traders in general have heterogeneous expectations and the expectation cannot be observed. Thus, much research has been carried out under experimental conditions or with simulation approaches. Some studies try to obtain survey data. ter Ellen et al. (2013) and Prat and Uctum (2015) obtained traders' expectation data using survey on the currency markets.

The discussion on traders' expectations has so far given an intuition of traders' interrelations in capital markets which are mainly investigated in this paper. The past behaviours on influential traders can form other traders' expectations of those influential traders, which will determine traders' trading behaviours in the next stage. Then, some of them impact on market volatility in either a positive or negative direction.

2.2 Forecast methods

Related works on methodology are categorized into two classes. The first class is statistical or econometric time series forecasting. As ARIMA suggested by Box and Jenkins (1976) is one of the most commonly used econometric methodologies, much research has been done with ARIMA and the areas to which ARIMA was applied are diverse.

Since the publication of Box and Jenkins (1976), "*Times series analysis:forecasting and control*", there have been enormous developments in time series forecasting (Tsay, 2000). Autoregressive Integrated Moving Average(ARIMA) was first introduced by them and widely used to forecast time series in many areas since then. With technical and theoretical developments, the trials to accurately predict time series data have been done with diverse approaches. Generalized autoregressive conditional heteroskedasticity(GARCH) type models were also introduced to capture the dynamic volatility of time series. The appearance of Markov chain Monte Carlo(MCMC) helped to solve more complex problems and increased simulation approaches (Tsay, 2000). Despite these huge statistical and econometric developments in time series forecasting, those models should make use of the theoretical model in order to predict. In practice, that requirement can be a strong restriction.

As enormous quantity of the previous literature has applied econometric models to forecast diverse variables. Malik et al. (2017) forecasted the stock prices of five large Pakistani banks. They also examined whether the Pakistan stock market was efficient with the ARIMA model. Dhingra et al. (2017) predicted daily Foreign Institutional Investment (FII) flow in the futures market with ARIMA. They analysed the relations of daily FII and the daily net position of foreign investors in the futures market. Their result enhanced the understanding of the influence of FII to the futures market. Diaz and Chen (2017) investigated the return of Currency EXchange-traded Notes(ETNs) with ARFIMA-FIGARCH which was an autoregressive fractionally integrated moving average-fractionally integrated generalized autoregressive conditional heteroskedasticity model. They found non-stationarity and non-invertibility and concluded that the currency ETNs market was not efficient. Sole Pagliari and Ahmed (2017) also used the ARIMA model in their research on capital flow volatility, macroeconomic and financial stability in emerging markets. Mehran and Shahrokhi (1997) forecasted Mexican Peso per US dollar rate with ARIMA. They showed that the ARIMA model predicted future spot rates better than the forward rate model, spot rate or regression model and Naive or Random walk. Tse (1997) analyzed property prices in Hong Kong with ARIMA method. They mentioned that ARIMA model had an excellent short term forecasting power. Herbst et al. (1989) suggested a more accurate currency hedge ratio using ARIMA, while the other statistical methods gave upward ller (1985) forecasted macroeconomic variables with vector ARIMA. Nagayasu (2003) investigated the efficiency of the Japanese stock market using the ARFIMA model which was a variant of ARIMA and found that the Japanese stock market was inefficient.

The second category is forecasting using neural network methods, which is also known as "machine learning". Time series forecasting with the neural network method is not restricted to the economic or financial fields. Some studies (Claveria et al., 2017) have tried to predict tourism and have produced an accurate prediction result. This means that the machine learning technique can be applied to a wider area than expected. However, in this section, I describe financial and economic forecasting mainly since a financial time series has particular attributes such as nonlinearity, nonstationarity, and random walk.

The most evident difference between econometric methods and machine learning techniques is that machine learning techniques like Artificial Neural Network(ANN) for time series prediction are free from the restriction of theoretical models. In the machine learning area there is no need to assume a relationship between the variables. Although theoretical analyses cannot be carried out in machine learning methods, recent research has shown their prediction results outperformed traditional econometric methods in most cases. In addition, in line with a rapid development of machine learning methods, they have been popularly applied in the area of time series prediction.

A number of studies have focussed on one of the most important areas: that of stock price prediction. Atsalakis and Valavanis (2009) surveyed, reviewed and classified over 100 articles which were published in or before 2006, focusing on input data, methodologies, and performance measures. They showed that machine learning techniques' forecasting performances excelled traditional models in general, although there were some difficulties in making a structure of models. In most cases, the model was built by trial and error procedures. Even after their survey, much more research on stock price forecasting has been done using diverse and hybrid methods.

Zhang and Wu (2009) predicted S&P 500 index using a neural network method and showed good performance. De Faria et al. (2009) forecasted the Brazilian stock index using Artificial Neural Network (ANN) and adaptive exponential smoothing methods. They found that the performance of ANN was more accurate than a statistical method. Chen et al. (2017) forecasted high-frequency (five minutes) stock price using a Double-layer Neural Network(DNN) and found that their forecasting outperformed other econometric methods such as ARMA-GARCH and ARMAX-GARCH. Chaudhuri et al. (2017) predicted the ratio of share prices of stock pair trading using the Support Vector Machine(SVM), Random Forest (RF) and Adaptive Neuro Fuzzy Inference Systems (ANFIS).

Another area in which machine learning methods were widely applied is currency value prediction. Chaudhuri and Ghosh (2016) forecasted exchange rates of the Indian rupee using Artificial Neural Network (ANN) and other time series econometric modeling such as GARCH and EGARCH. Majhi et al. (2009) forecasted foreign exchange rates using their proposed neural network method which were Functional Link Artificial Neural Network (FLANN) and Cascaded Functional Artificial Neural Network (CFLANN). Their approach showed better performance than standard LMS (Least Mean Squares) models. Maknickien et al. (2011) used the Recurrent Neural Network to forecast currency value and proposed a new approach to Evolution of Recurrent Systems with Linear Outputs(EVOLINO).

Derivatives price or volatility have been predicted with machine learning technologies. Cao and Tay (2003) used the Support Vector Machine (SVM) to forecast five real futures contracts. The performance of SVM was found to be better than the Back Propagation Neural Network. Son et al. (2016) showed that nonparametric machine learning models were better than conventional parametric models at forecasting CDS spreads. Wang (2009) forecasted stock option prices in Taiwan. In order to do this, volatility was predicted using GARCH models. The result was that the neural network option pricing model was better.

Various commodity prices are also another field to which machine learning techniques have been widely applied to forecast. Gao and Lei (2017) forecasted crude oil prices using streaming learning, which was the methodology fit for non-stationary continuous data. They found that their model outperformed the Artificial Neural Network (ANN) approach. Wu and Duan (2017) forecasted gold future prices in the Shanghai Futures Exchange using the Elman Neural Network. They showed that the predicted result of neural network had a high level of accuracy and could suggest an alternative investment strategy. Muzhou et al. (2017) predicted tungsten prices using the Hybrid Constructive Neural Network Method(HCNNM). They showed their suggested method was superior to traditional methods. Hernndez (2017) executed an analysis of the volatility prediction of metal prices. They utilized forecasted variables of GARCH models as input variables in a neural network model. Their results also showed that the neural network model improved the prediction power of time-series models.

Some research suggested novel and hybrid methods and tested their methods with multiple types of financial time series. These types of study proved that machine learning techniques can be applied to wider areas than expected. Parida et al. (2017) implemented their novel model: Locally Recurrent Neuro Fuzzy Information System (LRNFIS) which was a hybrid form of fuzzy neural network and a functionally linked neural system. They forecasted electricity prices, exchange rates and stock indexes. Pradeepkumar and Ravi (2017) attempted to predict the volatility of diverse financial time-series such as currency, gold, oil and stock indices. They suggested a novel approach, Particle Swarm Optimization - Trained Quantile Regression Neural Network (PSOQRNN). They found that their new method outperformed other previous methods in forecasting those time-series.

In addition to the financial data mentioned above, a variety of research has been done on different time series. Khwaja et al. (2017) improved short-term electric load forecasting performance using Boosted Neural Networks (BNN). Sokolov-Mladenovi et al. (2016) predicted GDP growth rates using Artificial Neural Network(ANN). Mahmoudi et al. (2017) predicted the earning management of Iranian listed companies of the Tehran stock exchange using Artificial Neural Network(ANN). Their results proved that ANN had prediction power. They also showed that their approach had many benefits compared to those used in earlier studies, in particular because ANN had no need to assume the relationship between the input variables and out variables.

Recently, some researchers have attempted to combine econometric models and machine learning techniques. Parida et al. (2017) proposed a hybrid approach of a fuzzy neural network and Chebyshev polynomial functions. They predicted three different time series which were electricity prices, currency exchange rates and stock indexes. Their results gave clues that time-series could be forecasted accurately. Pradeepkumar and Ravi (2017) suggested a novel approach, Particle Swarm Optimization Trained Quantile Regression Neural Network (PSOQRNN) and predicted the volatility of the financial time series. The time series they forecasted were exchange rates, crude oil prices and stock indexes. They showed that their approach outperformed Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Neural Network methods.

2.3 Market volatility or systemic risk spillover channels

To date, there is no precise definition of the concepts of systemic risk in financial markets, risk spillover and contagion channel. Pei and Zhu (2017) divided financial contagions into three categories which were volatility spillover, extra co-movements of asset returns, and severe systemic instability from a shock. They also suggested potential transmission channels, which were international trade links, investors' behaviours, information asymmetry, liquidity shortage and so on.

At the investigation of Guidolin and Pedio (2017) on financial risk contagions within European markets, four different risk contagion channels were identified. These are the flight-to-quality, flight-to-liquidity, risk premium, and correlated information channels. Flight to quality and flight to liquidity means when the shock is given, the investors move to safer and liquid assets. Risk premium is a situation in which the investors become more risk averse, which leads to an increase in the risk premiums of assets. Correlated information means that the shock which occurred in a market provides the information reflecting equilibrium values of other assets that is not directly influenced by that shock.

Among the studies which examined systemic risk spillover, some focused on the financial institutions as the contagion channel. Ghulam and Doering (2017) investigated the risk spillover among the financial institutions in the UK and Germany. They found that hedge funds played an important role in transmitting financial risk in both countries. Their finding is closely linked to financial regulation issues. In particular, German insurance companies are less interconnected with banks than in the UK since Germany has more powerful regulation over the insurance industry. Furthermore, although their result on hedge funds seems similar to Adams et al. (2014) using US data, European hedge funds do not transmit financial risk extremely as American ones.

On the contrary others concentrated on the market indexes. Leung et al. (2017) investigated hourly volatility contagion with three stock indexes (New York, London and Tokyo) and four exchange rates (USD, EUR, GBP and JPY). They found that during a crisis period the spillover effect increased. Their approach was distinct because they separated the drivers of contagion, which were pure contagions triggered by irrational investors, and fundamental contagions captured by macroeconomic fundamentals.

Some research attempted to connect network theory with risk spillover studies. Jeong and Park (2017) endeavoured to link the connectedness measures of Korean financial institutions and their stock volatilities. Their findings provided a proof of "Too interconnected to fail". Wei and Zhang (2016) analyzed Chinese P2P lending risk contagions using network modeling and simulations. They found that the financial institutions which had the relationships with P2P lending lenders amplified the risk within the network. Moreover, with the dynamic setting, information asymmetry played an important role within the network.

3 Methodology

In this paper, the analyses are divided into two parts. The first is the network estimation with expectation forecasting. The expectation of the daily net trading volumes of other traders on next day can be one of the key references for a trader deciding his or her trading the next day, since the massive trading of major players can bring about enormous changes in financial asset prices and traders' behaviours. However, traders' expectations of the trading of other traders on the following day is impossible to observe, so those forecast values are used as the proxy of the expectation. The detailed process and results are present in Appendix A.[5] The network structure, is then estimated based on the relations of the influence of forecast values on traders' trading volume. Network estimation processes are addressed below.

The second part is to measure traders' responses to the market shock and to investigate the market volatility spillover channels. As a market volatility spillover channel, traders' network (connectedness) measures and trading volumes are applied. Traders' network measures are acquired using the network structure which is already estimated. Then, the responses of traders' network measures and trading volumes are examined at the point of the shock of financial indexes. The details of how this was investigated are also given below.

3.1 Network estimation with expectation forecasting

In this part, I build the model to see how the traders reflect their utmost expectations on the net trading volume of other investors on the next day with nonlinear Granger causality measures which are applied in Hwang (2018*b*). Since there is no evidence that the relation

[5]I forecast every trader's daily net trading volume on next day as a proxy of traders' expectation on the trader. In order to determine the most appropriate method, I apply three methodologies which are traditional econometric model (ARMA/ARIMA), artificial neural network (ANN) and long short term memory (LSTM). After forecasting, I compare the performances of those three methods. As a result, LSTM shows the best forecasting performance. Therefore, I use the forecasting results with LSTM for network structure estimation.

between traders' net trading volume is linear, nonlinear Granger causality, which can also capture the linearity is used instead of the traditional linear Granger causality method.

The real trading process can be divided into two steps. Firstly, the expectation on other traders' trading behaviours is formed. In this step, each trader may have a different view on the same type of trader if the traders have relatively different information on the same trader. However, if the traders' expectation building processes are rational and the information they have is almost the same, it is not very probable that traders' expectations on other traders' trading behaviours will be different. The shorter the time for a process of decision making, the more homogeneous traders' expectations on of the same trader will be. The time lag between the release of the daily trading information of traders and the start of the next trading day is about 12 hours and this time period is during non-business hours. In addition, uninformed traders such as individual investors can easily have access to an intelligent advisory service. Thus, forecasted values using a machine learning technique, which is same for all traders, can be applied as a proxy of expectation value.

The next step is the actual execution of trading. Despite the same expectation on other traders' trading behaviours, each trader's real trading behaviour can be different. Although the expectation building process is rational and the intelligent advisory service is provided, each trader trades with his/her unique restrictions and preferences. Institutional investors may have position limits, or adopt complicated trading strategies which require contrarian trading. For instance, even if the price is expected to rise, selling can be more profitable to them. Some traders might simply copy influential traders' trading behaviours when they believe that it would be beneficial. [6]

Thus, traders' expectation values on other traders' trading behaviours on next day is included in the model and the influence of those expectations to the real trading behaviours of traders are analysed using the network study method.

[6] The rationality of traders in financial markets has been discussed by numerous researchers. Some (Ruth, 1931) agree on rational behaviours, but others(Shiller, 2000) assert that traders behave irrationally.

Table 1: Definition of variables

	IND	BANK	FI	CIS	OTH	INS	GOV	FOR
Stock	$x_{ind,su}$	$x_{bank,su}$	$x_{fi,su}$	$x_{cis,su}$	$x_{oth,su}$	$x_{ins,su}$	$x_{gov,su}$	$x_{for,su}$
Stock Drv.	$x_{ind,sd}$	$x_{bank,sd}$	$x_{fi,sd}$	$x_{cis,sd}$	$x_{oth,sd}$	$x_{ins,sd}$	$x_{gov,sd}$	$x_{for,sd}$
Bond	$x_{ind,bu}$	$x_{bank,bu}$	$x_{fi,bu}$	$x_{cis,bu}$	$x_{oth,bu}$	$x_{ins,bu}$	$x_{gov,bu}$	$x_{for,bu}$
Bond Drv.	$x_{ind,bd}$	$x_{bank,bd}$	$x_{fi,bd}$	$x_{cis,bd}$	$x_{oth,bd}$	$x_{ins,bd}$	$x_{gov,bd}$	$x_{for,bd}$
FX Drv.	$x_{ind,fxd}$	$x_{bank,fxd}$	$x_{fi,fxd}$	$x_{cis,fxd}$	$x_{oth,fxd}$	$x_{ins,fxd}$	$x_{gov,fxd}$	$x_{for,fxd}$

[Note] Definition of traders and market (For simplicity, time t is excluded in each variable.)
(trader)
IND = Individual trader, BANK = Bank, FI = Financial investment(mainly securities companies)
CIS = Collective Investment Scheme, OTH = others (small financial companies), INS = Insurance companies
GOV = Government, FOR = Foreign investment
(market)
SU = stock, SD = stock derivative, BU = bond, BD = bond derivative, FXD = FX derivative

3.1.1 VAR representation

In this paper, in order to investigate traders' relations, I use the daily net trading volume of each trader which is provided by the Korean exchange[7] and the Korea Financial Investment Association [8] Based on the data, eight types of trader: individual investors (IND), BANK, Financial investment (FI), collective investment scheme (CIS), insurance (INS), government (GOV), foreign investors (FOR), and others (OTH), from five different financial markets: stock (SU), stock derivative (SD), bond (BU), bond derivative (BU), and FX derivative (FX) markets are analysed. In Table 1, all traders and markets are shown. Daily net trading volume shows how much a trader buys or sells in net trading in a day after offsetting gross buying and selling. To avoid the excessive influence of large market and to analyse traders' trading in different market using same weights, I adjust daily net trading volumes as seen in Equation 1.

$$x_{t(i),m(j)} = \frac{\text{daily trading volume of trader i in market j} \times 2}{\sum |\text{daily trading volume of trader i in market j}|} \tag{1}$$

where t() indicates the trader and m() shows the market. The list of traders and markets is given in Table 1. For the sake of efficient analysis, the daily net trading volume of traders vector at time t (X_t), $X_t = (x_{ind,su,t},\ x_{bank,su,t},\ \dots\ ,\ x_{gov,fxd,t},\ x_{for,fxd,t})$ can be

[7] www.krx.co.kr
[8] www.kofia.or.kr

considered.

Then, a VAR(Vector Autoregressive) model with X_t can be considered as seen in Equation 2. The daily net trading volumes of traders are determined using the net trading volumes on the previous day. The model order one is consistent with the extant literature (Song and Taamouti, 2016; Hwang, 2018*a*). That is the restricted model.

$$X_{t+1} = \Phi^{re}(X_t) + \epsilon_t \tag{2}$$

Where $\Phi^{re}()$ is a nonlinear function, to which I apply Gaussian kernel regression for the sake of simplicity following Song and Taamouti (2016). ϵ_t is the error term.

The assumption which the past simply determines the future, however, is so restricted that an unrestricted model with expectation forecasting is suggested (Equation 3). Expectation forecasting is the utmost forecast on the daily net trading volume of a trader on next day by other market participants. In this paper, the value of expectation forecasting is estimated using LSTM(Long Short Term Memory), which is one of the most popularly used machine learning technologies in time series forecasting.[9] In the unrestricted model, the daily net trading volume of traders on time t, X_t and a certain trader's expectation forecasting vector at time t+1, $E_t[x_{st(k),sm(l),t+1}|X_t]$ whose dimension is 40×1 composed of the same value (the expectation forecasting on the trader), are used as independent variables. Here st() stands for source trader which means the trader with the expectation forecast and sm() means source market which is the market source to which the trader belongs. What matters is that the expected value is conditional on all other traders' trading history X_t. Thus, through the trader and market, 40 different unrestricted models can be made.

$$X_{t+1} = \Phi^{un,st(k),sm(l)}(X_t, E_t[x_{st(k),sm(l),t+1}|X_t]) + \varepsilon_t \tag{3}$$

[9]In this paper, I compare the forecast performance of traditional econometric method (ARMA/ARIMA), neural network, and LSTM as seen in appendix A. LSTM is shown to have the best performance.

Where $\Phi^{un,st(k),sm(l)}()$ is a nonlinear function, to which Gaussian kernel regression is applied. ε_t is the error term. According to the type of trader and the market to which the trader belong, 40 different unrestricted models are made.

3.1.2 Nonlinear Granger causality measures

I measure the degree to which traders are influenced by the expectation forecasting on a certain trader. For instance, individual investors in the stock market might refer to their expectations on foreign investors' trading in the stock derivative market on the following day. That influence can be captured with the Granger causality measure.

$$c_{t(a),m(i)\to t(b),m(j)} = ln(\frac{\sigma^2_{re}(x_{t(b),m(j)})}{\sigma^2_{un}(x_{t(b),m(j)|st(a),sm(i)})}) \tag{4}$$

where $\sigma^2_{re}(x_{t(b),m(j)})$ is the forecasted error of $x_{t(b),m(j)}$ with the restricted model and $\sigma^2_{un}(x_{t(b),m(j)|st(a),sm(i)})$ is the forecasted error of $x_{t(b),m(j)}$ with the unrestricted model which has the expectation forecast of source trader a and source market i. Regarding all traders, the pairwise causal relationship can be obtained with the Granger causality measure. Then, the causality matrix (C) can be acquired based on them as seen in Table 2. One important point here is that all causality measures need to be checked with a statistically significance test.

For the statistical significance of the Granger causality measure, a simple bootstrapping method is applied. Bootstrapping is the statistical method used to estimate the distribution of statistics with random sampling with replacement, which was introduced by Efron and Tibshirani (1993) and developed more since then. It is basically a computer-based method and in many cases requires time-consuming tasks. That is why a simple bootstrapping method is implemented in this paper although diverse versions of bootstrapping can be applied.

The simple bootstrapping method is composed of the following algorithm. After estimating the regression equation using the observed X_{t-1} and X_t, residuals ϵ can be computed.

Then, fixing X_{t-1} and randomly sampling the elements of ϵ with replacement, ϵ^* can be drawn. $\epsilon^* = (\epsilon_1, \epsilon_2, \ldots, \epsilon_n)$. The value of each ϵ_i is same with one of the elements of ϵ which can be with a probability of 1/n. Using ϵ^* and a fixed X_{t-1}, a new X_t^* can be calculated. Then with X_{t-1} and X_t^*, a new causality matrix C^* is calculated. All procedures above are repeated 1,000 times. The achieved significance level(ASL) can be obtained as shown below.

$$ASL = \#\{C^* \geq C\}/N \tag{5}$$

where N is repetition time. Here, hypothesis(H_0) is $C = 0$ and a one-tailed test are used since the causality measure is assumed to be greater than or equal to 0.[10] If a causality measure is statistically significant, it means that a trader is influenced by the expectation forecasting on a certain trader.

Every trader's influence on all other traders can be captured with Granger causality measures in this fashion. With those Granger causality measures, Granger causality matrix C can be created as in Table 2. The entry of Granger causality matrix C can be shown $c_{i,j}$, which means the expectation forecast on the trader on row i influence the trading of the trader in column j. In other words, the trader in column j refers his/her expectation on the trading of the trader in row i on following day. If the entry of the Granger causality matrix is statistically significant at 10% significance level, the value of the entry is 1, otherwise it is 0. Then, an adjacency matrix whose entries are composed of 1 or 0 can be drawn easily.

3.1.3 Connectedness measures

Although the Granger causality matrix is obtained, it is still difficult to measure a trader's influence on others within the network. Thus, a measure to capture the influence of

[10] I use causality matrix C instead of the entry (c_{ij}) of causality matrix C for simplicity. Here causality matrix C is expressed comprehensively as the combination of all causality measures which are the entries of causality matrix (C).

Table 2: Granger causality matrix

$c_{i,j}$	1	2	...	j	...	39	40
1	$c_{1,1}$	$c_{1,2}$	...	$c_{1,j}$	...	$c_{1,39}$	$c_{1,40}$
2	$c_{2,1}$	$c_{2,2}$	...	$c_{2,j}$	...	$c_{2,39}$	$c_{2,40}$
...	...	...	...	...	...	...	...
i	$c_{i,1}$	$c_{i,2}$	...	$c_{i,j}$	...	$c_{i,39}$	$c_{i,40}$
...	...	...	...	...	...	...	...
40	$c_{40,1}$	$c_{40,2}$	...	$c_{40,j}$	...	$c_{40,39}$	$c_{40,40}$

expectation forecasting on a trader to other traders needs to be defined. I use OUT and IN connectedness measures in this paper, which are similar concepts with degree centrality. It is one of the simplest and mostly used network measures in network literature (Newman, 2010). Centrality literally means how central a node or vertex is in the network and is defined as the sum of edges which connect the node. In a direct network which has a direction in the edge like the Granger causality matrix, two kinds of connectedness measures can be defined. One is the OUT connectedness measure which is a node's influence on others. The other is the IN connectedness measure which is the influence of others on a node.[11]

$$OUT(i) = \sum_{j=1, j \neq i}^{N} c_{i \to j} \tag{6}$$

where $c_{i \to j}$ is the value of the Granger causality measure from the expectation forecast on trader i to the trading of trader j which is the element of causality matrix C.

$$IN(i) = \sum_{j=1, j \neq i}^{N} c_{j \to i} \tag{7}$$

where $c_{j \to i}$ is the causality value from the expectation forecast on trader j to the trading of trader i which is the element of causality matrix C.

[11]For the actual computation, all OUT and IN connectedness measures are divided by the number of all traders (40). Because all causality values are binary (1 or 0) in this paper. In addition, it helps to avoid the scale problem in impulse response analysis.

3.1.4 Changes of network structure

Given the causality matrix and connectedness measures, network structure and influential traders can be easily investigated. However, one causality matrix during the entire analysed period is not sufficient to capture changes in traders' network structures. Here I estimate monthly and daily network structures. The process of estimating monthly and daily networks is described below.

Firstly, the entire data set needs to be divided into sub periods. Here I use the two years moving window method by one month. For instance, the values of December in 2010 are estimated using the data from the beginning of 2009 to the end of 2010. Regarding the data of all sub periods in two years, two processes of monthly network structure estimation are implemented. One is the prediction of expectation forecasting on 40 different traders. Expectation forecasting is predicted with LSTM, which has the best performance among traditional econometric method, Artificial Neural Network, and LSTM. The other is to estimate the monthly causality matrix and traders' connectedness measures. The causality matrix is estimated using the method, described above and connectedness measures are calculated as seen in Equations 6 and (7). In this way 96 monthly OUT/IN connectedness measures of 40 traders are obtained.

Although changes in network structures can be investigated using traders' monthly connectedness measures, it is still difficult to link the network measures and financial market index. Since the data frequency of most of financial market indexes is daily. Thus, daily connectedness measures are estimated with similar methods with monthly network structure estimation. Reflecting daily frequency, I use 30 days moving window method by one day. The same values of expectation forecasting are used.

3.2 Impulse response analysis

In this section, the relation of financial (or macro economic) variables, traders' connectedness measures and traders' actual trading is investigated. Given the fact that there must be trading activities in order for there to be financial market fluctuation, traders' network structures can play an important role in examining the propagation of financial market volatility. Whether market volatility can affect traders' connectedness measures, is also examined at the same time. Two versions of Impulse response analyses: monthly and daily, are applied to investigate this.

3.2.1 Monthly Impulse response analysis

In order to investigate the relation between traders' connectedness measures and financial or macro variables, the network (connectedness) measure vector $N_{a,t}$ needs to be defined. Network Vector $N_{a,t}$ is defined as the combination of all traders' connectedness measures and one of the financial or macro variables, as $N_{a,t} = [n_{t(ind),m(su),t}, \dots n_{t(for),m(fxd),t}, f_{a,t}]$'. $f_{a,t}$ (a=1,...,10) is one of the financial or macro variables. Financial variables are the monthly volatility of KOSPI (a=1), KRW/USD (a=2), S&P (a=3), NIKKEI (a=4), and HANGSENG (a=5). Macro variables are current account of the balance of payment (a=6), capital and financial account of balance of payment (a=7), inflation rate (a=8), unemployment rate (a=9), and base interest rate (a=10). All financial/macro data are adjusted from 0 to 1, since traders' connectedness measures are within 0 and 1. This adjustment has the benefit of avoiding the distortion of the difference of scale of the variables. For the entire data set, the minimum value is adjusted to 0, the maximum value is modified to 1 and others are interpolated between 0 and 1. Then, a simple VAR model, which is called the "baseline model" here can be built.

$$N_{a,t+1} = \phi_m(N_{a,t}) + \varepsilon_t \tag{8}$$

Where $\phi_m()$ is a nonlinear function, which is a Gaussian kernel here. ε_t is the error term. According to a (financial or macro variables), ten different VAR models can be built.

Then, to investigate the responses of traders' connectedness measures to the shock of financial or macro variables, the Impulse Response Function (IRF) needs to be defined.

In this paper, I follow the simulation approach used by Koop et al. (1996). This approach has the advantage of capturing nonlinear relations between impulse and response, which is consistent with the nonlinear baseline model. IRF is described by Equation 9.

$$IRF(h, \nu_t, w_{t-1}) = E[N_{a,t+h}|\nu_t, w_{t-1}] - E[N_{a,t+h}|w_{t-1}] \tag{9}$$

Where ν_t is the current shock on $f_{a,t}$, w_{t-1} is history and h is the predictive period (h=1, ... , 11).

3.2.2 Daily Impulse response analysis

The daily impulse response analysis is an analysis further developed on the basis of the monthly analysis. Due to the frequency involved, the volatility of the financial market index, traders' connectedness measures and the actual daily net trading volumes of traders can be linked with the daily analysis. The linkage of those three variables can give us a clue to understanding how the financial market volatility spills over. If the event of a market volatility increase occurs in a financial market, it might cause a change in the network structures in the capital market. The massive change in a certain trader's connectedness measure can make some traders trade abnormally. Then, this abnormal trading can cause subsequent abnormal trading among other traders. I define this chain link as three phased volatility spillover framework and analyse each phase with nonlinear impulse response analysis.

Three-phased volatility spillover, can be modelled using three different vectors. Firstly, I define the vector of each stage. $D_{a,t}$ is the vector combined with traders' daily connectedness measures and the volatility of a financial index, as $D_{a,t} = [d_{t(ind),m(su),t}, \dots d_{t(for),m(fxd),t}, fd_{a,t}]'$. $d_{t(i),m(j),t}$ is the daily connectedness measure of trader i from market j. $fd_{a,t}$ (a=1,2,3,4,5) is daily volatility of KOSPI (a=1), KRW/USD (a=2), S&P (a=3), NIKKEI (a=4), and HANGSENG (a=5).[12]

[12] KOSPI is the index to reflect the risk of Korean financial and economic situation the most and

$T_{b,t}$ is the vector composed of the daily net trading volume and daily connectedness measure of a traders. It can be defined as $T_{b,t} = [x_{t(ind),m(su),t},\ \dots\ x_{t(for),m(fxd),t},\ d_{b,t}]$'. $x_{t(i),m(j),t}$ is the daily net trading volume of trader i from market j. $d_{b,t}$ is the connectedness measure of trader b, which has the greatest response at the point of the shock of financial volatility at the first phase.

The last vector is X_t, which is a traders' trading volume and defined as before, as $X_t = (x_{ind,su,t},\ x_{bank,su,t},\ \dots\ ,\ x_{gov,fxd,t},\ x_{for,fxd,t})$. With those three vectors, a simple VAR model can be built as in Equations 10, 11, 12.

$$D_{a,t+1} = \phi_{d1}(D_{a,t}) + \varepsilon_t^{D,a} \tag{10}$$

$$T_{b,t+1} = \phi_{d2}(T_{b,t}) + \varepsilon_t^{T,b} \tag{11}$$

$$X_{t+1} = \phi_{d3}(X_t) + \varepsilon_t^{X} \tag{12}$$

Where ϕ_{d1}, ϕ_{d2} and ϕ_{d3} are nonlinear functions to which the Gaussian kernel is applied. The dimensions of D_t, T_t and X_t are respectively 41×1, 41×1 and 40×1. In D_t and T_t, one different entry is inserted in the vector. These are respectively $fd_{a,t}$ and $d_{b,t}$.

Based on those three simple VAR models, three nonlinear impulse response functions can be defined (Equations 13,14 and (15)) They are basically the same as the monthly IRF following Koop et al. (1996). The strategy to investigate the channel of market volatility spillover is given below. Firstly, assuming the shock is given at the point of volatility of one of the financial index (a), the responses of the most sensitive traders'

currency rate is very sensitive index due to Korea's export-driven economic characteristic. S&P is one of the most representative index for global financial risk. NIKKEI and HANGSENG are chosen for Korean economy is closely liked with Japanese and Chinese economy and the volatility of them can be the risk driver to Korean financial market. By the data provided by Korea Customs service Korea's biggest trade partner countries are US, China and Japan excluding oil exporting countries. I use each index's daily volatility over previous 30 days which is consistent with the window to estimate traders' connectedness measures.

connectedness measures are identified with IRF1. Secondly, if there is a shock on the most sensitive traders' connectedness measures in phase one, which is (b), IRF2 shows which traders trade abnormally. Lastly, given the shock at the point of abnormal daily net trading volume of traders in phase two, which is (c), the responses of the daily net trading volumes of traders are observed. With these three impulse response functions, the volatility of the financial index, traders' daily connectedness measures and the actual daily net trading volume of traders can be interlinked.

$$IRF1(h, \nu_t^{D,a}, w_{t-1}^{D,a}) = E[D_{a,t+h}|\nu_t^{D,a}, w_{t-1}^{D,a}] - E[D_{a,t+h}|w_{t-1}^{D,a}] \tag{13}$$

$$IRF2(h, \nu_t^{T,b}, w_{t-1}^{T,b}) = E[T_{b,t+h}|\nu_t^{T,b}, w_{t-1}^{T,b}] - E[T_{b,t+h}|w_{t-1}^{T,b}] \tag{14}$$

$$IRF3(h, \nu_t^{X,c}, w_{t-1}^{X,c}) = E[X_{c,t+h}|\nu_t^{X,c}, w_{t-1}^{X,c}] - E[X_{c,t+h}|w_{t-1}^{X,c}] \tag{15}$$

This econometric modelling can be interpreted as shown below. If there is a shock in the financial index, traders' expectation forecasting on other traders' reactions needs to be updated. In this process, the influence of each trader on others changes and the network structure among them is reformed. As the sensitivity of each trader's network measure differs, some traders' connectedness measures increase but those of others decrease. Given the change in network measures, several particular traders react to the influential traders more than others. In addition, if some traders react abnormally to central traders after the shock in the financial index, some traders react to them sensitively. In this spillover process, the network structure, which plays an important role for the central traders, becomes the channel through which the market volatility propagates.

Table 3: Descriptive statistics of traders' daily net trading volume

		IND	BANK	FI	CIS	OTH	INS	GOV	FOR
Stock									
	Mean	-0.01	-0.01	0.02	-0.08	0.00	0.02	0.09	-0.02
	Max	1.00	0.79	0.97	1.00	0.48	0.87	1.00	1.00
	Min	-1.00	-1.00	-0.94	-1.00	-0.67	-0.67	-1.00	-1.00
	Sted	0.60	0.11	0.23	0.44	0.04	0.13	0.30	0.61
	Skewness	-0.04	-2.51	-0.31	-0.01	-2.14	0.04	-0.20	-0.01
	Kurtosis	-1.28	24.70	2.47	-0.65	49.42	4.44	0.94	-1.30
Stock derivative									
	Mean	0.00	0.00	0.00	0.01	0.00	0.00	0.00	-0.02
	Max	1.00	0.67	1.00	1.00	0.41	0.88	0.94	1.00
	Min	-1.00	-0.59	-1.00	-1.00	-0.34	-0.64	-1.00	-1.00
	Sted	0.50	0.09	0.42	0.40	0.03	0.11	0.17	0.73
	Skewness	0.00	0.19	-0.02	0.00	1.23	0.54	-0.10	0.04
	Kurtosis	-0.98	8.49	-0.52	-0.17	44.44	8.39	4.90	-1.60
Bond									
	Mean	0.04	0.15	-0.85	0.28	0.02	0.11	0.16	0.09
	Max	0.44	0.91	0.97	1.00	0.51	0.66	0.88	0.86
	Min	-0.22	-1.00	-1.00	-0.74	-0.56	-1.00	-0.86	-1.00
	Sted	0.06	0.29	0.25	0.23	0.06	0.14	0.17	0.17
	Skewness	1.40	-0.76	2.87	-0.17	-0.33	-0.71	-0.02	-0.03
	Kurtosis	6.33	0.91	10.26	0.86	16.78	4.01	1.78	5.58
Bond derivative									
	Mean	0.00	-0.01	-0.01	0.00	0.00	0.00	0.00	0.03
	Max	0.89	1.00	1.00	0.90	0.33	0.96	0.66	1.00
	Min	-0.90	-1.00	-1.00	-0.93	-0.36	-0.87	-0.59	-1.00
	Sted	0.14	0.57	0.59	0.20	0.02	0.16	0.10	0.65
	Skewness	0.20	0.04	0.04	-0.10	0.31	0.17	-0.20	-0.05
	Kurtosis	7.20	-1.15	-1.29	2.25	70.36	6.02	4.07	-1.35
FX derivative									
	Mean	0.00	0.04	0.02	-0.06	0.00	0.00	0.00	0.00
	Max	1.00	1.00	1.00	1.00	0.70	0.75	0.34	1.00
	Min	-1.00	-1.00	-1.00	-1.00	-0.57	-0.61	-0.42	-1.00
	Sted	0.47	0.56	0.48	0.34	0.07	0.04	0.01	0.55
	Skewness	-0.01	-0.04	0.00	-0.11	0.31	-0.70	-7.65	0.01
	Kurtosis	-0.41	-1.04	-0.82	1.37	13.97	101.77	827.08	-1.01

[Note]
IND = Individual trader, BANK = Bank, FI = Financial investment(mainly securities companies)
CIS = Collective Investment Scheme, OTH = Others (small financial companies)
INS = Insurance companies, GOV = Government, FOR = Foreign investment

4 Data

I analyse the daily net trading volumes of eight types of traders from five different Korean financial markets, which are the stock (KOSPI), stock derivative (KOSPI200 futures), bond (all listed bonds), bond derivative (Korean Treasury Bond (3 years maturity) futures), and FX derivative (KRW/USD futures) markets. The period which the data is collected, is from 2006 to 2015. The descriptive statistic is given in Table 3.[13]

A daily net trading volume is defined as a trader's net selling or buying during a day. I standardize all daily net trading volumes by dividing them by a half of the summation of the absolute daily net trading volumes of all traders. Using this process, the distortion of the trader, the day, and the market by massive volumes can be avoided. All daily net trading volumes are stationary.

The values of expectation forecast on a trader's daily net trading volume on next day (hereafter "expectation forecast") are estimated with LSTM, which is one of the most popularly used machine learning methods in time series data prediction.

Financial indexes and macro variables are also used to investigate the relations of traders' connectedness measures and the volatility of financial market or macro economic conditions. Financial indexes are selected based on the trade dependence of the Korean economy.

5 Monthly result

Monthly network structures in capital markets are estimated and impulse response analysis is implemented to those in this section. First, I start with the forecasting of the daily net trading volume of every trader on following day. Every daily net trading volume is forecasted with LSTM as mentioned in previous section. Once the forecasting is completed, the Granger causality matrix is estimated for every 24 months with the moving

[13] I use same data with Hwang (2018*a*) and Hwang (2018*b*) for comparison purpose.

windows method. The entry of each Granger causality matrix is a logarithmic ratio of the forecasted error of the restricted model over the forecasted error of the unrestricted model. The only difference between the restricted model and unrestricted model is whether the forecasted daily net trading volume on a trader is included as an independent variable or not.

Then, the connectedness measure of each trader, which is similar to degree centrality, is obtained with the causality matrix. Consequently traders' OUT/IN measures are respectively acquired. Before calculating connectedness measures, all Granger causality matrices are tested for the statistical significance using the bootstrapping method. If the entry of the Granger causality matrix is statistically significant, it is transformed to 1 and otherwise to 0. After all entries are converted to 1 or 0, the Granger causality matrix becomes a binary adjacency matrix, which represents the network structure. OUT/IN connectedness measures can be obtained by the adjacency matrix easily.[14]

All the monthly connectedness measures of traders are compared and influential traders are identified. However, if one is only using the connectedness measures, it is difficult to assess the impacts of financial or macro economic variables on traders' connectedness measures.

Therefore, impulse response analysis is also implemented which is an effective method to see the changes of variables at the point of the shock of a certain variable. Here, given the shock of five financial indexes and five macro variables, the change of each trader's OUT/IN connectedness measure is analyzed.

5.1 Network structure with expectation forecast

The monthly average OUT connectedness measures of several particular traders' have explicitly higher values than those of others, while all monthly average IN connectedness measures are shown to be similarly low, as can be seen in Figure 1. They are foreign

[14] Row sum of the adjacency is a trader's OUT connectedness measures and column sum of the adjacency matrix is a traders' IN connectedness measure.

investors(FOR) in the stock, stock derivative, bond derivative and FX derivative markets: individual investors (IND) in the stock and FX derivative markets, BANK in the bond derivative and FX derivative markets and financial investment (FI) in the bond derivative market. The average values of all IN connectedness measures are within the range of 0.06 to 0.14.

This result is strong evidence of influential traders in capital markets. Traders refer to their expectation on some influential traders' trading on the next day. Foreign investors (FOR) in all markets but the bond market, individual investors (IND) in the stock and FX derivative markets seem to have strong impacts on other traders. This is also consistent with the results of previous literature (Hwang, 2018*a*,*b*).

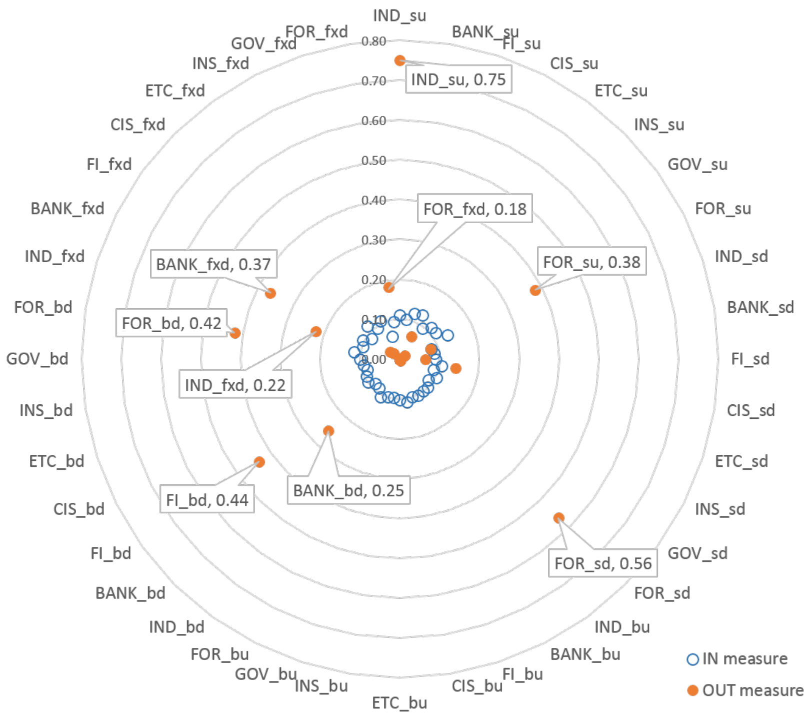
Despite this meaningful result, it is still difficult to identify a practical implication under the monthly setup. Since trading data is fundamentally daily and most financial data is daily, the meaningful connection of traders' connectedness measures and financial volatility is difficult with a monthly analysis. Nonetheless, it can be linked with monthly macro economic data significantly.

5.2 Impulse response analysis

I consider both positive and negative shocks at the same time using impulse response analysis. In case of the volatility of a financial market, a positive shock can be more influential than other variables. In contrast, a negative shock of a macro variable such as current account, can significantly impact on other variables. The responses of network measures are shown not to for more than two periods. The responses are present in the first period and fade away later. The directions and scales of responses of traders' connectedness measures, however, contrast evidently at the point of same shock. Thus, I focus on the top three positive and negative responses at each positive and negative shock of financial and macro economic variable.

The three most sensitive responses of traders' OUT connectedness measures at the point

Figure 1: Average monthly OUT/IN connectedness measures



[Notes]
1. Traders' monthly OUT and IN measures are averaged during the investigated period.
2. OUT degree is orange circle and IN degree is white circle.
3. Trader
IND = Individual trader, BANK = Bank, FI = Financial investment(securities companies)
CIS = Collective Investment Scheme, OTH = others (small financial companies)
INS = Insurance companies, GOV = Government, FOR = Foreign investment
4. Market
su = Stock, *sd* = Stock derivative, *bu* = Bond, *bd* = Bond derivative, *fxd* = FX derivative

Table 4: Impulse response analysis with monthly OUT connectedness measures

		Positive response			Negative response		
		$1st$	$2nd$	$3rd$	$1st$	$2nd$	$3rd$
	Positive shock						
Finance	Kospi	GOV_{fxd}	CIS_{fxd}	GOV_{bu}	CIS_{su}	FOR_{su}	OTH_{bd}
	Krw/usd	IND_{su}	$BANK_{fxd}$	FI_{bd}	IND_{fxd}	FOR_{su}	FOR_{sd}
	S&P	$BANK_{fxd}$	IND_{su}	FI_{bd}	IND_{fxd}	FOR_{sd}	FOR_{su}
	Nikkei	FI_{bd}	$BANK_{fxd}$	IND_{su}	IND_{fxd}	FOR_{sd}	FOR_{su}
	Hangseng	$BANK_{fxd}$	IND_{su}	CIS_{sd}	IND_{fxd}	FOR_{su}	FOR_{sd}
Macro	Crt.at	FOR_{sd}	IND_{fxd}	FI_{sd}	IND_{sd}	$BANK_{fxd}$	CIS_{su}
	C&F.at	FOR_{sd}	IND_{fxd}	FI_{sd}	$BANK_{fxd}$	IND_{sd}	IND_{su}
	Inf.	$BANK_{fxd}$	IND_{su}	IND_{sd}	FOR_{sd}	FI_{sd}	FOR_{bd}
	Nepl	$BANK_{bd}$	FOR_{fxd}	$BANK_{fxd}$	IND_{fxd}	FOR_{su}	FOR_{bd}
	B.int	IND_{sd}	$BANK_{fxd}$	FI_{fxd}	FOR_{sd}	FI_{sd}	$BANK_{bd}$
	Negative shock						
Finance	Kospi	GOV_{fxd}	CIS_{fxd}	GOV_{bu}	CIS_{su}	FOR_{su}	OTH_{bd}
	Krw/usd	IND_{fxd}	FOR_{su}	FOR_{sd}	IND_{su}	$BANK_{fxd}$	FI_{bd}
	S&P	IND_{fxd}	FOR_{sd}	FOR_{su}	$BANK_{fxd}$	IND_{su}	FI_{bd}
	Nikkei	IND_{fxd}	FOR_{sd}	FOR_{su}	FI_{bd}	$BANK_{fxd}$	IND_{su}
	Hangseng	IND_{fxd}	FOR_{su}	FOR_{sd}	$BANK_{fxd}$	IND_{su}	CIS_{sd}
Macro	Crt.at	IND_{sd}	$BANK_{fxd}$	CIS_{su}	IND_{fxd}	FOR_{sd}	FI_{sd}
	C&F.at	IND_{sd}	$BANK_{fxd}$	IND_{su}	FOR_{sd}	IND_{fxd}	FI_{sd}
	Inf.	FOR_{sd}	FI_{sd}	FOR_{bd}	$BANK_{fxd}$	IND_{su}	IND_{sd}
	Nepl	IND_{fxd}	FOR_{su}	FOR_{bd}	$BANK_{bd}$	FOR_{fxd}	$BANK_{fxd}$
	B.int	FOR_{sd}	FI_{sd}	$BANK_{bd}$	$BANK_{fxd}$	IND_{sd}	FI_{fxd}

[Note]

1. The responses of traders' OUT connectedness measures are present at the shock financial / macro variables. For each shock, the traders with top 3 positive(negative) are shown.

2. Financial variables are the monthly volatility of KOSPI, KRW/USD, S&P, NIKKEI, HANGSENG.

3. Macro economic indexes are monthly Current account(Crt.at), Capital and financial account(C&F.at), Inflation rate(Inf.), Unemployment rate(Nepl), and Base interest rate(B.int).

4. Trader
IND = Individual trader, BANK = Bank, FI = Financial investment, CIS = Collective Investment Scheme, OTH = others, INS = Insurance companies, GOV = Government, FOR = Foreign investment

6. Market
su = stock, sd = Stock derivative, bu = Bond, bd = Bond derivative, fxd = FX derivative

of shock to financial and macro economic variables are presented in Table 4. The OUT connectedness measures are, by definition, the extent to which all traders use their expectation forecast on the trader's trading volume on the following day for their trading reference. In other words, it is the trader's influence on all other market participants. Thus, if a traders' OUT connectedness measure increases (decreases) at the point of a shock, it is interpreted that the shock causes that trader to be more influential (uninfluential).

An important finding with OUT connectedness measures is the parallel relation of shock and response, which is that the positive responses to a positive shock are similar to negative responses to a negative shock. The parallel relation is also found in negative responses to a positive shock and positive responses to a negative shock. It shows that traders' connectedness measures are consistently linked to financial and macro economic variables, regardless of the direction of shock.

Several close relations with traders and foreign financial indexes including local FX markets, are found in Table 4. When the volatility of KRW/USD and foreign financial market indexes increases, BANK in the FX derivative market, individual investors (IND) in the stock market and financial investment (FI) in the bond derivative market become more influential. In contrast, the negative reactors to the same positive shock seem to be more evident. Individual investors (IND) in the FX derivative market, and foreign investors (FOR) in the stock and stock derivative markets lose their influence.

These results give rise to significant implications. First, when the international market turns volatile, the importance of BANK's trading in the FX derivative market increases, which can result from a bank's monopolistic role as a mediator in the foreign exchange market.[15] Second, foreign investors' (FOR) influence on the domestic market decreases when a foreign financial market volatility increases. This means that at least foreign investors are not the main driver in contributing to market volatility increase during crisis time, and that they are more likely to be contrarian investors than trend followers, which

[15]By Korean law, "*Foreign exchange transactions Act*", foreign exchange financial transaction should be implemented only through Korean commercial banks.

is consistent with the results of Hwang (2018a) and Hwang (2018b). The other is about the trait of individual investors (IND). When the global financial market is unstable, they play an destabilizing role in the domestic stock market but become inactive in the FX derivative market.

There are two opposite patterns of responses to the shock of macro economic variables. Macro economic variables can be divided into good and bad signs unlike the financial market volatility. The good signs are the increase of balance of payment accounts and the decrease of inflation, unemployment rate and base interest rate. In contrast, the bad signs are the contraction of balance of payment account and the rise of inflation, unemployment rate and base interest rate.

BANK in the FX derivative markets actively respond to the bad signs, while foreign investors (FOR) in the stock derivative markets react sensitively to good signs. BANK's increased importance in the FX derivative market at the bad times is in line with its increase in influence at the turmoil in the international financial markets. However, the increased influence of foreign investors in the stock derivative market at an economically good time seems reasonable and is consistent with previous literature in that investment increase of foreign investors is closely related to economic fundamentals.

The IN connectedness means how much a trader refers their expectation forecast of the trading volume of other traders on the following day. The result of impulse response analysis with IN connectedness measures is presented in Table 5. It captures the sensitivity of a trader to other traders, which contrasts with the independence of a trader. If a traders' IN connectedness measures increase at the point of a shock, it means that the trader receives more influence from other traders. In contrast, when an IN connectedness measure decreases at the point of a shock, the trader trades more independently.

Parallel effect is also found with regard to IN connectedness measures. Positive responses to a positive shock seem very similar to negative responses to a negative shock. At the same time negative responses to a positive shock appear similar to positive responses to a negative shock.

Table 5: Impulse response analysis with monthly IN connectedness measures

		Positive response			Negative response		
		$1st$	$2nd$	$3rd$	$1st$	$2nd$	$3rd$
	Positive shock						
Finance	Kospi	GOV_{fxd}	CIS_{fxd}	GOV_{bu}	CIS_{su}	FOR_{su}	OTH_{bd}
	Krw/usd	IND_{bu}	GOV_{su}	INS_{bu}	CIS_{su}	FOR_{su}	OTH_{bd}
	S&P	IND_{bu}	CIS_{fxd}	GOV_{su}	CIS_{su}	FOR_{su}	OTH_{bd}
	Nikkei	IND_{bu}	GOV_{su}	IND_{bd}	CIS_{su}	OTH_{su}	FOR_{su}
	Hangseng	CIS_{fxd}	GOV_{su}	GOV_{bu}	CIS_{su}	OTH_{bd}	FOR_{su}
Macro	Crt.at	OTH_{bd}	INS_{su}	FI_{su}	OTH_{su}	CIS_{fxd}	GOV_{bu}
	C&F.at	OTH_{bd}	INS_{su}	FI_{su}	OTH_{su}	CIS_{fxd}	GOV_{bu}
	Inf.	CIS_{fxd}	GOV_{bu}	$BANK_{su}$	OTH_{bd}	CIS_{su}	FI_{su}
	Nepl	FI_{su}	FI_{bu}	$BANK_{bu}$	GOV_{fxd}	FOR_{bd}	$BANK_{su}$
	B.int	GOV_{fxd}	GOV_{bu}	CIS_{bu}	OTH_{bd}	FI_{su}	INS_{bu}
	Negative shock						
Finance	Kospi	GOV_{fxd}	CIS_{fxd}	GOV_{bu}	CIS_{su}	FOR_{su}	OTH_{bd}
	Krw/usd	CIS_{su}	OTH_{bd}	FOR_{su}	GOV_{su}	IND_{bu}	INS_{bu}
	S&P	CIS_{su}	FOR_{su}	OTH_{bd}	CIS_{fxd}	IND_{bu}	GOV_{su}
	Nikkei	CIS_{su}	OTH_{su}	FOR_{su}	IND_{bu}	GOV_{su}	IND_{bd}
	Hangseng	CIS_{su}	OTH_{bd}	FOR_{su}	CIS_{fxd}	GOV_{su}	GOV_{bu}
Macro	Crt.at	OTH_{su}	CIS_{fxd}	GOV_{bu}	OTH_{bd}	INS_{su}	FI_{su}
	C&F.at	CIS_{fxd}	OTH_{su}	GOV_{bu}	OTH_{bd}	INS_{su}	FI_{su}
	Inf.	OTH_{bd}	CIS_{su}	FI_{su}	CIS_{fxd}	GOV_{bu}	$BANK_{su}$
	Nepl	GOV_{fxd}	FOR_{bd}	$BANK_{su}$	FI_{su}	FI_{bu}	$BANK_{bu}$
	B.int	OTH_{bd}	FI_{su}	INS_{bu}	GOV_{fxd}	GOV_{bu}	CIS_{bu}

[Note]
1. The responses of traders' IN connectedness measures are present at the shock financial / macro variables. For each shock, the traders with top 3 positive(negative) are shown.
2. Financial variables are the monthly volatility of KOSPI, KRW/USD, S&P, NIKKEI, HANGSENG.
3. Macro economic indexes are monthly Current account(Crt.at), Capital and financial account(C&F.at), Inflation rate(Inf.), Unemployment rate(Nepl), and Base interest rate(B.int).
4. Trader
IND = Individual trader, BANK = Bank, FI = Financial investment, CIS = Collective Investment Scheme, OTH = others, INS = Insurance companies, GOV = Government, FOR = Foreign investment
5. Market
su = stock, sd = Stock derivative, bu = Bond, bd = Bond derivative, fxd = FX derivative

The response of traders to the shock of financial variables are divided. Some traders gain more sensitivity such as individual investors (IND) in the bond market, government (GOV) in the stock market, and collective investment schemes (CIS) in the FX derivative market. Others including collective investment schemes (CIS) and foreign investors (FOR) in the stock market, in contrast, lose their sensitivity but trade more independently when the financial markets turn to volatile periods. This can be seen as evidence that foreign investors and institutional investors are superior in terms of investment information compared with individual traders.

In case of the shock of macro variables, it is not easy to find evident patterns. The three most sensitive traders, however, are same at the point of a shock of the current account and the capital and financial account.

The result of the monthly impulse response analysis provides a preliminary understanding of the relations of financial/macro variables and traders' connectedness measures. The reactions of traders' connectedness measures to financial and macro variables seem somewhat different. Even among financial variables, the responses of connectedness measures at the point of the shock of domestic and foreign indexes differ. The reactions to foreign indexes and currency rates, however, seem similar. In the case of macro variables, the reactions of connectedness measures to the shock of balance of payments seem similar. Yet, other reactions do not seem similar. The relations of the specific financial / macro variables and traders' connectedness measures can be studied in greater depth.

In spite of these findings, there is still some rooms for more development. First, the feature of network change cannot be explained sufficiently using monthly data. The influence of connectedness measures to real daily net trading volumes also cannot be described with the result given above. Therefore, an investigation with daily data and a wider scope, is done in next section.

6 Market volatility spillover channels with daily results

In this section, a daily network structure estimation and impulse response analysis are implemented in a similar fashion to the monthly analysis. The analysis with a daily framework has a few benefits when compared to the monthly analysis. Firstly, due to the data frequency, more dynamic changes of network structures including some findings which can be ignored with the monthly analysis framework, can be identified. Secondly, traders' actual trading can be linked with the volatility of financial indexes and traders' connectedness measures in the analysis. This feature enables the investigation of traders' connectedness measures as a spillover channel of the financial market volatility. With three consecutive impulse response functions, I model and analyse three phased market volatility spillover frameworks.

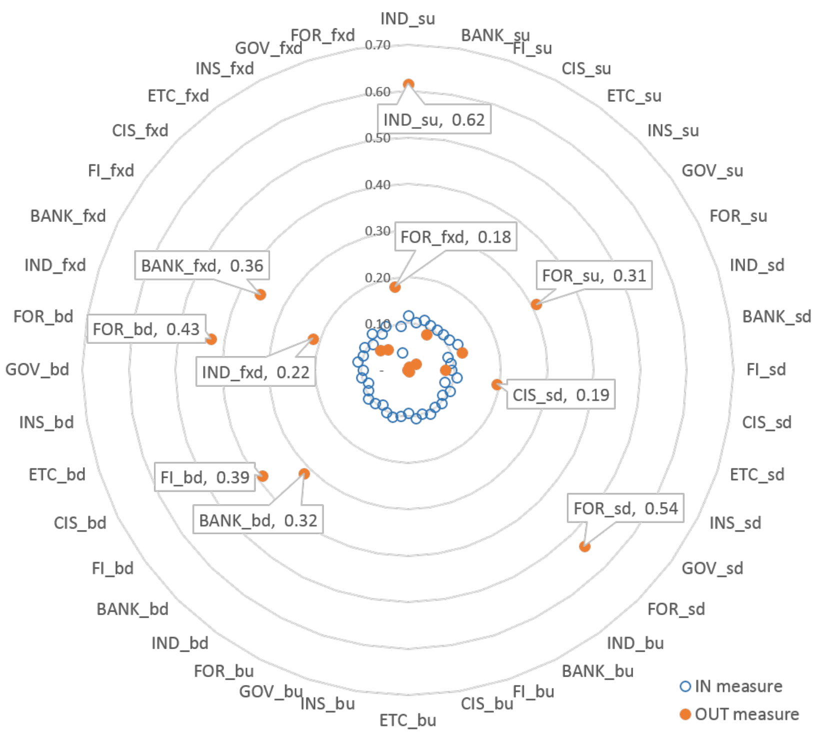
6.1 Network structure with expectation forecast

The daily network estimation result appears almost the same as the monthly result. Several influential traders with higher OUT connectedness measures are found, and all traders' IN connectedness measures are similarly low.

An important finding is that influential traders under a daily setup are almost the same as the influential traders under a monthly setup. The only difference is that collective investment schemes (CIS) in the stock derivative market are added to monthly influential traders.

This result also provides evidence of the existence of influential traders in capital markets, which can be considered to be stronger evidence due to the more frequent setup. The consistency of the result makes the monthly result more reliable at the same time.

Figure 2: Average daily OUT/IN connectedness measures



[Notes]

1. Traders' daily OUT and IN measures are averaged during the investigated period.
2. OUT degree is orange circle and IN degree is white circle.
3. Trader

IND = Individual trader, BANK = Bank, FI = Financial investment(securities companies)
CIS = Collective Investment Scheme, OTH = others (small financial companies)
INS = Insurance companies, GOV = Government, FOR = Foreign investment

4. Market

su = Stock, *sd* = Stock derivative, *bu* = Bond, *bd* = Bond derivative, *fxd* = FX derivative

6.2 Market volatility spillover channels

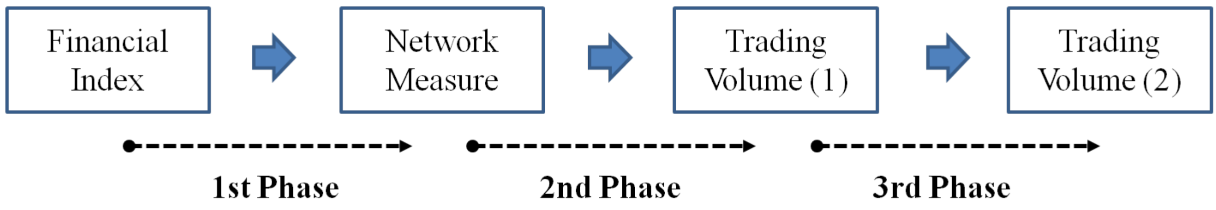
The spillover of financial market volatility throughout traders' connectedness measures and trading activities is investigated in this section. One of the main benefits of network studies in finance is to assess systemic risk, which is not the risk on a single entity or a contract, but the risk on the entire system or the market. In addition, the spillover of the risk can be assessed using the method of network studies, if there is a certain type of risk in the entire system. The inter-linkage between the agents in the system can function as a map when the risk spills over within the system. The inter-connections among traders are investigated to see if they can play a role as a volatility spillover channel.

6.3 Framework

Financial market volatility spillover channels are investigated with three-phased framework which includes financial indexes, traders' connectedness measures and daily net trading volumes. The first phase is from financial market indexes to traders' connectedness (network) measures as in Figure 3. If there is an abnormal shock in five different financial indexes respectively, the reactions of traders' connectedness measures are observed. Here I use the OUT connectedness (network) measure, since it captures a trader's influence on others. Given the stressed situations involved, some traders become central within the network in the capital markets. The second phase is from traders' connectedness measures to their daily net trading volumes. If a trader becomes central within the network, some traders' trading behaviours are more sensitive to the shock on the connectedness measure of the central trader. The last phase is from traders' daily net trading volumes to traders' daily net trading volumes. Traders react differently to changes in the net trading volumes of other traders. In particular, there would be some specific patterns of reactions to a certain shock of daily net trading volumes.

I focus on the most sensitive three connectedness measures and traders' net trading volumes for the sake of simplicity of analysis at the second and third phases. For example, if there is an unexpected shock in KOSPI, the most sensitive three connectedness measures are investigated. And then given the shocks on those connectedness measures, the three traders with the greatest responses are identified. In the same fashion, under the shock of the daily net trading volumes of these top three traders, the net trading volumes of three most sensitive traders are also investigated.

Figure 3: 3 phased market volatility spillover structure



6.4 Result of 1st phase

Evidently, the responses of connectedness measures in the first phase are almost same regardless of the source of shock, as seen in Table 6. The three most sensitive connectedness measures to all financial indexes are individual investors (IND) in the stock market, collective investment schemes (CIS) in the FX derivative market and collective investment schemes (CIS) in the stock market. This means that when there is an unexpected increase in financial indexes, those three trader's connectedness measures increase. The result is also consistent with common sense in capital markets. Individual investors (IND) are usually overly sensitive to movement in the market index and mutual funds (CIS) also move together with the index in general.

In terms of negative responses, the reactions of traders' connectedness measures seem comparable to positive responses. The most sensitive negative responses at the shocks in five financial indexes are almost the same. The exception is that BANK in the FX derivative market replaces foreign investors (FOR) in the stock market at the point of the shock in the NIKKEI. The three top negative reactions are found in foreign investors

Table 6: Connectedness measure changes at the shock of financial indexes

		Shock at the financial market volatility				
		Kospi	Krw/usd	S&P	Nikkei	Hangseng
Positive	1st	IND_{su}	CIS_{fxd}	CIS_{fxd}	CIS_{fxd}	CIS_{fxd}
	2nd	CIS_{fxd}	IND_{su}	IND_{su}	IND_{su}	IND_{su}
	3rd	CIS_{su}	CIS_{su}	CIS_{su}	CIS_{su}	CIS_{su}
Negative	1st	FOR_{bd}	FOR_{bd}	FOR_{bd}	FOR_{bd}	IND_{fxd}
	2nd	IND_{fxd}	IND_{fxd}	IND_{fxd}	IND_{fxd}	FOR_{bd}
	3rd	FOR_{su}	FOR_{su}	FOR_{su}	$BANK_{fxd}$	FOR_{su}

[Note]
1. Top 3 positive(negative) responses of traders' OUT connectedness measure at financial variable's shock.
2. Financial variables are the daily volatility of KOSPI, KRW/USD, S&P, NIKKEI, and HANGSENG.
3. Trader
IND = Individual trader, BANK = Bank, FI = Financial investment, CIS = Collective Investment Scheme, OTH = others, INS = Insurance companies, GOV = Government, FOR = Foreign investment
4. Market
su = stock, *sd* = Stock derivative, *bu* = Bond, *bd* = Bond derivative, *fxd* = FX derivative

(FOR) in the bond derivative market, individual investors (IND) in the FX derivative market, and foreign investors (FOR) in the stock market.

The implication is that market participants do not refer to their expectations on foreign investors' trading in the bond derivative and stock markets when the market is volatile. This result supports the findings of previous literature (Hwang, 2018*a*,*b*), which are that foreign investors lose their influence during crisis times and trade independently. Thus, the common conception which says that foreign investors destabilize financial markets during crisis, needs to be reconsidered and the excessive concern of the media about the exit of foreign investors during crisis seems to lack evidence.

6.5 Result of the second phase

The daily net trading volumes of the three most sensitive traders in second phase at the point of shock of influential traders' connectedness measures can be found in diverse markets, which means that financial market volatility can spill over into different markets through central traders, as seen in Table 7. I assume there is a positive shock at the top three positive reactive traders and a negative shock at the top three negatively responsive

Table 7: Trading volume changes at the shock of OUT connectedness measure

		Shock at traders' connectedness measures					
		Positive Shock			Negative Shock		
		IND_{su}	CIS_{fxd}	CIS_{su}	FOR_{bd}	IND_{fxd}	FOR_{su}
Positive	1st	CIS_{fxd}	$BANK_{fxd}$	FOR_{bd}	IND_{su}	$BANK_{fxd}$	CIS_{su}
	2nd	$BANK_{bu}$	FOR_{su}	$BANK_{bu}$	CIS_{sd}	IND_{su}	CIS_{fxd}
	3rd	FI_{bd}	FI_{su}	IND_{su}	FI_{fxd}	CIS_{sd}	FOR_{fxd}
Negative	1st	$BANK_{fxd}$	CIS_{su}	CIS_{su}	FOR_{su}	FOR_{su}	FOR_{su}
	2nd	INS_{bu}	CIS_{fxd}	INS_{bu}	IND_{sd}	FOR_{fxd}	$BANK_{fxd}$
	3rd	FI_{fxd}	GOV_{su}	$BANK_{bd}$	IND_{fxd}	IND_{fxd}	FOR_{bu}

[Note]
1. Top 3 positive(negative) responses of traders' daily net trading at shock of OUT connectedness measure .
2. The most responsive traders are 6 traders at table 6.
- positive (negative) shock is given to positively (negatively) responsive trader.
3. Trader
IND = Individual trader, BANK = Bank, FI = Financial investment, CIS = Collective Investment Scheme, OTH = others, INS = Insurance companies, GOV = Government, FOR = Foreign investment
4. Market
su = stock, *sd* = Stock derivative, *bu* = Bond, *bd* = Bond derivative, *fxd* = FX derivative

traders in phase one. For instance, when the shock was given at the connectedness measure of individual investors (IND) in the stock market, the traders in the FX derivative, bond, and bond derivative markets react more actively.

In addition, two interesting phenomena are found at the positive shock. One is that Collective investment schemes (CIS) and BANKs in the FX derivative market respond in opposite directions. CIS have a positive response and BANKs have a negative reaction at the point of shock on individual investors (IND) in the stock market, while at the point of the shock on CIS in the FX derivative market, BANKs are shown to respond positively and CIS are observed to react negatively. The other is that, when there is a positive shock in CIS in the FX derivative or stock markets, their daily net trading volumes react negatively. This means that mutual funds reduce their position when their influence on a capital market increases.

Market volatility spillover to diverse markets is also observed in the case of negative shock on traders' connectedness measures. The shock in the bond derivative market can be spread to the stock, stock derivative, and FX derivative markets. The responses of foreign investors (FOR) to a negative shock need to be discussed more extensively in particular. First, when there is a negative shock in the connectedness measure in foreign investors (FOR) in the bond derivative and stock markets, and individual investors (IND) in the FX derivative market respectively, foreign investors in the stock market sell. This means that, when there is an event such as an increase in financial market volatility, foreign investors' may sell their stocks while their connectedness measures in each financial market decrease at the same time.

Strong co-movements of foreign investors (FOR) in different markets, then, are found in addition. Given the shock on individual investors (IND) in the FX derivative market, foreign investors (FOR) in the stock and FX derivative markets decrease their net trading volumes. And in the case of the shock on foreign investors (FOR) in the stock market, and foreign investors (FOR) in the stock and bond markets sell their securities as well.

6.6 Result of the third phase

In third phase strong evidence of "auto correlation"[16] are found, which means that the most sensitive response is same as the origin of the shock, regardless of whether the shock is positive or negative. (Table 8) Once a shock is given to the daily net trading volumes of most sensitive traders in the second phase, the first positive responses of the positive shocks are found in CIS in the FX derivative market, BANK in the FX derivative market and FOR in the bond derivative market.

The trader who responds sensitively to the shock of his/her own trading can be interpreted as having a similar trading pattern on the following day, since in the third phase the responses and the shocks are the daily net trading volumes of the traders.

Auto correlation is also found at the point at a negative shock. The negative reactions to the negative shock in FOR in the stock market and BANK in the FX derivative market

[16]It could be slightly different from the precise definition of autocorrelation. However, the phenomena, which the same trader has shown the biggest reaction at his trading shock, can be observed evidently. Thus, I call this as autocorrelation.

Table 8: Trading volume change at the shock of trading volume change

		Shock at traders' daily net trading volume					
		Positive Shock			Negative Shock		
		CIS_{fxd}	$BANK_{fxd}$	FOR_{bd}	FOR_{su}	FOR_{fxd}	$BANK_{fxd}$
Positive	1st	CIS_{fxd}	$BANK_{fxd}$	FOR_{bd}	CIS_{su}	FOR_{su}	CIS_{fxd}
	2nd	IND_{su}	FOR_{su}	FOR_{sd}	IND_{su}	FOR_{fxd}	FI_{fxd}
	3rd	CIS_{sd}	FOR_{bd}	$BANK_{fxd}$	CIS_{sd}	FI_{bd}	$BANK_{bd}$
Negative	1st	$BANK_{fxd}$	CIS_{fxd}	$BANK_{bd}$	FOR_{su}	FI_{fxd}	$BANK_{fxd}$
	2nd	FOR_{su}	FI_{fxd}	FI_{bd}	$BANK_{fxd}$	IND_{su}	FOR_{su}
	3rd	IND_{sd}	$BANK_{bd}$	FOR_{su}	IND_{sd}	CIS_{su}	FI_{bd}

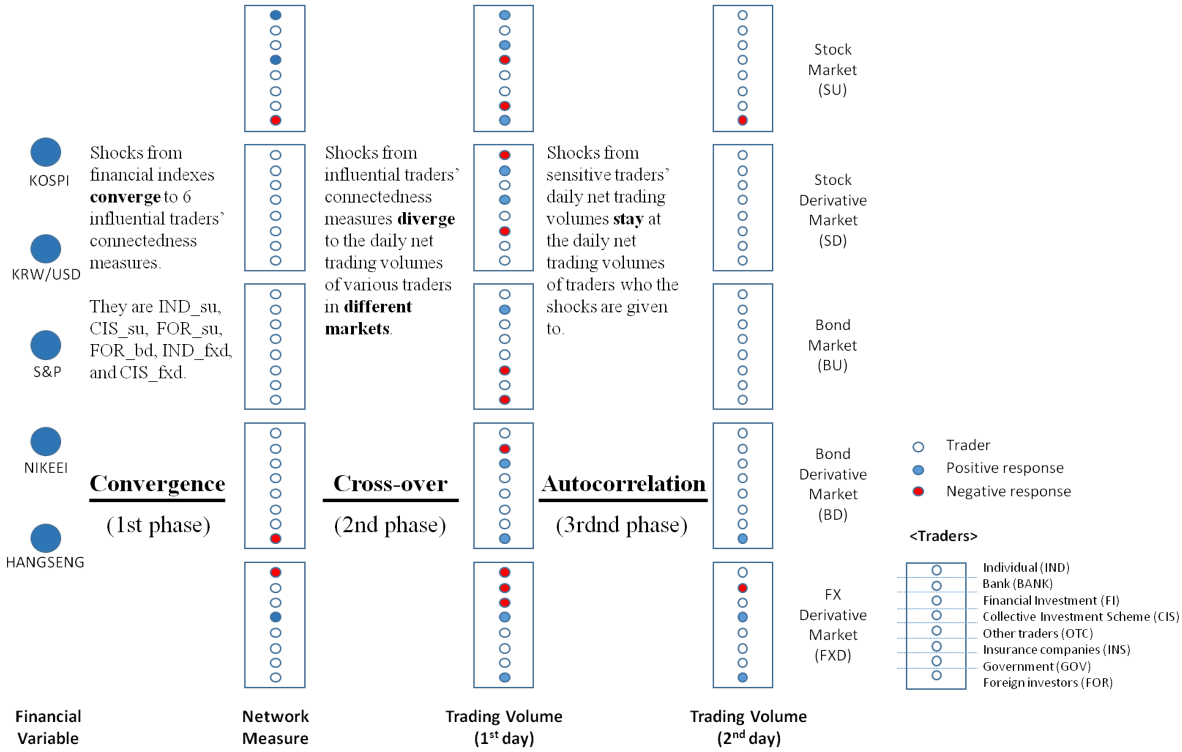
[Note]
1. Top 3 positive(negative) responses of traders' daily net trading at shock of trader's daily net trading.
2. The most responsive traders are 6 traders at table 7.
- positive (negative) shock is given to positively (negatively) responsive trader.
3. Trader
IND = Individual trader, BANK = Bank, FI = Financial investment, CIS = Collective Investment Scheme, OTH = others, INS = Insurance companies, GOV = Government, FOR = Foreign investment
4. Market
su = stock, sd = Stock derivative, bu = Bond, bd = Bond derivative, fxd = FX derivative

are FOR in the stock market and bank in the FX derivative market. However, the auto correlation is not found in the net trading volume of FOR in the FX derivative market, but instead FOR in the FX derivative market trade more given the negative shock of FOR in the FX derivative market. IND and CIS in stock market reduce their net trading volume under the negative shock of FOR in the FX derivative market, while they increase their net trading volume when FOR in the stock market trades less.

6.7 Discussion

Combining the results above within one picture as in Figure 4 market volatility spillover structures can be identified. More detailed results are presented in Figures 5 to 10. Firstly, the increase in market volatility which originated from five different financial indexes converges into six traders' connectedness measures in the first phase. The shock which converged into six influential traders diverges to the daily net trading volumes in different markets in the second phase. Then, the shock from sensitive traders in various markets consequently remains in the trader to whom the shock is given in the third phase.

Figure 4: Result of analysis on 3 phased market volatility spillover channels



The results above suggest the existence of certain routes of market volatility spillover channels and the functions of financial traders' network measures and trading activity as market volatility spillover channels. As the market volatility shock is given, some influential traders' connectedness measures respond more actively than those of other traders. These phenomena can be interpreted as a result of changes in traders' expectations which reflect all traders' past experiences and expectations for the future, as the result of impulse response analyses is acquired through the simulation approach for a random future with the expectation values forecasted using machine learning technology.

The change in traders' connectedness measures during market turbulence can be seen as change of interactions among traders. Some traders who acquire more influence can lead the trend of trading or herding behaviours, while others who lose influence trade independently. The increase in influence of mutual funds and individual traders may show that their trading behaviours are sensitive and closely linked to a change in external environment regardless of the kind of market. This also reflects all other traders' expectations. In addition, their increase in influence can lead to herding behaviours in local traders, if other traders trade similarly with those influential traders. However, the loss of influence among foreign investors is notable, since it contrasts with the common conception, which says that foreign investors have a tremendous impact on local traders during periods of market turbulence. This phenomenon may be caused by their information superiority. They can sell earlier with more information about the global market than local traders. When the local traders sell with fear of incurring losses, foreign investors can buy at low prices. The opposite case also applies. Individual traders in the FX derivative market need to be seen from a different point of view in the stock market. Individual traders seem not to trade aggressively in the FX derivative market unlike in the stock market, since they may incur more losses in the derivative market than in the stock market and the attributes of individual traders in the FX derivative market may differ from their attributes in the stock market.

The lesson of the second phase is that the sudden shock of influential traders' connectedness measures is contagious to the different financial markets. In this process some traders sell and others buy abnormally, which activity originates from the shock of influential traders' connectedness measures. The traders' network structure is shown to function as a channel of the shock contagion and to impact on real trading behaviours. The result of second phase enlarges the understanding of the mechanism in capital markets. When at sudden shock is given to traders' connectedness measures, the most responsive traders are found in all of the different markets, not only the market in which the shock occurred. This seems reasonable since the price of financial derivative products reflects the change of underlying asset price. Thus, the traders in derivative markets need to be aware of the influential traders in the underlying asset market (stock or bond). This result also suggests the information of the bridge which links different financial markets.

A particular pattern is found on closer examination. The sensitive traders are found in the stock (and/or stock derivative), bond (and/or bond derivative) markets, or in combination with the FX derivative market and one of those. No case is found in combination of stock (and/or stock derivative) and bond (and/or bond derivative) markets. This division of stock and bond markets reflects that the possibility that the rationale of trading in each market differs and the traders behave differently. In the stock market, company profits is an essential piece of information, but in the bond market the credit risk of a company or country are more important factors. In addition, the link between stock (or bond) and FX can be understood with the currency hedging of mutual funds and arbitrage transactions of foreign investors. Mutual funds which invest in foreign assets normally have currency hedging transactions with FX derivatives. In the event that there is an increase in the influence of mutual fund, traders in the stock market can be sensitive to them, and traders in the FX derivative market may also react to them sensitively. In this fashion, the currency hedging of mutual funds can link the stock (or stock derivative) and FX derivative markets.

The link between the bond (or bond derivative) and FX derivative markets can be explained using arbitrage transactions. The investors who can the finance foreign currency denominated fund cheaply can have earn arbitrage profits from the combination of swap and bond investments. If a trader borrows foreign currency with interest rate (r_f), he can change that into local currency with an FX swap and invest in local bond, which pay interest rate (r_d). If the interest rate difference (r_d-r_f) is larger than the swap rate, which is the difference between the forward currency rate and the spot currency rate, the trader can earn an arbitrage profit. If traders (mainly foreign investors) actively participate in arbitrage transactions and have a sudden change of influence on other traders, then some traders in the bond (or bond derivative) or FX derivative markets respond sensitively.

Finally at the third phase, the shock seems to continue to reside in the same trader. This phenomenon can be interpreted as follows: the trader influenced by the market volatility shock through influential traders is likely to continue to be impacted in their trading. It shows that the external market volatility shock can impact on influential traders, and consequently also impact on the sensitive traders for longer periods. In other words, the sensitive traders trade abnormally for more than a day when they have information on market turbulence combined with their expectations about the behaviour of influential traders. Their serially correlated trading can be seen as the behaviour reflecting the impact of market shock and a trader's influence shock as investment information. A few previous studies on informed traders and the serial correlation of their trading behaviours (Kelly and Steigerwald, 2001; Chung et al., 2005) supports this result. They showed that informed traders in the US stock market generated serial correlations in their trading. Combining all these results, the six most responsive market volatility channels are found. As the shock on market volatility is given, traders' expectations of other traders' trading behaviours changes. Those changes give rise to the changes of traders' network structures. Given the sudden change in the influence of a few traders to other traders, the shock of market volatility can spread to different financial markets. Here the linkages between the stock (or stock derivative) and FX derivative, and between the bond (or bond derivative) and FX derivative markets are found. At the point of trading shock of sensitive traders, same traders are shown to have an impact for more than a day.

Several important implications to financial policy makers or financial regulators can also be provided. Given the results of traders' connectedness measures and their trading activity, the financial market stabilization policy can be introduced with a trader-tailored form rather than a comprehensive measure. For instance, instead of making market-wide emergency policies, the temporary trading restriction on collective investment scheme, individual investors or foreign investors can be considered. If the market turbulence is severe, a kind of tax rate increase for mutual funds investors, which can reduce the influence of mutual funds can also be considered. For the longer term, the effort of reducing investment information imbalances between foreign investors and local investors needs to be made. Then, monitoring the sensitive traders' trading behaviours which can be observed at the third stage in this paper can be adopted. For if the expectation on influential traders' behaviours changes due to the policy, the sensitive traders such as foreign investors in the stock and stock derivative markets, and banks and mutual funds in the FX derivative market would trade differently. These changes can show the effectiveness of the market stabilization policy.

After Global Financial Crisis and European Fiscal Crisis, Korean government gave a counter incentive to foreign investors to invest in the Korean bond market when excessive funds flowed into Korea, while it waived the interest income tax for foreign investors to invest in the bond market when the funds flowed out. The measure was effective in stabilizing the FX market and treasury bond markets during crisis and into maintaining confidence among market participants all over the world. However, there was no approach allowing a broader view to see the market combining derivative markets and other influential traders. If those policy suggestions above were implemented concurrently, market stabilization might have been shown more effectively and efficiently.

Finally the result of this study give rise to implication for financial product professionals. The demand for development of financial products which combine stocks (and/or stock derivatives) and FX derivatives, or bonds (and/or bond derivatives) and FX derivatives, is found. Although the markets are interlinked through the traders, the investors need to find the financial products separately in different markets to meet their needs including currency hedging and arbitrage trading. Thus, the combined financial products, such as FX and bonds or FX and stocks, can reduce investors' search costs and meet their needs efficiently.

7 Conclusion

In this paper I estimate traders' network structures with both monthly and daily analysis frameworks. In order to avoid excessively restrictive econometric assumptions and to reflect actual trading decision making processes, an expectation forecast which is estimated using one of the machine learning techniques, LSTM (Long short term memory), is applied. Network structures are analysed with the connectedness measures. Then, the relations between financial (macro economic) variables, traders' connectedness measures and traders' daily net trading volumes are also investigated with a nonlinear impulse response analysis. In particular, traders' connectedness measures and their daily net trading volumes are examined to determine whether they play a role as market volatility spillover channels under a daily analysis framework.

A few traders such as foreign investors and individual investors are shown to have a strong influence on other traders in particular. This phenomenon is found under both monthly and daily frameworks and the influential traders under each framework are almost the same. Those results are consistent with the previous literature.

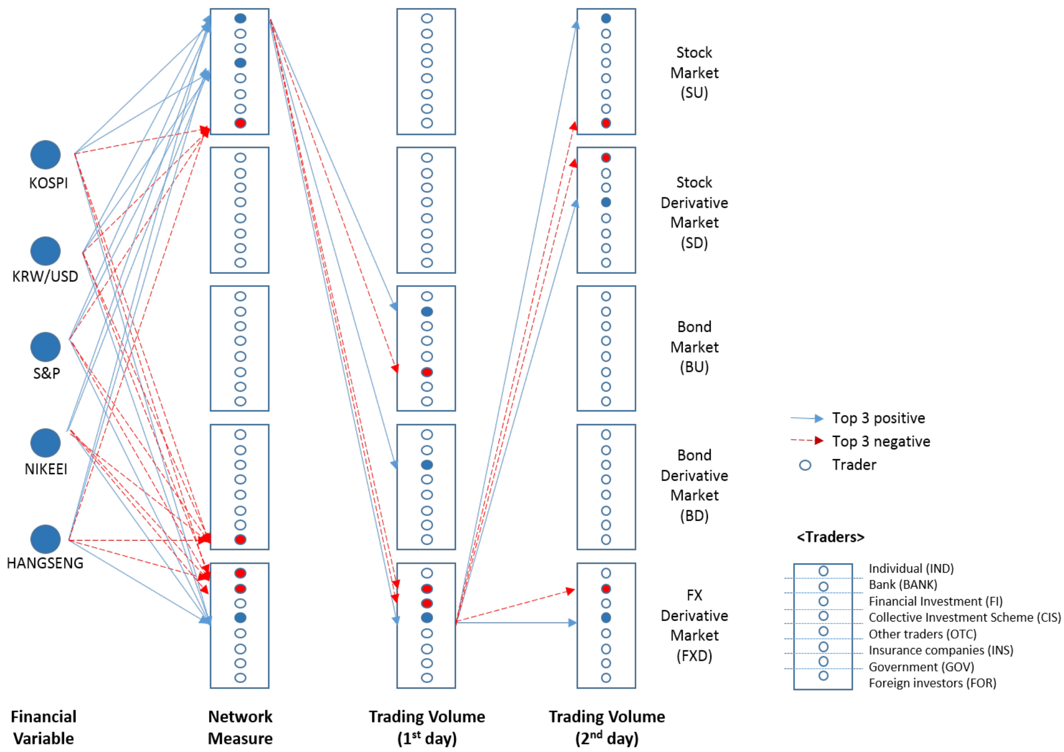
Traders' specific trading patterns at the shock of financial markets are identified with a monthly analysis framework. Some traders including banks in the FX derivative market are found to be more influential at the point of a shock in the foreign exchange market and international financial markets. In contrast, other traders such as foreign investors in the stock derivative market lose their influence but instead trade more independently in response to the same shock. It is reaffirmed in this paper that the over-concern about exits of foreign investors from local financial markets lacks reasonable evidence.

Finally, traders' connectedness measures are shown to function as market volatility spillover channels based on the result of three-phased impulse response analysis framework. Regardless of the kind of financial markets, three specific traders' connectedness measures are found to have the most sensitive responses at the point of the shock of a financial market. At the point of a shock of one of three traders' connectedness measures, the sensitive traders' trading volumes disperse to different markets. Then, strong autocorrelation is found at the point of shock of the most sensitive traders' trading volumes.

This paper has a number of contributions to previous research and policy makers including financial regulators. Firstly, a methodology reflecting actual trading decision making processes is used to estimate a network structure in capital markets. Utilising the network structures, I enlarge the understanding of relations among traders and further investigate market volatility spillover channels in capital markets. The inter-relations among financial indexes, network measures and net trading volumes of traders can provide implications for policy makers and financial regulators to enact a new regulations.

There are still a number of further research topics. Enhancement of forecasting precision with newly developed machine learning techniques is possible, as machine learning is one of the most actively studied areas recently. More in-depth research on market volatility spillover structures could be carried out. The reverse impulse relationship between net trading volumes, network measures, and financial indexes is also a possible example.

Figure 5: Market volatility spillover structure from IND in stock market



[Notes]

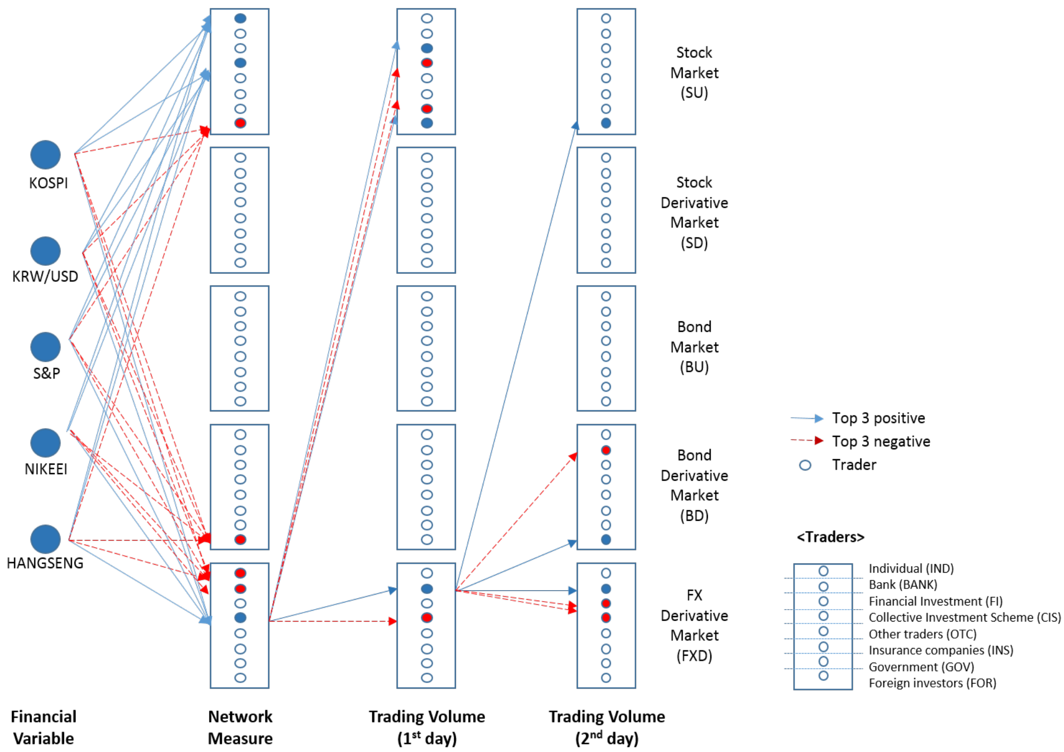
3-phased market volatility spillover channel is present. Since 6 traders are shown the most responsive at the shock of financial variables regardless of the kind of financial variables, the spillover channel which is originated from individual traders in stock market at 2nd phase, is shown.

(**1st phase**)
Impulse : A positive shock on KOSPI, KRW/USD, S&P, NIKKEI, HANGSENG
Response :
Top 3 positive to IND_su, CIS_su and CIS_fxd
Top 3 negative to FOR_su, FOR_bd, IND_fxd

(**2nd phase**)
Impulse : A positive shock on the daily connectedness measure of IND_su
Response :
Top 3 positive to BANK_bu, FI_bd, CIS_fxd
Top 3 negative to INS_bu, BANK_fxd, FI_fxd

(**3rd phase**)
Impulse : A positive shock on the daily net trading volume of CIS_fxd
Response :
Top 3 positive to IND_su, CIS_sd, CIS_fxd
Top 3 negative to FOR_su, IND_sd, BANK_fxd

Figure 6: Market volatility spillover structure from CIS in FX derivative market



[Notes]

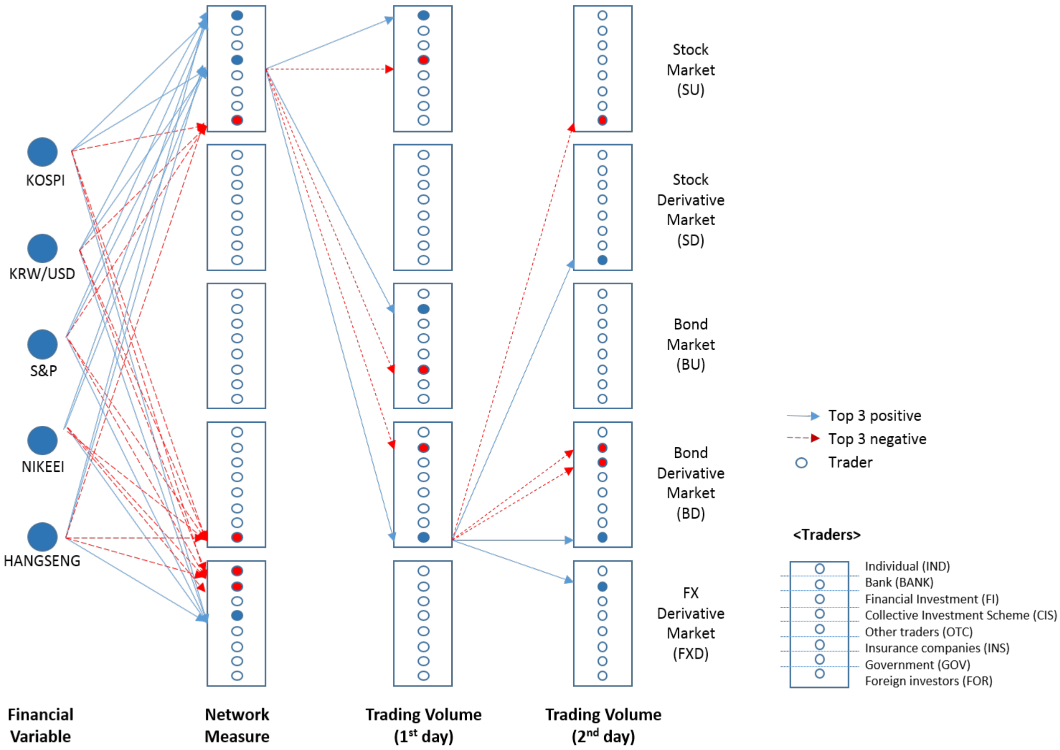
3-phased market volatility spillover channel is present. Since 6 traders are shown the most responsive at the shock of financial variables regardless of the kind of financial variables, the spillover channel which is originated from collective investment scheme in FX derivative market at 2nd phase, is shown.

(**1st phase**)
Impulse : A positive shock on KOSPI, KRW/USD, S&P, NIKKEI, HANGSENG
Response :
Top 3 positive to IND_su, CIS_su and CIS_fxd
Top 3 negative to FOR_su, FOR_bd, IND_fxd

(**2nd phase**)
Impulse : A positive shock on the daily connectedness measure of CIS_fxd
Response :
Top 3 positive to FI_su, FOR_su, BANK_fxd
Top 3 negative to CIS_su, GOV_su, CIS_fxd

(**3rd phase**)
Impulse : A positive shock on the daily net trading volume of BANK_fxd
Response :
Top 3 positive to IND_su, FOR_bd, BANK_fxd
Top 3 negative to BANK_bd, FI_fxd, CIS_fxd

Figure 7: System risk spillover structure from CIS in stock market



[Notes]

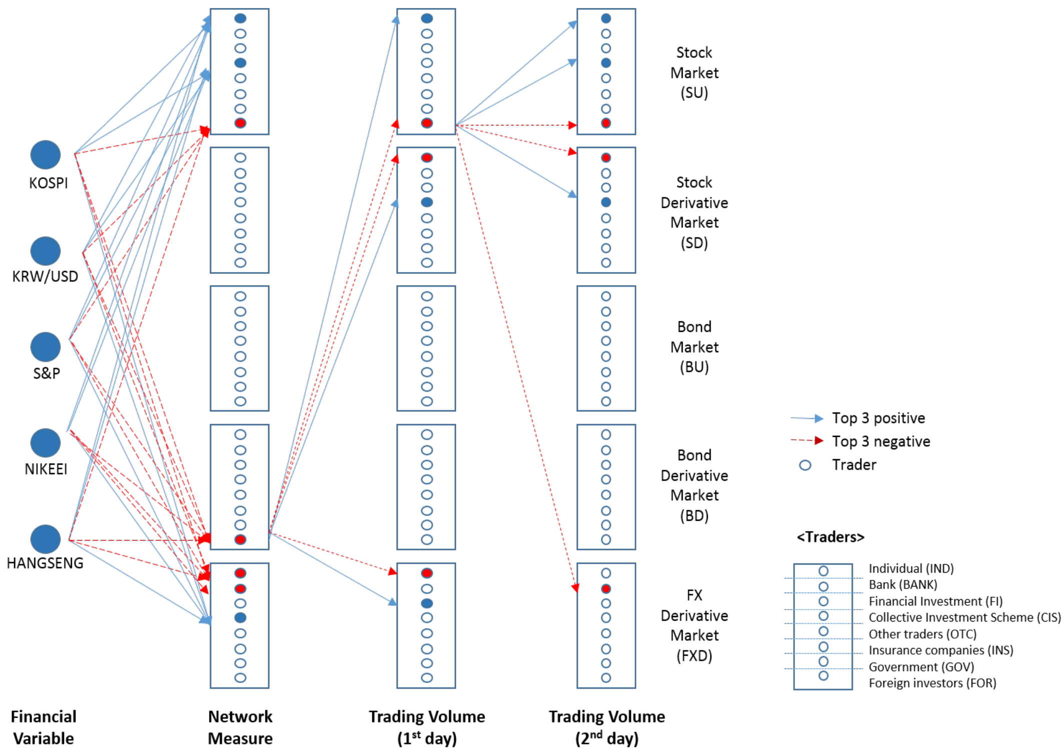
3-phased risk spillover channel is present. Since 6 traders are shown the most responsive at the shock of financial variables regardless of the kind of financial variables, the spillover channel which is originated from collective investment scheme in stock market at 2nd phase, is shown.

(**1st phase**)
Impulse : A positive shock on KOSPI, KRW/USD, S&P, NIKKEI, HANGSENG
Response :
Top 3 positive to IND_su, CIS_su and CIS_fxd
Top 3 negative to FOR_su, FOR_bd, IND_fxd

(**2nd phase**)
Impulse : A positive shock on the daily connectedness measure of CIS_su
Response :
Top 3 positive to IND_su, BANK_bu, FOR_bd
Top 3 negative to CIS_su, INS_bu, BANK_bd

(**3rd phase**)
Impulse : A positive shock on the daily net trading volume of FOR_sd
Response :
Top 3 positive to FOR_sd, FOR_bd, BANK_fxd
Top 3 negative to IND_su, BANK_bd, FI_bd

Figure 8: Market volatility spillover structure from FOR in bond derivative market



[Notes]

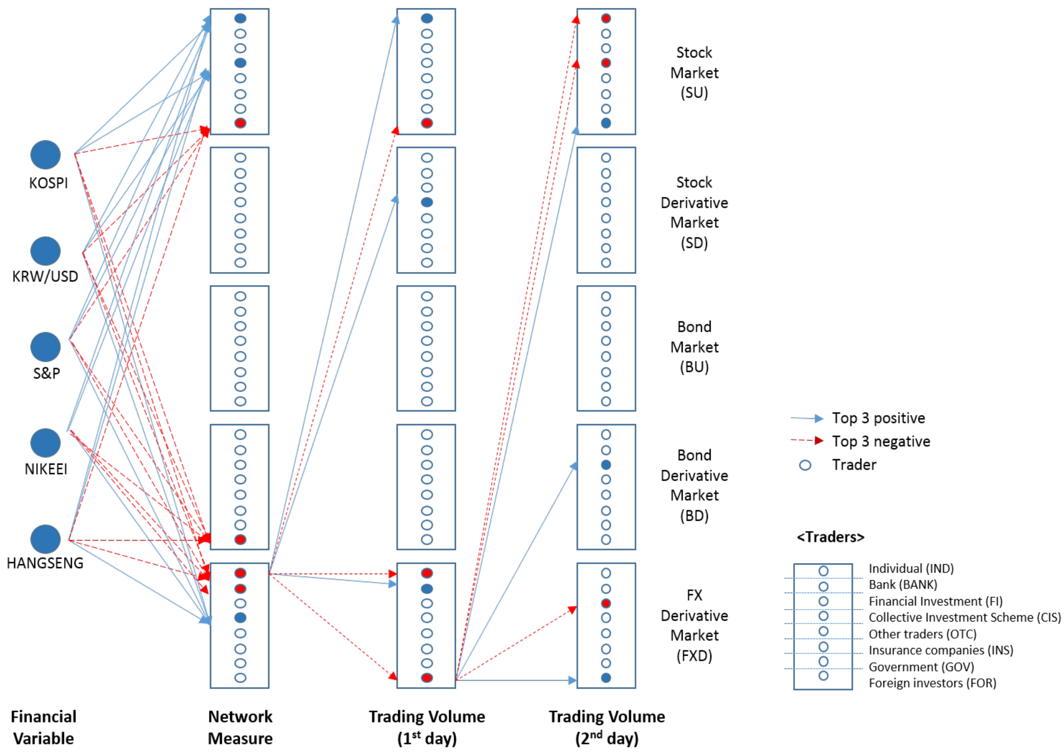
3-phased market volatility spillover channel is present. Since 6 traders are shown the most responsive at the shock of financial variables regardless of the kind of financial variables, the spillover channel which is originated from foreign investors in bond derivative market at 2nd phase, is shown.

(**1st phase**)
Impulse : A positive shock on KOSPI, KRW/USD, S&P, NIKKEI, HANGSENG
Response :
Top 3 positive to IND_su, CIS_su and CIS_fxd
Top 3 negative to FOR_su, FOR_bd, IND_fxd

(**2st phase**)
Impulse : A negative shock on the daily connectedness measure of FOR_bd
Response :
Top 3 positive to IND_su, CIS_sd, FI_fxd
Top 3 negative to FOR_su, IND_sd, IND_fxd

(**3rd phase**)
Impulse : A negative shock on the daily net trading volume of FOR_su
Response :
Top 3 positive to IND_su, CIS_su, CIS_sd
Top 3 negative to FOR_su, IND_sd, BANK_fxd

Figure 9: Market volatility spillover structure from IND in FX derivative market



[Notes]

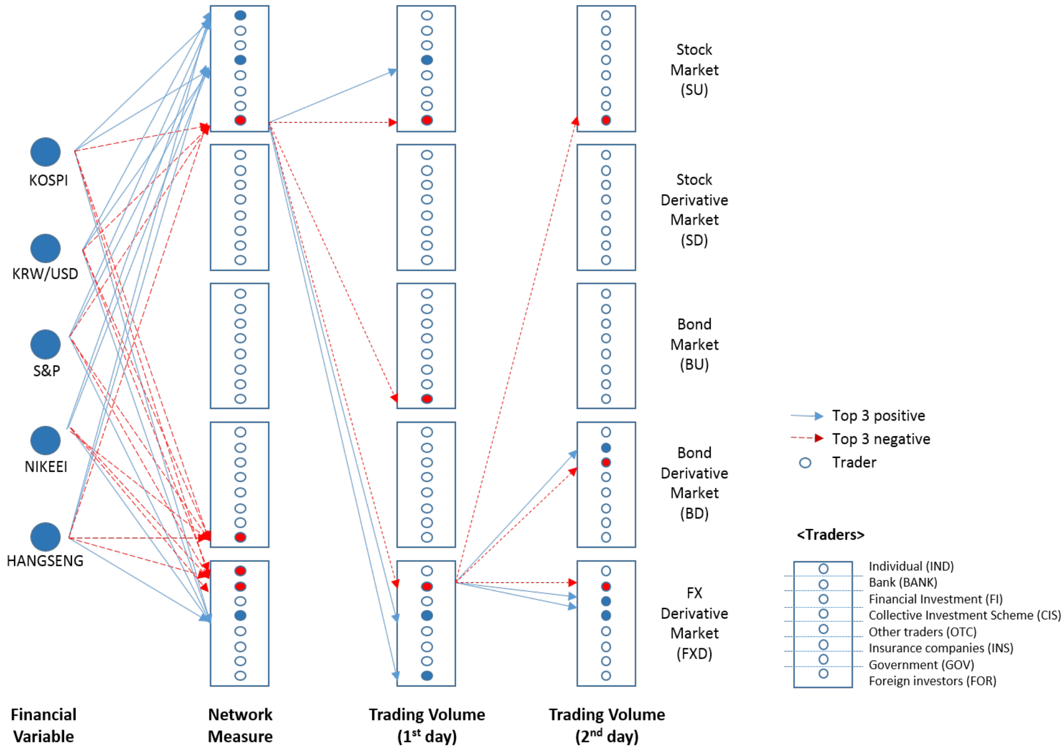
3-phased market volatility spillover channel is present. Since 6 traders are shown the most responsive at the shock of financial variables regardless of the kind of financial variables, the spillover channel which is originated from individual traders in FX derivative market at 2nd phase, is shown.

(**1st phase**)
Impulse : A positive shock on KOSPI, KRW/USD, S&P, NIKKEI, HANGSENG
Response :
Top 3 positive to IND_su, CIS_su and CIS_fxd
Top 3 negative to FOR_su, FOR_bd, IND_fxd

(**2nd phase**)
Impulse : A negative shock on the daily connectedness measure of IND_fxd
Response :
Top 3 positive to IND_su, CIS_sd, BANK_fxd
Top 3 negative to FOR_su, IND_fxd, FOR_fxd

(**3rd phase**)
Impulse : A negative shock on the daily net trading volume of FOR_fxd
Response :
Top 3 positive to FOR_su, FI_bd, FOR_fxd
Top 3 negative to IND_su, CIS_su, FI_fxd

Figure 10: Market volatility spillover structure from FOR in stock market



[Notes]

3-phased market volatility spillover channel is present. Since 6 traders are shown the most responsive at the shock of financial variables regardless of the kind of financial variables, the spillover channel which is originated from foreign investors in stock market at 2nd phase, is shown.

(**1st phase**)
Impulse : A positive shock on KOSPI, KRW/USD, S&P, NIKKEI, HANGSENG
Response :
Top 3 positive to IND_su, CIS_su and CIS_fxd
Top 3 negative to FOR_su, FOR_bd, IND_fxd

(**2nd phase**)
Impulse : A negative shock on the daily connectedness measure of FOR_su
Response :
Top 3 positive to CIS_su, CIS_fxd, FOR_fxd
Top 3 negative to FOR_su, FOR_bu, BANK_fxd

(**3rd phase**)
Impulse : A negative shock on the daily net trading volume of BANK_fxd
Response :
Top 3 positive to BANK_bd, FI_fxd, CIS_fxd
Top 3 negative to FOR_su, FI_bd, BANK_fxd

(Appendix A) Forecasting of traders' trading volume on next day

A.1. Objective

I forecast traders' expectations of the daily net trading volume of other traders on following day in order to overcome the restrictive assumption of traditional econometric methods and reflect the actual trading decision making processes. In traditional econometric models such as VAR (Vector autoregressive model), there is an inexplicit assumption, which is that the past determines the future. This assumption, however, is not valid in a dynamic financial market environment.

In addition, traders might have an expectation regarding an influential traders' trading on next day, if there is an influential trader in the financial markets. The relation of traders' expectation of a trader's trading on the following day and the daily net trading volume of other traders can be a clue to understanding traders' networks (inter-relations). In a real market, it is difficult to find those data. Thus as a proxy, I forecast the expected value of the daily net trading volume of a trader on following day. This is because the rational traders' with the public information can be forecasted.

To select the most appropriate method to forecast, three different methodologies, the traditional econometric model (ARMA/ARIMA), Artificial Neural Network (ANN) and Recurrent Neural Network (RNN), are applied in order to carry out the forecast. Three different results are compared with the measures popularly used in the previous literature. After the comparison, the method which performs best is used to forecast for further analysis.

A.2. Methodology

In this part detailed explanations of the three methods used to forecast are described. Following this, the forecasting framework is provided.

A.2.1 Econometric method

For a traditional econometric method, the ARMA/ARIMA model by Box and Jenkins is used. Much research tried to forecast financial time series such as stock prices or currency rates using this method. In order to use this method, the data should be stationary, which can be checked using ADF test. According to the results of ADF test, the daily net trading volumes of five foreign investors are all stationary. Although according to the traditional Box-Jenkins method a correlogram is used to identify the model, it is sometimes difficult to determine whether there is autocorrelation and partial correlation. Therefore, I repeatedly estimate models for foreign investors' daily net trading volumes in five different markets which are the stock, stock derivative, bond, bond derivative and FX derivative markets. Then I compare the results with the Akaike Information Criterion(AIC) and select the most appropriate model. After selecting the model and estimation parameter, a Q-test is implemented to check that the residuals are white noises. In addition, in order to see the daily change in the net trading volume of foreign investors, first differential data is also used for analysis. In this case the ARIMA model is used, while with level data the ARMA model is used.

A.2.2 Artificial Neural Network (ANN)

ANN is the computing system which operates in a similar way to biological neural networks. The smallest unit in ANN is a neuron. Neurons are organized as a set in layer. A simple form of neural network structure consists of input, hidden and output layers as shown in Figure 11. For the objectives of analysis more hidden layers can be added in the network. Neurons in each layer are connected to the neurons in other layers. What matters here is that the connection is only possible between neighbouring layers (e.g. between input and hidden and between hidden and output), and that the information flows unidirectionally from input to hidden and from hidden to output, which is called forward propagation. The connection between neurons can be represented mathematically with weight (ω), bias (b) and activation function (ϕ).

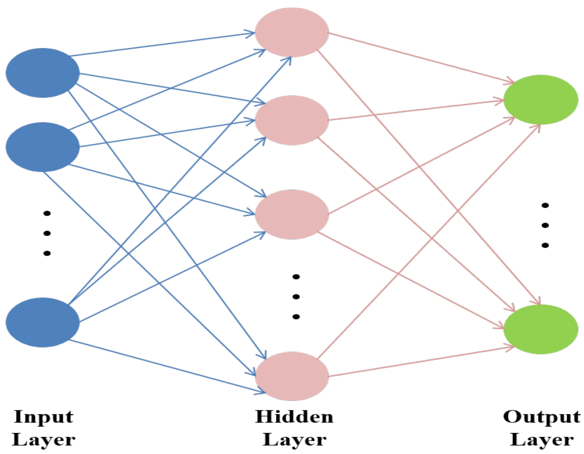


Figure 11: The structure of an artificial neural network

At first I denote x^i and y^i respectively with a sample of the entire dataset. In real forecasting, x^i is the vector of traders' net trading volumes and y^i is a certain trader's trading volume the following day. Here x ($x \in \mathbb{R}^n$) is the components of input layers and y is the value of output layer. y is a binary or trinary variable in the classification model, but in the regression model, it can be any value between -1 and 1. In order to obtain the value between -1 and 1 the data is generally normalized, but in this present paper all values of net trading volumes are within -1 and 1 already. Let z^m be the variables in the hidden layer. m can be determined by trial and error in practice. The relationship between x, y and z can be expressed as in the equations below.

$$z = \phi_1(x\omega_1 + b_1) \tag{16}$$

$$\hat{y} = \phi_2(z\omega_2 + b_2) \tag{17}$$

ω_1 and ω_2 are the weights and b_1 and b_2 are random numbers. ω_1 is n by m matrix and ω_2 is m by 1 matrix. ϕ is the activation function, which is able to tackle the nonlinearity of th edata. The most popular activation function is the sigmoid (logistic) function or hyperbolic tangent activation function. In the present paper, I use sigmoid as ϕ_1 and hyperbolic tangent activation function(tanh) as ϕ_2 , as the value of daily net trading volume is between -1 and 1.

$$\phi_1(x) = \frac{1}{1+e^{-x}} = sigmoid(x) \tag{18}$$

$$\phi_2(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} = tanh(x) \tag{19}$$

The core process of the artificial neural network is to find the most appropriate weight in the equation above. This process is called training the network. A loss function is essential to training. One of the most popular loss functions is mean squared errors as given below. K is the dimension of the output layer. Here the output layer is 1 and the total cost function is given below. The process to seek optimal weights is iterative and forward propagations is used to minimize loss function, which is called optimization. In this process the weights play important roles in forecasting an output accurately since it is continually adjusted to seek local minima place of loss functions as seen in the equation below.

$$J_i(W, x^i, y^i) = \frac{1}{2}\sum_{k=1}^{K}(\hat{y_k^i}) - y_k^i)^2 \tag{20}$$

$$J(W) = \frac{1}{S}\sum_{i=1}^{S} J_i(W, x^i, y^i) \tag{21}$$

where W is the vectors of weights (ω_1 and ω_2) and S is the number of total samples.

Many optimization methods have been introduced. The simplest one is gradient descent, which is the way to find local minima with the equation below. The weight is continually updated subtracting the multiplication of learning rate η which is also determined by trial and error and the gradient of loss functions. ω_2 is also calculated in the same fashion. For standard gradient descent, which is called batch gradient descent, the entire train set is used in this optimization process.

$$\omega_1^{(l)}(n+1) = \omega_1^{(l)}(n) - \eta\frac{\partial J(n)}{\partial \omega_1^{(l)}(n)} \tag{22}$$

In order to overcome this inefficient computation, Stochastic Gradient Descent (SGD) was developed. In the case of SGD, the weights are updated after each sample data as in the equation below. In this paper, Adam(A method for stochastic optimization) which is one of the variants of SGD is used. Instead of using constant learning rate in case of SGD, Adam computes the adaptive learning rate using first and second moment estimates of the gradients. Adam is now one of the most commonly used optimization methods (Sebastian Ruder, 2016).

$$\omega_1^{(l)}(n+1) = \omega_1^{(l)}(n) - \eta \frac{\partial J_i(n)}{\partial \omega_1^{(l)}(n)} \tag{23}$$

The last step of training is the calculation of the gradient. The gradients are calculated by chain rule, which was introduced by Rumelhart et al.(1986). This process, used to update weights, is called backpropagation. Unlike forward propagation, the adjustment process for a weight is implemented backwards. Using the partial derivative of loss function with respect to the weights, new weights of a hidden layer for the computation of the output layer can be computed. New weights of the input layer for the hidden layer are similarly calculated. The network can be trained through the iteration over forward propagation and backpropagation to minimize loss function.

To train a network, the initial values of weights are needed. Although for many cases, random numbers are used as initial weights, it sometimes cause a problem such as being stuck in local minima, which leads to a failure to find the minimum value of the loss function and finally poor learning. Much research has attempted to solve this problem. Recently normalized initialization which was suggested by Glorot and Bengio (2010) is one of the most commonly used. In this paper, normalized initialization is used.

The greatest drawback of machine learning is overfitting, which occurs when the result of the train set is accurate, but the result of the test set is not accurate enough. There are multiple ways to tackle overfitting. One of these is regularization with a regularization term in the loss function. This regularization term penalizes large weights. The loss function with the regularization term is given below. λ is the parameter, n and m are respectively the number of neurons in the input and hidden layers.

$$J_i(W, x^i, y^i)_{new} = J_i(W, x^i, y^i)_{old} + \frac{\lambda}{2}\Sigma_{j=1}^{n}\Sigma_{k=1}^{m}(\omega)^2 \tag{24}$$

Dropout is also a popular method of avoiding overfitting. This methodss is to drop some neurons randomly as training unfolds, which helps avoid being overly trained in a train set.

A.2.3 Recurrent Neural Network (RNN)

Recurrent Neural Network (RNN) is a kind of neural network technique with sequential information. Unlike normal multi-layer neural network, RNN uses the information of past input data. Long Short Term Memory (LSTM) is a variant of RNN which was introduced by Hochreiter and Schmidhuber (1997) and has been very commonly used since. As seen in Figure 12, LSTM has a particular structure resembling a chain and in an each module there are special tools which are called respectively forget gates, input gates and output gates.

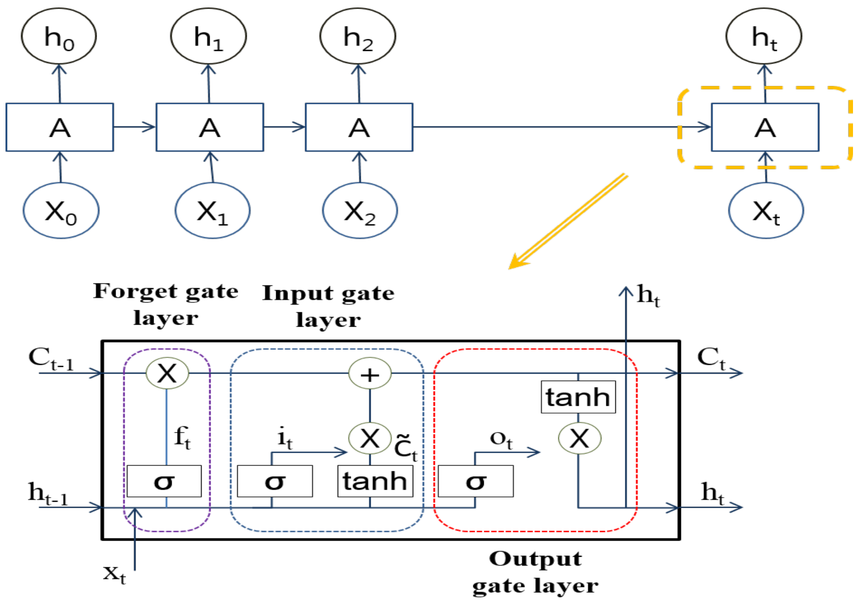


Figure 12: The structure of an LSTM

In LSTM cell state C_t and the horizontal line h_t have critical roles. As the forget gate manages the information from input vector x, the target value will be drawn. Firstly, the forget gate layer decides which information to forget, as seen in the equation. x_t is the input vector at time t, h_{t-1} is the output at time t-1, W_f is the weight vector, b_f is random vector, and σ is activation function, which is the sigmoid(logistic) function here. The Sigmoid function gives an output between 1 and 0 and the information of input vector x can be delivered to the cell state as the optimally required amount.

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{25}$$

Next, input gate layer i_t chooses which information is important and new candidate values $\widetilde{C}_t$ updates cell state C_t as shown in the following equation.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{26}$$

$$\widetilde{C}_t = tanh(W_C[h_{t-1}, x_t] + b_C) \tag{27}$$

$$C_t = f_t \times C_{t-1} + i_t \times \widetilde{C}_t \tag{28}$$

The final step is the output which is calculated using the multiplication of output layer o_t and hyperbolic tangent of new cell state C_t.

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{29}$$

$$h_t = o_t \times tanh(C_t) \tag{30}$$

Although training RNN seems very similar to ANN, there are a few points which should be considered. Firstly, RNN shares the weight parameters throughout all steps while multi-layer ANN estimates different values of weight parameters at each layer. Due to this attribute, in the backpropagation of RNN, the gradient at previous steps should be calculated, which is called Backpropagation Through Time (BPTT).

The training procedures including mean squared errors loss function, Adam optimization, and nomalized initializer are all the same as ANN.

A.2.4 Forecasting framework

To estimate the forecasting model, the data from 2006 to 2013 is used. In machine learning this period is commonly called the training period. The data from 2014 and 2015 is used to test the forecasting model.

For independent variables, which are input variables in machine learning methods, the net trading volumes of 40 traders from the previous day are used. The daily net trading volume of each type of investors in each market on next day is used as the dependent variable, which is the output variable in a machine learning method.

Firstly, the ARMA model is estimated. To enhance prediction power, the variables with statistically significant coefficients from the results of simple regression with 40 net trading volumes as independent variables, are included in the ARMA model estimation. Based on AIC (Akaike Information Criteria), the most appropriate model is selected for the net trading volume of each foreign investors. Although all variables are stationary, first differential data are analyzed in order to see the change in the daily net trading volumes of traders. For first differential data, the model selection procedure is the same as level data and the selected model is equivalent with the ARIMA model of level data.

For the sake of the objective of comparison, the input data for ANN and LSTM chosen are the same as the ARMA and ARIMA models.

A.3. Forecast results

A.3.1 Performance measure

To compare the forecasting power of each model, the values of most commonly used measures are calculated. These are RMSE, MAE, MAPE and NMSE.

- Root mean square error(RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{N}^{n=1}(x^n_{t+1} - \hat{x}^n_{t+1})^2} \tag{31}$$

- Mean absolute error (MAE)

$$MAE = \frac{1}{N}\sum_{n=1}^{N}|x^n_{t+1} - \hat{x}^n_{t+1}| \tag{32}$$

- Normalized Mean Squared Error (NMSE)

$$NMSE = \frac{1}{N}\frac{\sum_{n=1}^{N}(x^n_{t+1} - \hat{x}^n_{t+1})^2}{var(x^n_{t+1})} \tag{33}$$

A.3.2 Forecasting result

Foreign investors' daily net trading volumes are forecasted using the ARMA/ARIMA model, and ANN and LSTM models. The forms of forecasted data are both level and first differential net trading volumes. Level data can be seen as a snapshot of foreign investors' trading on the next day, whereas the first differential value can be meaningful since it shows dynamic changes in trading behaviour. The forecasting performances are assessed with three measures (RMSE, MAE, and NMSE). In addition, the results of the train and test set are also respectively given for the purpose of comparison. The train set is the data used to estimate the model and the test set is the data which is not used to estimate the model.

Forecasting Results data are presented in Table 9. Overall forecasting performances of LSTM are more precise than in other methods. This is valid in different markets, in different data sources which are train and test sets, and in different data types which are level and first difference.

However, it is difficult to recognize the performance difference between the models in some

Table 9: Prediction performance

		Level			1st Diff.		
		RMSE	MAE	NMSE	RMSE	MAE	NMSE
Stock market							
Train	ARIMA	0.75	0.58	1.47	0.52	0.43	0.73
	ANN	0.55	0.43	0.79	0.52	0.43	0.73
	LSTM	0.51	0.41	0.68	0.50	0.42	0.68
Test	ARIMA	0.77	0.59	1.00	0.54	0.44	1.00
	ANN	0.55	0.43	1.00	0.53	0.45	1.00
	LSTM	0.51	0.42	1.00	0.51	0.43	1.00
Stock derivative market							
Train	ARIMA	0.96	0.80	0.80	0.73	0.67	0.99
	ANN	0.90	0.76	0.70	0.73	0.67	0.99
	LSTM	0.87	0.74	0.67	0.73	0.67	0.98
Test	ARIMA	0.91	0.75	1.00	0.74	0.67	1.00
	ANN	0.87	0.72	1.00	0.74	0.68	1.00
	LSTM	0.84	0.71	1.00	0.74	0.68	1.00
Bond market							
Train	ARIMA	0.18	0.13	0.78	0.44	0.37	6.20
	ANN	0.18	0.13	0.77	0.17	0.11	0.90
	LSTM	0.18	0.13	0.75	0.16	0.11	0.84
Test	ARIMA	0.17	0.12	1.00	0.45	0.39	1.01
	ANN	0.17	0.12	1.00	0.14	0.10	1.00
	LSTM	0.17	0.12	1.00	0.14	0.10	1.00
Bond derivative market							
Train	ARIMA	0.77	0.61	0.98	0.66	0.54	1.06
	ANN	0.69	0.55	0.77	0.62	0.54	0.93
	LSTM	0.70	0.55	0.80	0.61	0.52	0.89
Test	ARIMA	0.87	0.69	1.00	0.73	0.60	1.00
	ANN	0.78	0.63	1.00	0.68	0.59	1.00
	LSTM	0.78	0.63	1.00	0.67	0.58	1.00
FX derivative market							
Train	ARIMA	0.64	0.52	0.68	0.53	0.44	0.99
	ANN	0.64	0.52	0.68	0.52	0.44	0.98
	LSTM	0.58	0.48	0.57	0.52	0.44	0.98
Test	ARIMA	0.83	0.68	1.00	0.64	0.56	1.00
	ANN	0.82	0.68	1.00	0.63	0.56	1.00
	LSTM	0.74	0.62	1.00	0.63	0.56	1.00

[Note]
RMSE = Root Mean Square Error, MAE = Mean Absolute Error,
NMSE = Normalized Mean Squared Error

cases such as level data in the bond market and first difference data in the stock derivative market. However, the forecasting performance of LSTM is not worse than others in those cases.

The overfitting problem can be addressed by the performance difference between the train and test sets. If the forecasting performance of the train set is overwhelmingly better than the one of the test set, the overfitting problem needs to treated with scepticism. In this case, the model which is overly optimized for train data, cannot forecast appropriately. Based in Table 9, significant overfitting does not seem problematic although performance differences between train and test sets are found in the bond derivative and FX derivative markets. In addition, the consistency among estimating models can be lost if the process used to estimate the model is changed in order to avoid a small overfitting problem.

A.4. Discussion

Forecasting results in five different financial markets differ. In most cases LSTM shows the best performance, while in some cases no significantly better forecasting power among the three methods is found. Therefore, the forecasting result with LSTM is used for subsequent analyses.

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VII Summary of Conclusions

In this thesis, I investigate the network structure which is compose of eight different types of traders from Korean five most representative financial markets. I estimate the network structure in terms of pairwise causal relations which are estimated with linear (nonlinear) granger causality and generalized variance decomposition methods. Then, I analyse the network structures with traders' connectedness measures and find influential traders and markets. Furthermore, I examine the relation between financial traders' connectedness and financial market volatility. I measure the contribution of traders' connectedness to the financial market volatility as well as the impact of financial market volatility to the traders' connectedness.

I find the influential traders such as foreign investors and influential traders including stock and FX derivative market. Strong connections which means that there is a close relationship between an influencing trader and an influenced trader, are shown. In addition, particular conditions such as time period and foreign investors' trading patterns enhancing the influential traders' influence, are also found. The contribution of traders' connectedness to financial market volatility provide an insight to understand financial market. I find that the influential traders are not necessarily to increase market volatility. In particular, foreign investors are found that they don't contribute to increase market volatility on average. First paper is the first trial to estimate financial traders' network structure and to compare the results of granger causality and generalized variance decomposition to my best knowledge.

Second paper supplements the weakness of first paper. Despite the meaningful insights of first paper, the results are based on the assumption that traders' relationship is linear. In case that traders have nonlinear relationship, the results can differ in some extant. Moreover, the actual impact of influential traders to other traders are not investigated. Thus, in second paper the network structures are estimated with nonlinear granger causality and nonlinear generalized variance decomposition methods. The responses of traders at the shock of influential traders' sudden selling are also investigated with nonlinear impulse response analyses. The final results are shown almost similar with the result of first paper in spite of some differences. The contribution of second paper is further development of first paper in terms of methodologies and more actual implication in the real financial markets.

Third paper develops further based on the first and second paper. I estimate traders' financial network reflecting traders' real trading circumstances which refer the expectation on influential traders' trading on next day. However, given the fact that expectation data is not available, I forecast the expectation on influential traders' trading behaviours with machine learning technique, LSTM (Long Short Terhm Memory). This is one of the main contributions of third paper. Then, I investigate the spill over channels of financial market volatility with three-phased impulse response analyses framework. I find that there are a few volatility spill over channels in financial markets, and that traders' connectedness and their trading behaviours can be spill over channels. This paper shows the importance of traders' network structure as a volatility spill over channel.

This thesis have a few contributions to not only previous relevant literature, but also policy makers or financial regulators. First of all, this thesis highlights the importance of traders' connectedness, which has not been investigated by numerous researchers. Abundance of methodologies are applied to estimate traders' network structures, which shows the possibility of diverse approaches to analyse network structures. Furthermore, another point of view to analyse the market volatility is suggested. Financial policy makers or financial regulators can achieve more practical benefits from this thesis. Particularly when the market need to be stabilized, tailored policy to certain types of traders which have more stronger influences than others can make the market stable with minimum side effects.