Financial traders network and systemic risk spillover channels

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Abstract

In this paper I estimate the financial network among 8 types of traders across 5 different capital markets, which are stock, stock derivative, bond, bond derivative, and foreign exchange derivative market. The causal relationship between two traders are identified with nonlinear granger causality and each trader's connectedness measure is obtained by the network structure. In order to overcome the limit of VAR which most of previous literature assumes and reflect real trading decision making procedures, expectation forecasting of traders' net trading volume on next day is included in analyses. Expectation forecasting values are predicted with LSTM (Long Short Term Memory) which is one of the most popularly used machine learning method.

In addition, the systemic risk spillover channels are investigated using network measures. I model 3-phased systemic risk spillover channel which is the link of the volatility of financial indexes, traders network measure and traders daily net trading volumes. I find that given the shock of financial indexes, 3 traders among 40 traders become central and another 3 traders rapidly lose their influence regardless of the sort of financial indexes. Secondly, when the shock is given in those traders network measures, the traders in different markets are shown to have more sensitive responses. Finally with the shock on the sensitive traders daily net trading volumes, strong auto-correlation between impulse and response as well as the phenomenon which traders from different markets respond actively, are also found. These are the evidences of systemic risk spillover channels through traders.

This research can contribute to the previous research in that the financial networks which reflect real trading environments are estimated, and that machine learning methods are applied to network estimation. Furthermore, the results of systemic risk spillover channels can be helpful to policy makers including financial regulators and practitioners.

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1 Introduction

As "Too interconnected to fail" replaces gradually "Too big to fail" since Global Financial Crisis (GFC) in 2008, the number of research on network structure in capital market has increased exponentially. The network structure among the traders in capital market, however, is still not studied in depth, although bankruptcy and liquidity shortage contagions in inter-bank market or market risk spillover across capital market and stocks are investigated enormously. It might result from the difficulty of obtaining appropriate data for analysis.

If the network structure in capital market can be investigated properly, it means that central and influential traders, who can spread systemic risk into the market through other traders, can be identified. Those information can be critical to policy makers and financial regulators whose main role is stabilizing financial markets.

The other challenge of network study on traders in financial market is the econometric methodology. In principal strands of network studies granger causality and variance decomposition methods are applied. Both of them generally use VAR (Vector autoregression), which assumes that past data determine the future econometrically. Yet this assumption critically contradicts real circumstances of trading decision making. If the traders are rational enough to make profit, they should have the expectation of price and other traders trading behaviours on next day given the best information.

In present study, I investigate the network structures of 8 types of traders who are individual investors(IND), BANKs, financial investment(FI), collective investment scheme(CIS), other traders(ETC), insurance companies(INS), governments(GOV) and foreign investors(FOR) across 5 Korean financial markets which are stock (KOSPI), stock derivatives (KOPSI200 futures), bond (Korea Exchange listed), bond derivatives (Korea Treasury Bond (3-year) futures), and foreign exchange derivatives (KRW/USD futures). I choose Korean financial markets for 3 reasons. Korean financial market is fully open to global investors. Due to that characteristic, network structure of Korean financial market can give the clue to understand foreign investors influence to local markets. That issue has been actively investigated by the number of researchers. The size of Korean market is also quite big enough not to be distorted by a few abnormal movements of some big players. Moreover, Korea Exchange (KRX) and Korean Financial Investment Association (KOFIA) provide daily net trading volumes of 8 types of traders since 2006. Thus, I estimate network structure of Korean financial markets using those daily net trading volumes for 10 years and analyse systemic risk spillover channels with the perspective of traders.

First of all, I estimate the network structure with nonlinear granger causality method suggested by (Song and Taamouti (2016)). By that method, the limit which nonlinear causality cannot be captured by linear methods can be overcome. In addition I add expectation forecasting of a traders net trading volume next day in the model in order to reflect real trading decision making procedures. Expectation forecasting values are forecasted by Long Short Term Memory (LSTM, Hochreiter and Schmidhuber (1997)) which is one of the most popularly used machine learning method in finance and economics area. The reason why LSTM is applied, is because the forecasting performance of LSTM is superior to the ones of Artificial Neural Network (ANN) and traditional econometric methods.

Network estimations are implemented with static and dynamic point of views. Static network is estimated with whole dataset and focused on foreign investors. Dynamic network is investigated as monthly and daily forms. In a monthly dynamic network, the relation of traders network measures and financial/macro variables can be observed. However, only with static and monthly network it is still hard to identify systemic risk spillover channels, since matching traders network measures and real trading activities is not possible.

In the daily network setting, financial variables, traders network measures and traders daily net trading volumes can be linked successively with simulation based nonlinear impulse response analysis (Koop et al. (1996)). When theres an abnormal shock in financial variables, some traders network measures react more sensitively than others. If theres a shock in those traders network measures, a certain traders daily net trading volumes response more actively. Finally given the shock at those traders daily net trading volumes, some traders trade responsively. With those 3-phased impulse response analysis, how the systemic risk in financial market would be spread can be found.

Within the estimated network foreign investors are found influential to other traders in particular in FX derivative market, which is consistent with the common sense. As a result of monthly dynamic network analysis, some traders who are foreign investors (FOR) in stock, stock derivative, bond derivative and FX derivative market, individual investors (IND) in stock and FX derivative market, banks in bond derivative and FX derivative market, financial investments (FI) in bond derivative market, are found to have bigger influence to others. In addition, it is shown that with the shock of financial variables (KRW/USD, S&P, NIKKEI) individual investors (IND) in bond market, government (GOV) in stock market, Mutual funds (CIS) in FX derivative market seem to have more influence from other traders, and that given the shock of macro variable (balance of payment) other traders (ETC) in bond derivative market, insurance companies (INS) in stock market, and financial investments (FI) in stock market tend to be more impacted from others. By contrast, individual investors (IND) in stock market, banks in FX derivative market and financial investments (FI) in bond derivative market become more influential at the shock of financial variables (KRW/USD, S&P, NIKKEI). Foreign investors (FOR) in stock derivative market, individual investors (IND) in FX derivative market and financial investments (FI) in stock derivative market tend to be more central at the shock of macro variable (balance of payment).

As the result of daily network estimations present, systemic risk spillover channels can be identified. At first, regardless of the indexes, 6 traders are shown to have the most sensitive reactions among 40 traders. At a shock which means the volatility of financial indexes unexpectedly increase, individual investors (IND) and mutual funds (CIS) in stock market, and mutual funds (CIS) in FX derivative market turn to more influential to others, while foreign investors (FOR) in stock and bond derivative market and individual investors (IND) in FX derivative market lose their influence sharply to other traders.

At second phase of systemic risk spillover, given the shock of the centralities on those 6 traders, how traders daily net trading volumes change on next day is investigated. The most impressive finding here is that the traders in different markets are actively responsive to the shock of a traders centrality in one market. This proves that the systemic risk which was originated from local or global market, spreads over to the different local markets through the central traders. In addition some particular relationships between traders are also found. Mutual funds (CIS) and banks in FX derivative market react oppositely, and foreign investors in different markets have strong co-movements at the negative shock of some traders centralities.

The responses of traders net trading volumes at the shock on net trading volume of the trader who has the most sensitive response at second phase, are investigated at last phase. Here besides the phenomenon of risk spillover to other market, one other interesting finding is also observed. That is strong auto correlation of the impulse and the response. When the shock is given to a traders daily net trading volume, the very trader is shown to have the strongest response on next day. This provides an evidence that there is a channel which systemic risk spreads through.

In this paper, a few contributions to earlier relevant literature are presented. To my best knowledge, the forecasting of foreign investors' net trading volume is first trial in machine learning literature and even in econometric research. The result of forecasting helps to understand traders' utmost expectation on foreign investors' trading behavior and their influence to others. In addition, this paper could fill the gap in understanding network structure in capital market through the nonlinear impulse response analysis on financial/macro variables and the network measures.

Lastly, with the framework of systemic risk spillover channels through which the risk in financial indexes flows to the traders' net trading volume can be investigated. This result have a few benefits to not only the researchers, but to policy maker and practitioners. Policy makers or regulators are able to better measure the market risk with the information of the channel of risk spillover and to prepare for the extremely risky situations in advance. Risk managers in financial institutions would possibly make their assets and liabilities adjusted properly and portfolio managers could enhance their investment return.

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 forecast result is discussed. Dynamic network change and systemic risk transfer is presented in relatively section 5 and 6. Finally section 7 describes conclusion and final remarks.

2 Literature review

In financial network analysis literature the essence is to investigate pair wise causality of two nodes and to capture the responses of impulses. Here I introduce the previous literature of causality and impulse response analysis method for network estimation at first.

Financial network structure has been actively studied by the previous literature, mainly focused on financial assets' returns and volatilities. In order to find pairwise causality, the causality testing by Granger (1969) and Sims (1972) has been popular in economics and finance studies on dynamic relationship between variables. However, by the definition of Granger causality which assumes linear relation, it cannot explain non-linear relationship. Hence, some studies (Billio et al. (2012), He et al. (2014), Song and Taamouti (2016), Rahimi et al. (2016)) try to develop nonlinear measurement to investigate network structure. Billio et al. (2012) introduced nonlinear Granger causality, He et al. (2014) derived a new nonlinear partial directed coherence method. Song and Taamouti (2016) also proposed a new measure to capture linear and nonlinear causality and Rahimi et al. (2016) found that nonlinear Granger causality where no linear causality exists.

The dynamic change of time-series variables can be investigated as impulse response analysis which was suggested by Sims (1972) and Pesaran and Shin (1998). Although Pesaran and Shin (1998) overcame the problem of variables ordering in the model of Sims (1972), it was not able to be applied to nonlinear impulse response function. Thus, simulation-based nonlinear impulse response function model has been developed by Koop et al. (1996), Potter (2000), and Forero and Vega (2016).

In this paper, I follow the approaches Song and Taamouti (2016) and Koop et al. (1996) which can be applied to linear and nonlinear relationship.

Nextly, in order to predict the expectation forecasting, the literature regarding forecasting are described below.

Since Box and Jenkins (1976) ' publication of *Times series analysis:forecasting and control*, there have been enormous developments in time series forecasting.(Tsay (2000)) Despite of statistical and econometric development in time series forecasting, those models should have the theoretical model in order to predict, which can be a strong restriction practically.

However, in machine learning method for time series forecasting there's no such restriction. These methods have been applied to diverse economic and financial time series forecasting such as stock(Atsalakis and Valavanis (2009), Zhang and Wu (2009), De Faria et al. (2009), Chen et al. (2017), currency(Majhi et al. (2009), Maknickien et al. (2011), financial derivatives(Son et al. (2016), Wang (2009)) and so on. And in most studies, the forecasting performance of machine learning has been shown better than the ones of traditional econometric methods.

There have been much studies on systemic risk spillover, although by far, there's no precise definitions of systemic risk in financial markets, risk spillover and contagion channels. Thus, I also present the previous literature on systemic risk definitions and spillover.

Pei and Zhu (2017) divided financial contagions into 3 categories which were volatility spillover, extra comovements of asset returns, and severe systemic instability by a shock. And they also suggested potential transmission channels, which were international trade links, investors behaviors, 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 which 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 that the investors become more risk averse, which leads to increase risk premiums of assets. Correlated information means that the shock occurred in a market provides the information reflecting equilibrium values of other assets that is not directly influenced by that shock.

Among the literature studied 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 UK and Germany. They found that hedge fund played an important role to transmit financial risk in both countries. Their finding is closely linked to the financial regulation issues. In particular, German insurance companies are less interconnected with bank than in UK since Germany has more powerful regulation on insurance industry. Furthermore, although their result on hedge fund seems similar to Adams et al. (2014) using US data, European hedge funds dont transmit the financial risk such as extremely like American ones. On the contrary others concentrated on the market indexes. Leung et al. (2017) investigated hourly volatility contagion with 3 stock indexes (New york, London and Tokyo) and 4 exchange rates (USD, EUR, GBP and JPY). They found that during crisis period spillover effect increased. Their approach was distinguishing for they separated the drivers of contagion, which were pure contagions triggered by irrational investors and fundamental contagions captured by macroeconomic fundamentals.

In spite of recent development of network analysis in capital market, there are not many researches on the network between traders (players). Only a few researches tried to examine the relationship between traders in network, but there are some limitations. Billio et al. (2012) investigated network structures of four financial players; hedge funds, banks, broker/dealers, insurance companies. Yet their analysis was limited to just 4 types of traders. Adamic et al. (2017) tried to analyze over 7.2 million S&P futures transactions data for one month. Although their research was excessively impressive, it was still hard to find to critically influential traders.

3 Methodology

In this section, 4 different methodologies are introduced. First of all, forecasting methodologies which are not only traditional econometric method, but also machine learning techniques, are presented. Then, in order to estimate network structure expectation forecasting model is described, which releases the assumptions on simple VAR model and reflects traders' real trading decision procedures. Thirdly, network measures estimation and impulse response analysis to capture the influence of financial indexes to network measures are introduced. These analysis techniques help to expand the understanding of dynamic characteristics of network. Finally the methodology to investigate systemic risk spillover structure is presented.

3.1 Forecasting

I forecast foreign investors' daily net trading volumes with 3 different methodologies which are traditional econometric model (ARMA/ARIMA), Artificial Neural Network (ANN) and Recurrent Neural Network (RNN). 3 different results are compared with the measures popularly used in previous literature. After the comparison, the method which has best performance is used to forecast for further analysis.

3.1.1 Econometric method

For a traditional econometric method, ARMA/ARIMA model by Box and Jenkins is used. Much research tried to forecast financial time series like stock price or currecy rate with this method. In order to use this method, the data should be stationary, which can be checked with ADF test. By the results of ADF test, 5 foreign investors' daily net trading volumes are all stationary. Although by Box-Jenkins traditional method a correlogram is used to identify the model, it is sometimes hard to determine with autocorrelation and partial correlation. Therefore, I repeatedly estimate models for foreign investors' daily net trading volumes in 5 different markets which are stock, stock derivative, bond, bond derivative and FX derivative market. Then I compare the results with Akaike Information Criterion(AIC) and select the most appropriate model. After selection model and estimation parameter, Q-test is implemented for checking the residuals are white noises. In addition, in order to see daily change of foreign investors' net trading volume, 1st differential data is also used for analysis. In this case ARIMA model is used, while with level data ARMA model is used.

Beyond the traditional ARMA/ARIMA model, in order to enhance the prediction power significant other traders daily net trading volumes on previous day are used as independent variables. These variables are selected through simple regression. In other words, out of 40 independent variables which are traders' daily net trading volumes on previous day, the variables which have significant coefficients after a simple regression are chosen. Final model is given below.

$$X_t = \alpha_0 + \sum_{i=1}^{p}(\alpha_i X_{t-i} + \beta_i Z_{t-1}) + \sum_{j=1}^{q}\gamma_j \varepsilon_{t-j} + \upsilon_t \tag{1}$$

where X_t is foreign investors daily net trading volume in each market at time t, ε_t is error term at time t and Z_t is other traders' daily net trading volume vector at time t. Forecasting values are estimated with simple OLS.

3.1.2 Artificial Neural Network (ANN)

ANN is the computing system which operates similar with how biological neural networks do. 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 the figure 1. 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 only can be possible between neighboring 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).

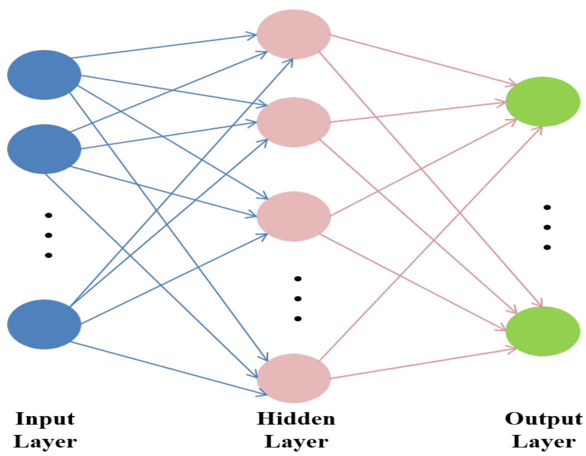


Figure 1: The structure of an artificial neural network

At first I denote x^i and y^i relatively ith sample of whole data. In real forecasting, x^i is the vector of traders' net trading volumes and y^i is a certain trader's trading volume next day. Here x ($x \in \mathbb{R}^n$) is the components of input layers and y is the value of output layer. y is binary or trinary variable in classification model, but in regression model, it can be any value between -1 and 1. In order to get 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 hidden layer. m can be determined by trial and error in practice. The relationship between x, y and z can be expressed like below equations.

$$z = \phi_1(x\omega_1 + b_1) \tag{2}$$

$$\hat{y} = \phi_2(z\omega_2 + b_2) \tag{3}$$

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 nonlinearity of data. The most popular activation function is sigmoid (logistic) function or hyperbolic tangent activation function. In present paper, I use sigmoid as ϕ_1 and hyperbolic tangent activation function(tanh) as ϕ_2 , for the value of daily net trading volume is between -1 and 1.

$$\phi_1(x) = \frac{1}{1+e^{-x}} = sigmoid(x) \tag{4}$$

$$\phi_2(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} = tanh(x) \tag{5}$$

The core process of artificial neural network is to find the most appropriate weight in above equation. This process is called to train the network. For training, loss function is essentially needed. One of the most popular loss function is mean squared errors as given below. K is output layer's dimension. Here output layer is 1 and total cost function is given below. The process to seek optimal weights is iterative forward propagations to minimize loss function, which is called optimization. In this process the weights play important roles to forecast an output accurately since it is continually adjusted to seek for local minima place of loss function as seen in the below equation.

$$J_i(W, x^i, y^i) = \frac{1}{2}\sum_{k=1}^{K}(\hat{y_k^i}) - y_k^i)^2 \tag{6}$$

$$J(W) = \frac{1}{S}\sum_{i=1}^{S} J_i(W, x^i, y^i) \tag{7}$$

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 most simple one is gradient descent, which is the way to find local minima with below equation. The weight is continually updated subtracting the multiplication of learning rate η which is also determined by trial and error and loss functions' gradient. ω_2 is also calculated with same fashion. For standard gradient descent which is called batch gradient descent, entire training set is used in this optimization process.

$$\omega_1^{(l)}(n+1) = \omega_1^{(l)}(n) - \eta \frac{\partial J(n)}{\partial \omega_1^{(l)}(n)} \tag{8}$$

In order to overcome this inefficient computation, Stochastic Gradient Descent (SGD) was developed. In case of SGD, the weights are updated after each sample data like below equation. 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 adaptive learning rate with first and second moment estimates of the gradients. Adam is now one of the most commonly used optimization method(Sebastian Ruder, 2016).

$$\omega_1^{(l)}(n+1) = \omega_1^{(l)}(n) - \eta \frac{\partial J_i(n)}{\partial \omega_1^{(l)}(n)} \tag{9}$$

The last step of training is the calculation of gradient. The gradients are calculated by chain rule, which was introduced by Rumelhart et al.(1986). This process to update weights is called backpropagation. Unlike forward propagation, the adjustment process for weight is implemented backward. Using the partial derivative of loss function with respect to the weights, new weights of hidden layer for computing output layer can be computed. New weights of input layer for hidden layer are similarly calculated. Through the iteration over forward propataion and backpropagation to minimize loss function, the network can be trained.

For training a network, the initial values of weights are needed. Although for many cases random numbers are used as initial weights, it would sometimes make a problem such as being stuck in local minima, which leads to failing to find minimum value of loss function and finally poor learning. Much research have tried 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 biggest drawback of machine learning is overfitting, which is that the result of train set is accurate, but the result of test set is not accurate enough. There are multiple ways to tackle overfitting. One instance is regularization with a regularization term in loss function. This regularization term penalizes big weights. Loss function with regularization term is given below. λ is the parameter, n and m is relatively the number of neurons in input and hidden layer.

$$J_i(W, x^i, y^i)_{new} = J_i(W, x^i, y^i)_{old} + \frac{\lambda}{2}\Sigma_{j=1}^{n}\Sigma_{k=1}^{m}(\omega)^2 \quad (10)$$

Dropout is also an popular method to avoid overfitting. This methods is to drop some neurons randomly as training unfolds, which helps not to be overly trained in train set.

3.1.3 Recurrent Neural Network (RNN)

Recurrent Neural Network (RNN) is a kind of neural network techniques 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 has been introduced by Hochreiter and Schmidhuber (1997) and very commonly used since.
As seen in the figure 2, LSTM has a particular structure like chain and in an each module there are special tools which are called relatively forget gate, input gate and output gate.

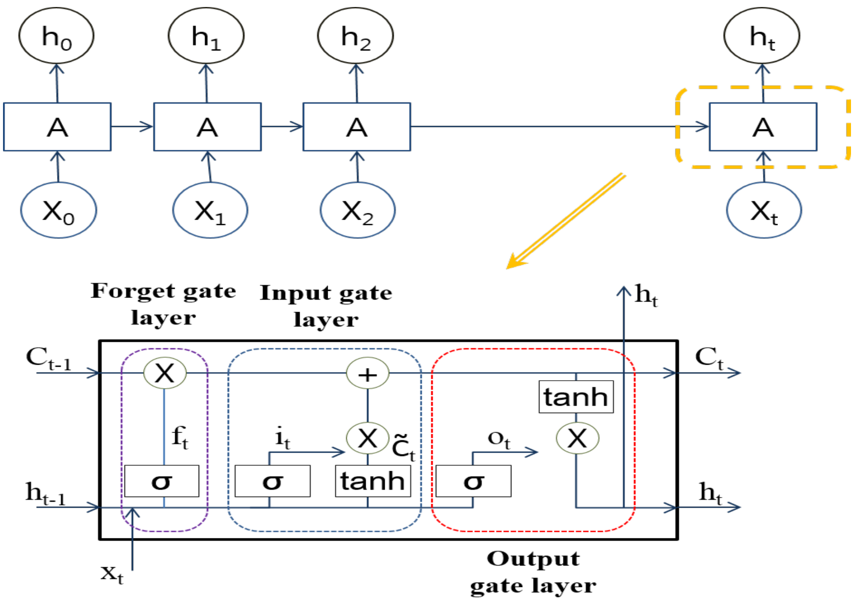


Figure 2: The structure of an LSTM

In LSTM cell state C_t and horizontal line h_t have critical roles. As forget gate manages the information from input vector x, the target value will be drawn. First of all, 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} output at time t-1, W_f is the weight vector, b_f is random vector, and σ is activation function, which here it is sigmoid(logistic) function. Sigmoid function gives output between 1 and 0 and the information of input vector x can be delivered to the cell state as optimally needed amount.

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{11}$$

Nextly, input gate layer i_t chooses which information important and new candidate values $\widetilde{C_t}$ updates cell state C_t as shown in equation.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{12}$$

$$\widetilde{C_t} = tanh(W_C[h_{t-1}, x_t] + b_C) \tag{13}$$

$$C_t = f_t \times C_{t-1} + i_t \times \widetilde{C_t} \tag{14}$$

Final step is the output which is calculated with the multiplication of output layer o_t and hyperbolic tangent of new cell state C_t.

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{15}$$

$$h_t = o_t \times tanh(C_t) \tag{16}$$

Although training RNN seems very similar with ANN, there are a few points needed to consider. First of all, RNN share the weight parameters throughout all steps while multi-layer ANN estimate different values of weight parameters at each layers. Due to this attribute, in 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, nomalized initializer are all same with ANN.

3.2 Network with expectation forecasting

In this part, I build the model to see whether the traders reflect their utmost expectation on foreign investors' net trading volume on next day with nonlinear Granger causality measures which are used in previous chapters. Since there is no evidence that the relation between traders' net trading volume is linear, generalized nonlinear causality which can also capture the linearity is used.

3.2.1 VAR representation

First of all, letting X_t be the vector of traders' daily net trading volume at time t, X_t can be described like $X_t = (x_{t,ind\_su},\ x_{t,bank\_su},\ \ldots,\ x_{t,gov\_fxd},\ x_{t,for\_fxd})'$ and the list of traders is given in the table 1. x_{t,ind_su} is individual traders' daily net trading volume in stock market at time t.

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 Derivative	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 Derivative	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 Derivative	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 (For simplicity, time t is excluded in each variable.)
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

Then, let's assume a VAR(Vector Autoregressive) model with X_t. Traders' daily net trading volumes are determined by the net trading volumes at previous day. That is the restricted model.

$$X_{t+1} = \Phi(X_t) + \epsilon_t \tag{17}$$

Then, $E_t[y_{t+1}|X_t]$, expectation forecasting on foreign investors' net trading volume on next day is inserted into restricted VAR model as independent variable, where y_t is foreign investors' daily net trading volume at time t in a certain market. ε_t is error term. This is the unrestricted model. $X^u_{t+1} = (x^u_{t,ind\_su},\ x^u_{t,bank\_su},\ \ldots,\ x^u_{t,gov\_fxd},\ x^u_{t,for\_fxd})'$ is forecasted vector. $\Phi()$ is non-linear function, which is here Gaussian kernel regression.

$$X^u_{t+1} = \Phi(X_t, E_t[y_{t+1}|X_t]) + \varepsilon_t \tag{18}$$

3.2.2 Network estimation

In order to see foreign investor's influence to each trader, causality measure $C_{t,m}$ needs to be defined like below. t=1,2,...,8 is the trader type and m=1,2,3,4,5 is market. Since foreign investors trade in 5 different markets, 5 different networks can be estimated by the market in which each type of foreign investors invest. Practically since foreign investors in a same market don't need to forecast their own net trading volume on next day, on network estimation foreign investors' daily net trading volume at time t as an independent variable is removed at right-hand side.

$$C_{t,m} = ln(\frac{\sigma^2(x^r_{t,m})}{\sigma^2(x^u_{t,m})}) \tag{19}$$

where $\sigma^2(x^r_{t,m})$ is forecasted error of $x_{t,m}$ with restricted model and $\sigma^2(x^u_{t,m})$ is forecasted error of $x_{t,m}$ with unrestricted model.

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

Simple bootstrapping method is composed of following algorithm. After estimating regression equation with the observed X_{t-1} and X_t, residuals ϵ can be computed. Then, fixing X_{t-1} and randomly sampling 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 ϵ which can be with probability of 1/n. Using ϵ^* and fixed X_{t-1}, new X^*_t can be calculated. Then with X_{t-1} and X^*_t, new causality matrix $C^*_{t,m}$ calculated. All above procedures are repeated 1,000 times. Achieved significance level(ASL) can be obtained like below.

$$ASL = \#\{C^*_{t,m} \geq C_{t,m}\}/N \tag{20}$$

where N is repetition time. Here, hypothesis(H_0) is $C_{t,m} = 0$ and one-tailed test is used since causality measure is assumed to be greater than or equal to 0. If a causality measure is statistically significant, it means that a trader is influenced by the foreign investors in a certain market.

3.3 Monthly dynamic change of network

From here the scope of origin of influence within the network is extended from only foreign investors to all traders. In a sense of modelling, the way of adding expectation forecasting term to baseline VAR model is same with previous section "Network with expectation forecasting." Nonetheless, in this part the forecast of every trader's net trading volume needs to be included in the model in the procedure to estimate network structure, while in previous section as a expectation forecasting term just foreign investors are included for estimating network.

In addition, the perspective on time to analyze network alters from static to dynamic one. For that, analysis period is divided into sub-periods with 2-year moving window approach. Furthermore, the changes of network measure given the shock of financial / macro economic variables are also captured with simulation method.

3.3.1 Baseline model

Restricted model and unrestricted model are basically same with the ones in previous section like below.

$$X_{t+1} = \Phi(X_t) + \epsilon_t \tag{21}$$

$$X^u_{a,t+1} = \Phi(X_t, E_t[x_{a,t+1}|X_t]) + \varepsilon_t \tag{22}$$

where a=1,2,...,39,40. However, in this part instead of foreign investors' forecasting $E_t[y_{t+1}|X_t])$, every trader's forecasting $E_t[a, x_{t+1}|X_t])$ needs to be added in the model.

3.3.2 Granger Causality Measure

Granger causality measure ($C_{i,j}$) can be defined like below. For the simple notation, time t is omitted in every notation.

$$C(x_i \rightarrow x_j) = C_{i,j} = ln(\frac{\sigma^2(x_{j,t+1}|X_t)}{\sigma^2(x_{j,t+1}|X_t, E_t[x_{i,t+1}|X_t])}) \tag{23}$$

where i=1,2,...,39,40. $C_{i,j}$ means that the net trading volume of trader j is influenced by the expectation forecasting on trader i's net trading volume on next day.

In order to check the statistical significance of each granger causality measure, same bootstrapping with previous section is also implemented.

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	$C_{40,1}$	$C_{40,2}$	...	$C_{40,j}$	...	$C_{40,39}$	$C_{40,40}$

3.3.3 Network Measure

If the entry of granger causality matrix is statistically significant at 10% significance level, the value of the entry is 1, otherwise it is 0. Then, adjacency matrix whose entries are composed of 1 or 0 can be drawn easily.

Degree centrality is one of the simplest and mostly used centrality measure in network literature. Centrality means literally how central a node or vertex in the network. Degree centrality means the sum of edges which connect the node. In direct network which has direction in the edge like granger causality matrix, there are two kinds of degree centrality which are in and out degree centrality. In degree centrality is the sum of edges which ends at a node. Out degree centrality is the sum of edges which starts from a node. More simply, in a granger causality matrix in degree centrality of trader i is sum of column vector and out degree centrality of trader i is sum of row vector. For a analysis purpose all degree centrality are divided by the number of all traders 40.

3.3.4 Dynamic network

Next step is to estimate the dynamic change of network among the traders. For dynamic analysis I divide entire data set into monthly sub samples with 2-year moving window. For instance, in order to get degree centrality of December in 2015, I use the daily net trading volume data from January in 2014 to December in 2015. In this way I move the window by one month and acquire 96 monthly in/out degree centrality values of 40 traders.

3.3.5 Impulse response analysis

Although degree centralities are obtained, the drivers which can influence on the degree centrality are unknown. Thus, I build another regression model with degree centrality measures and financial / macro variables. Financial variables are the volatility of KOSPI, KRW/USD, S&P, NIKKEI, and Hangseng index. For the consistency the volatility is calculated for the same period during which the degree centrality are estimated. Macro variables are current account, capital and financial account, inflation rate, unemployment rate, and base interest rate. For comparison objective, all financial/macro data are adjusted from 0 to 1. For entire data set, minimum value is adjusted to 0, maximum value is modified to 1 and others are interpolated between 0 and 1.

Based on the new model, nonlinear impulse response analysis is implemented in order to investigate how the centrality measures respond to the shock of financial/macro variables. Impulse response analysis is based on the simulation approach by Koop et al.(1996). Detailed explanation is also described below.

$$M_{t+1} = \phi(M_t) + \varepsilon_t \tag{24}$$

Where $\phi()$ is nonlinear function and $M_t = [m_{1,t},\ m_{2,t},\ \ldots,\ m_{40,t},\ f_{a,t}]$ is the vector which combined with traders monthly network measure vector and financial index $f_{a,t}$ which is the daily volatility estimated for same period. For simplifying the analysis, $f_{a,t}$ is included one by one. a = 1, ..., 10. Financial index f_1, f_2, f_3, f_4 and f_5 are relatively KOSPI, currency rate(KRW/USD), S&P, NIKKEI and HANGSENG index. Macro economic index f_6, f_7, f_8, f_9 and f_{10} are relatively current account, capital and financial account, inflation rate, unemployment rate, and base interest rate.

$$IRF(h, \nu_t, w_{t-1}) = E[M_{t+h}|\nu_t, w_{t-1}] - E[M_{t+h}|w_{t-1}] \tag{25}$$

Where ν_t is current shock on $f_{a,t}$, w_{t-1} is history and h=1, ... , 11. Here I concentrate the response of traders in/out degree centrality by the shock of financial/macro data. The shock is the (plus / minus) one standard deviation of financial/macro data. With plus one standard deviation, the response of traders centrality to the increase of financial/macro variable can be investigated. And the response of connectedness of traders to the decrease of financial/macro variable can be seen with the shock of minus one standard deviation

3.4 Systemic risk spillover channels with daily network

Although many implications can be found with the methodology of previous section, it is still hard to see how the network changes under more frequent setting and the financial risk transfer through the network. It is because the analysis above is based on the monthly data and the trading activity occur on every trading day. Moreover, the connection of network measure and daily net trading volume is still not uncovered. In this section daily network measure is estimated and the inter-connection of financial risk, network measure, and traders' net trading volumes.

Once the volatility of financial index increases and network in capital market transforms reflecting the changes of market. Then, the change of network structure which means the influence of a traders to others alters occurs and leads to the impact on traders' net trading volumes.

3.4.1 Daily network measure estimation

Before estimating daily network measure, daily financial index needs to be defined. The indexes I use are KOSPI, KRW/USD, S&P, NIKKEI, and HANGSENG. KOSPI is the index to reflect the risk of Korean financial and economic situation the most and 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. I use each index's daily volatility over previous 30 days. Because daily rate of return can be too volatile to analyze, which leads to inadequate result. Macro data is not used in this section since most of macro data is monthly announced, although in previous section macro data is used.

Consistent with the period of financial index, daily network is estimated with the data of previous 30 days. Same baseline model in previous section is used with the different period. Granger causality matrix, bootstrapping, adjacency matrix and degree centrality are obtained in same order with previous section.

3.4.2 Risk transfer structure

Risk trasnfer strcture is composed of 3 stages. First stage is the connection of financial index and network measures, which captures the reaction of network measures at the shock of financial index. Second stage is the link of network measures and net trading volumes, which investigates the impact of a trader's centrality on other traders' real net trading volumes. Final stage is the influence of net trading volumes of previous day to next day net trading volumes. All three stages are investigated with impulse response analysis which is same with the previous section.

If there is a shock in financial index, traders expectation forecasting on other traders reaction needs to be changed. In this process the influence of each trader to others changes and the network structure among them is reformed. As the sensitivity of each traders network measure differs, some traders centrality increases but others decreases. Given the change of network measures, a few particular traders react to the central traders more than others. In addition, if some traders react abnormally to central traders after the shock in financial index, a few certain traders react to them. In this contagious process, the network structure which plays an important role for the central traders become the channels through which the shock in financial index flows.

4 Forecast

In this section, the characteristics of data are investigated before forecasting. In each market, the relationship between the market index and foreign investors' trading behaviors have been presented differently. In some markets foreign investors trading move together with market indexes, but in others their moving seems irrelevant. In former case, particulary forecasting of foreign investor's net trading volume is important. Then, with 3 different methodologies which are traditional econometric approach (ARMA/ARIMA), artificial neural network (ANN) and recurrent nerual network(RNN), foreign investors in 5 different markets are forecasted. After comparison of the performance of those 3 methods, the best one is chosen for the analysis .

4.1 Data

In order to forecast foreign investors' daily net trading volumes in stock, stock derivative, bond, bond derivative and FX derivative market, daily net trading volumes of 8 types of traders in each market are used. The period is from 2006 to 2015. An expectation forecasting value on next day is forecasted by LSTM, since the perfomance of LSTM outperforms ANN and ARMA/ARIMA under most of cases.

Daily net trading volume is the ratio of the net trading volume of a certain type of trader over a half of all traders' absolute net trading volumes. The reason why the denominator is the half of all traders' absolute net trading volumes sum is that some traders' net trading volumes are buying and other traders' net trading volumes are selling. Thus, the value of daily net trading volume is within -1 and 1. Descriptive statistics are given in table 3. While a level data of daily net trading volume is able to show the picture at the end of trading day, from the 1st differential value of traders' trading behaviors change can be shown. In present paper, level and 1st differential are all analyzed. In addition, since all level data of daily net trading volumes are stationary, the objective of making the data 1st differential value is not to make the time series stationary but to see the dynamic attribute of traders' trading behaviors.

From the figure 4 to the figure 8, foreign investor's daily gross and net trading volumes are described with market indexes and all traders' daily gross trading volumes. On upper part of each figure, all traders' gross trading volumes, foreign investors' gross trading volume and market index are described. In each financial market, foreign investors' trading behaviors look not identical in the perspectives of the relation with other traders or market index and clustering effect which means that same trading patterns on previous day repeat on next day. On lower part of each figure, foreign investors' net trading volume is given. The volatility and the size look different depending on the market.

As seen in upper part of the figure 4, Foreign investors seem to be closely linked to price index. When the index move downward, foreign investors' selling amount increases. This graph shows that local traders' concern about foreign investors' selling off is not based on no evidences. In lower part, the other attribute of foreign investors in stock market is witnessed, which buying and selling patterns repeat for some period. In addition, their relative amount of trading is close to -1 and 1. They are a big player in this market in a sense of net trading volume.

Foreign investors in stock derivative market trade differently from what they do in stock market as shown in the figure 5, although KOSPI200, market index in stock derivative move similarly with KOSPI, stock index in stock market. It's hard to find an apparent pattern between market index and foreign investor's trading. Moreover, foreign investors' daily net trading volume in lower part looks very volatile. Their impact to the market, however seems be crucial since their net trading volume is close to 1 or -1.

In bond market, foreign investors do not have a pivotal role as seen in the figure 6. While price index move upward continually, they trade relatively small amount of bond except just a few times in 2008, 2009 and 2011. This phenomena can be seen more evidently in lower part of graph. Most of foreign investors' net trading volumes are small positive values and not volatile.

Although market index of bond derivative market looks more volatile than the index of bond market, it is still hard to find the pattern between the market index and foreign investors' net trading volume. However, in bond derivative market, the size of foreign investors' net trading volume is significant compared to all traders' volume. In the lower part of the figure 7, foreign investors' net trading volume seems to be close to -1 or 1 and there seems to have the clustering effect.

In the figure 8 there seems to have a weak positive relationship between market index and foreign investors' selling. Here market index is the currency rate of Korean won over US dollar. Therefore, positive relation means that when currency value is depreciated, foreign investors sell the currency futures. In the lower part of graph, foreign investors seem to have critical impact since their net trading volume is close to 1 or -1. In addition, slight cluster effect is also found before 2010, and after then the net trading volume somewhat volatile.

4.2 Forecasting framework

For estimating forecasting model, the data from 2006 to 2013 is used. For machine learning this period is commonly called as train period. The data during 2014 and 2015 is used to test the forecasting model.

For independent variables, which are input variables in machine learning methods, 40 traders' net trading volumes on previous day are used. Foreign investors' daily net trading volume in each market next day is used as dependent variable, which is output variable in machine learning method.

First of all, ARMA model is estimated. For enhancing prediction power, the variables with statistically significant coefficients at the results of simple regression with 40 net trading volumes as independent variables, are included in ARMA model estimation. Based on AIC (Akaike information criteria), the most appropriate model is selected for each foreign investors' net trading volume. Although all variables are stationary, 1st differential data are analyzed in order to see traders' daily net dynamic change. For 1st differential data, model selection procedure is same with level data and the selected model is equivalent with ARIMA model of level data.

For comparison objective, the input data for ANN and LSTM are chosen as same as ARMA and ARIMA model.

4.3 Performance measure

For the comparison of 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)

$$RMSE = \sqrt{\frac{1}{N}\sum_{N}^{n=1}(x_{t+1}^{n} - \hat{x}_{t+1}^{n})^2} \tag{26}$$

- Mean absolute error (MAE)

$$MAE = \frac{1}{N}\sum_{n=1}^{N}|x_{t+1}^{n} - \hat{x}_{t+1}^{n}| \tag{27}$$

- Mean absolute percentage error (MAPE)

$$MAPE = \frac{1}{N}\sum_{N}^{n=1}|\frac{x_{t+1}^{n} - \hat{x}_{t+1}^{n}}{x_{t+1}^{n}}| \tag{28}$$

- Normalized Mean Squared Error (NMSE)

$$NMSE = \frac{1}{N}\frac{\sum_{n=1}^{N}(x_{t+1}^{n} - \hat{x}_{t+1}^{n})^2}{var(x_{t+1}^{n})} \tag{29}$$

4.4 Forecasting result

Foreign investors' daily net trading volumes are forecasted with ARMA/ARIMA model, ANN and LSTM model. The forms of forecasted data are both level and 1st differential net trading volumes. While level data can be seen as a snapshot of foreign investors' trading on next day, 1st differential value can be meaningful since it shows dynamic change of trading behavior. The performances of forecasted are described with 4 measures (RMSE, MAE, MAPE and NMSE). In addition, the results of train and test set are also relatively given for comparison purpose.

The results of forecasting with level data are presented in figure 9 and in figure 10 1st difference forecasting results are given. In stock market forecasted values of each methods move similarly with actual value. In table 4 LSTM shows the best result followed by ANN and ARIMA. The difference of machine learning methods and econometric is evidently shown. In stock derivative market the forecasted values in the figure 9seem to stay around zero although actual value fluctuates by a great deal. Based on the table 4, LSTM also shows the best performance compared to ANN and ARIMA. However, in case of 1st differential data the performances of all methods don't differ significantly.

In case of bond market forecasted results of econometric model and machine learning methods are shown explicitly different. While the forecast of econometric model looks highly volatile, machine learning forecasting results move smoothly. The performances, however, are hard to differentiate which one is better. In 1st differential data forecasting, machine learning methods forecast more accurately.

Forecasted values in bond derivative market seem to move together with actual value, although the extreme value close to 1 or -1 cannot be forecasted as seen in the figure 9. LSTM and ANN outperform ARIMA and the prediction powers of ANN and LSTM seem similar in the table 4. However, in case of 1st differential LSTM is still the best forecast.

Forecasting result of FX derivative market looks similar with the one in stock derivative market. While actual value jumps up and down, forecasted values move stably in the figure 9. One distinctive finding is that forecasting powers of ARIMA and ANN are similar, although LSTM is the best forecast. In addition, based on the table 4, there's no difference in 1st differential forecasting power among 3 methods.

4.5 Discussion

Forecasting results in 5 different financial markets differ. In most case LSTM shows the best performance, while in some cases no significantly better forecasting power among 3 methods is hardly found. Therefore, forecasting result with LSTM is used for subsequent analyses.

5 Network with expectation forecasting

With the values of forecasted foreign investors' net trading volume on next day with LSTM, whether other traders' reactions are influenced by their expectation forecasting on foreign investors' trading on next day, is investigated. This investigation is implemented within the framework of 5 different financial markets and 8 different traders in each market. However, the foreign investors in the same market which the foreign investors whose net trading volume is forecasted belong to, is not analyzed. For instance, the impact of foreign investors in stock market is removed from the analysis when investigating the influence of foreign investors in stock market on other traders.

5.1 Framework

First of all, in simple VAR model the expectation forecasting of next net trading volume of foreign investors in 5 different markets are included in turn. From each model granger causality matrix are calculated, and then statistically significant entries of granger causality matrix are identified by bootstrapping. If the entry is statistically significant, that trader is influenced by the foreign investors within the network. For there are 5 different markets which the foreign investors belong to, 5 different granger causality matrices can be made. 5 matrices can be described as a network graph, which a type of foreign investors in each of 5 different markets can have maximum 40 connections.

The investigation is implemented with both level and 1st difference data. The result suggests whether other traders are influenced by their expectation forecasting on foreign investors' trading on next day in a certain market. The other probable implication of the result is that foreign investors are superior to local traders at global investment information, since local traders follow foreign investors' trading due to the expertise of them.

5.2 Level data

Granger causality measure is the ratio of forecasted error of restricted model over unrestricted model's forecasted error. As seen in table 5, traders' reaction at the forecasted net trading volumes with level data are investigated.

On foreign investors in stock market, FI, CIS and INS in stock market are influenced by them, while CIS in stock derivative market and FOR in bond market use their net trading volume as references. In case of foreign investors in stock derivative market, much wider influence can be found. Beside all traders who use their expectation forecasting on foreign investors' trading in stock market, a few traders in stock, bond derivative and FX derivative market are influenced by them. 5 types of traders in bond derivative market as well as 6 type of traders in stock market are influenced by foreign investors in bond market. The traders in bond market and FX derivative market are not significantly influenced by the foreign investors in bond market. Regarding foreign investors in bond derivative market do not significantly make an impact on the traders in bond derivative market, but in bond and stock market their impact seem significant. Finally, all traders are significantly influenced by foreign investors in FX derivative market.

Above results are summarized in the figure 11 with 10% significance level. These results present that the local traders are influenced by their expectation forecasting on the foreign investors trading on next day, and that the dependence on foreign investors is not only valid within one market but also holds across the markets. Among the traders, in particular IND in stock market, CIS in stock and stock derivative market, FI in stock market are shown to be much influenced by foreign investors.

5.3 1st differential data

The result with 1st differential data is present on table 6. 1st differential data shows that the traders' dynamic changes of their net trading volume occur on their expectation forecasting of foreign investors' net trading volume changes. What matters is that level data is stationary, and that the reason to see 1st differential data is not to make data stationary but to see the traders' reactions.

Based on the table, the traders in stock market are significantly influenced by their expectation forecasting on foreign investors behaviors change in stock market. Yet the traders in stock derivative and FX derivative market do not seem to have significant influence from foreign investors. The traders are relatively less responsive to the expectation forecasting on the change of foreign investors in the stock derivative market. In addition, no traders in bond, bond derivative and FX derivative market seem to have statistically significant impact from the foreign investors in stock derivative market. Foreign investors' volume change in bond market has the significant impacts on 10 traders. There's no market in which no trader has the impact from them, although in bond and bond derivative market just one trader has the influence from them. The influence from foreign investors in bond derivative market is similar with one from bond market. There are also 10 traders who have impact from them and 7 out of them overlap the ones who have influence from foreign investors in bond market. All traders are significantly responsive to the daily net trading change of foreign investors in FX derivative market like the result with level data.

The results above are also described in the figure 12 as a summary. It shows that some traders are sensitive to the foreign investors from multiple markets, who are IND in stock market, FI in bond market, CIS in stock and stock derivative market, INS in stock and stock derivative market and GOV in stock market.

5.4 Discussion

With this method, foreign investor's influence to other traders can be found with the perspectives of both level and 1st differential data. In other words, the traders who consider foreign investors' net trading volumes and the change of their trading volumes as their trading reference can be identified. By the figure 11 and 12, the relationship between traders and foreign investors are present in the network structure forms. In particular some traders who are IND, CIS and INS in stock market have influences from the foreign investors in multiple markets. This result can help the policy makers and market practitioner to understand the capital market and its mechanism better.

In spite of these findings, there are still some points to investigate more deeply. First of all, the result is static thus dynamic feature of network cannot be captured. Furthermore, how influential the foreign investors within network cannot be described compared to other traders.

Subsequent section is the solution to these issues, so that the scope of the analysis is extended trader-wide and time-wide. Network measure (degree centrality) is also included. Moreover, in order for the simplicity of analysis and effectiveness of calculation, only level data is used.

6 Monthly dynamic change of network

Here with the perspective to see dynamic features of network structures, which traders are central in capital markets can be found. Furthermore, the response of network measure to the shock of financial and macro variables expands understanding of the link between financial and macro risk and the network within the capital markets.

6.1 Framework

In this section, monthly network structure in capital market is estimated and impulse response analysis with that is implemented. The first step of estimation starts with forecasting of every trader's net trading volume at next day. Every net trading volume is forecasted with LSTM as mentioned previous section. Once the forecasting is done, sub samples are divided from entire data set. Within each sub sample, granger causality matrix is estimated. The entry of granger causality matrix is logarithmic ratio of restricted model's forecasted error over unrestricted model's forecasted error. The only difference between restricted model and unrestricted model is whether the forecasted value of net trading volume is included as an independent variable. In order to see the influence of one trader to others, it is easy to see the row vector of granger causality matrix. In case of ith row the forecasted net trading volume of trader i is not included in the restricted model to estimate each traders' net trading volume, by which trader i's influence to others can be understood.

Next task to understand network structure is to estimate the network measure of each node(trader) which degree centrality is used. In directed network structure which has the direction between the connection like granger causality matrix, two type of degree centrality can be obtained. One is Out degree centrality which measures the influence of one node to others and the other is In degree centrality which means the influence from others to one node. For checking statistical significance, bootstrapping method is used for granger causality matrix. If the entry of granger causality matrix is statistically significance, it is transformed to 1 and otherwise to 0. This matrix with binary entries is called adjacency matrix. Out/in degree centrality can be obtained by adjacency matrix easily.

Impulse response analysis is an effective method to see the variables to change at the shock of given variable. Here given the shock of 5 financial index and 5 macro variables, dynamic change of each trader's OUT/IN degree centrality is analyzed.

6.2 Results

The average values of in degree centrality of all traders for 96 months are similar within the range of 0.06 and 0.14. By contrary, average out degree centrality values disperse as seen in figure 13. In particular foreign investors in stock, stock derivative, bond derivative and FX derivative market, individual investors in stock and FX derivative market, bank in bond derivative and FX derivative market, financial investment in bond derivative market have bigger out degree centrality values. The evidence that foreign investors play an central role in capital markets is found one more time here.

Impulse response analysis is implemented with two type of shocks. One is a positive shock which means that the volatility of financial market or macro variable increased by one standard deviation of errors. The other is a negative shock which is opposite with positive shock. The responses of network measures dont last for two periods. At first period the responses are shown and faded. However, some measures increase and others decrease on the same shock. From table 7 to table 10 it is shown that the biggest 3 traders with positive and negative reaction respectively.

On the positive shock of financial variables the traders with positive reaction differ by the type of variables. Government and Collective investment schemes (CIS) in FX derivative markets become principal in the network at the shock of KOSPI while individual in bond market, government in stock market are mainly shown as central investors at the KRW/USD and foreign stock market. The traders with negative response, however, seem identical who are CIS, foreign investors in stock market, and other traders in bond derivative market. This result suggests that at volatile stage of the financial market, main players such as foreign investors and CIS in stock market try to act with their own, not by the influences of others. In case of the macro variable, it is not easy to find evident pattern. However, the traders with top 3 reactions are same at the shock of current account and capital and financial account.

This result seems as expected. At the negative shock, top 3 traders in negative direction at positive shock are shown as top 3 in positive direction and vice versa with just a few change. This phenomenon holds for both financial and macro variables.

When the volatility of FX market and foreign financial market increases, bank in FX derivative market, individual investors in stock market and financial investment in bond derivative market become more central. However, at the positive shock in KOSPI, government and CIS in FX derivative market transforms to be principal. Negative reactors seem to be more evident. Individual investors in FX derivative market, and foreign investors in stock and stock derivative market lose their centrality. Here two significant implications are found. One is that foreign investors influence in domestic market decreases when foreign financial market volatility increases. This could tackles excessive fear on foreign investors sudden outflow during financial turmoil. Second implication is about the trait of individual investors. When global financial market is unstable, they play unstablizing roles in domestic stock market but become inactive in FX derivative market. Foreign investors reaction in stock derivative market to the shock of macro variable seems to be impressive. In case of the increase of current account and capital and finance account they become more central, but their centrality fades when inflation rate, unemployment rate and base interest rate increases. Individual investors in FX derivative market and financial investment in stock derivative market react in similar way.

The traders reaction to negative shock seems similar with the case of in degree centrality. Top 3 positive reaction traders at the positive shock are inclined to be in top 3 negative reaction traders at the negative shock with just a few exceptions.

6.3 Discussion

The result of dynamic change of network provides the foundation of understanding the relationship between the financial/macro variables and network measure of each trader. In particular the reactions to financial variables and macro variables seem somewhat different. Among financial variables, dynamic changes of network measures to domestic indexes and to foreign indexes differ. However, the reaction to foreign indexes and currency rate seems similar. In case of macro variables, network measures' reaction to balance of payments move similarly. Yet, other reactions don't look similar. The research on the relationship between the specific financial / macro variable and traders could be studied further in depth.

There, however, is still some room for more development. First of all, with monthly data dynamic feature of network change cannot be explained enough. In addition the influence of network measure to real net trading volume cannot be also described with that result. Therefore in next section the investigation with daily data and wider scope is done.

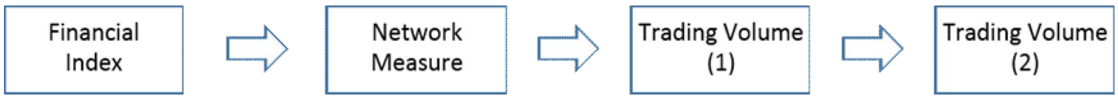
7 Systemic risk spillover structure

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. If there is a certain type of risk in the system, the contagion or spillover of the risk can be assessed with the method of network studies. Here the spillover of systemic risk in financial market throughout traders is investigated.

7.1 Framework

In this section risk spillover channels are investigated with 3 stages which are composed of financial indexes, network measures of traders and net trading volumes of traders. First stage is from financial index to network measure like figure 3 . If there is an abnormal shock in 5 different financial indexes relatively, the reactions of traders' network measures are acquired. Given the stressed situation, some traders become central within the network in the capital markets. Second stage is from network measure to net trading volume. If a trader become central within the network, some traders' trading behaviors are more sensitive to that shock on the centrality of that trader. Last stage is from traders' net trading volumes to traders' net trading volumes. Traders react to other traders' net trading volumes. In particular, there would be the patterns of reaction to a certain shock of net trading volumes.

Figure 3: Systemic risk spillover structure



In each stage, impulse response analysis is implemented. The only difference is the frequency of data. In this section daily data is used. In order to forecast the net trading volume of next day and centrality measure, immediate previous 30 days data is used. Forecasting and network estimation method are same with the previous section. After all impulse response analysis, risk spillover structure can be assessed by combining the results.

For the simplicity of analysis at the second and third stages, I focus on top 3 network measures and traders' net trading volumes. For example, if there is an unexpected shock in KOSPI, the most sensitive 3 centrality measure are investigated. And then given the shock on those centrality measures, the most subsequent 3 traders are identified. With the same fashion, under the shock of those top 3 traders' net trading volumes, the most 3 sensitive traders' net trading volumes are also investigated.

7.2 Result

As seen in table 11, the responses of network measures are same except KOSPI. However, 3 of the most sensitive network measures to all financial indexes are identical, which are Individual investors(IND) in stock market, Collective investment scheme (CIS) in FX derivative market and Collective investment scheme (CIS) in stock market. This result means that when there is an unexpected increase in financial indexes, those 3 trader's centralities rise. The result is also consistent with the common sense in capital market. Individual investors are usually overly sensitive to market index's movement and mutual funds also move together with index in general.

In case of negative directions, the reaction of centrality seems comparable to positive response. All response of the shock in 5 financial indexes are almost same. Exceptionally bank in FX derivative market replace foreign investors in stock market at the shock of NIKKEI. 3 top negative reactions are found in foreign investors (FOR) in bond derivative market, individual investors (IND) in FX derivative market, and foreign investors (FOR) in stock market. The implication of this result is that those traders lose their influence when financial indexes move upward.

2nd stage is the responses of net trading volumes at the shock of network measures. In this stage, assuming there is a positive shock at top 3 positive centralities and a negative shock at top 3 negative centralities, the responses of traders' net trading volume are investigated like table 12. As seen in table 12, the most sensitive 3 traders' trading volumes can be found in diverse markets, which means that a systemic risk can be spilled over to different markets through central traders. For instance, when the shock was given at the centrality of individual investors (IND) in stock market, the traders in FX derivative, bond, and bond derivative market react more actively. In addition at the positive shock, two interesting phenomena are found. One is that Collective investment scheme (CIS) and banks in FX derivative market respond in opposite direction. At the shock on individual investors (IND) in stock market CIS have a positive response and banks have a negative reaction, while at the shock on CIS in FX derivative market, banks are shown to respond positively and CIS are observed to react negatively. The other one is that when there is a positive shock in CIS in FX derivative market and stock market, their daily net trading volumes react negatively. It means that mutual funds reduce their position when their influence in capital market increases.

The phenomenon of systemic risk spillover to diverse markets are observed in case of negative shock on traders' centralities. The shock in bond derivative market can be spread to stock, stock derivative, and FX derivative market. At negative shock cases, the responses of foreign investors (FOR) need to be focused in particular. Firstly, when there is a negative shock in the network measure in foreign investors (FOR) in bond derivative market, individual investors (IND) in FX derivative market and foreign investors (FOR) in stock market relatively, foreign investors in stock market sell. When there's some event which increase systemic risk in financial indexes, foreign investors' could sell their stocks although their centralities in each financial market. In addition a strong co-movements between foreign investors (FOR) in different markets are found. Given the shock on individual investors (IND) in FX derivative market, foreign investors (FOR) in stock and FX derivative market decrease their net trading volumes. And in case of the shock on foreign investors (FOR) in stock market, foreign investors (FOR) in stock and bond market sell their securities as well.

The last phase of the analysis is the response of traders' net trading volumes on the shock of other traders' net trading volumes. Once a shock is given to the top 3 net trading volume responses, strong evidences of auto correlation are found as seen in table 13. 1st positive responses of the positive shocks in CIS in FX derivative market, bank in FX derivative market and FOR in bond derivative market. In addition, strong positive relationship are observed, which are between CIS in FX derivative market and IND in stock market, and between bank in FX derivative market and FOR in bond derivative market. negative relation is also found among CIS in FX derivative market and bank in FX derivative market and FOR in stock market. Furthermore the phenomena which the traders in different markets from the one which the shock is originated from respond more actively, is also found.

Under a negative shock, auto correlation is also found. 1st negative reactions of the negative shock in FOR in stock market and bank in FX derivative market are FOR in stock market and bank in FX derivative market. However, the auto correlation is not found in the net trading volume of FOR in FX derivative market but instead FOR in FX derivative market trade more given the negative shock of FOR in FX derivative market. IND and CIS in stock market reduce their net trading volume under the negative shock of FOR in FX derivative market, while they increase their net trading volume when FOR in stock market trades less.

Combining above results within one picture like from figure 14 to figure 19, systemic risk spillover structure can be identified. Systemic risks which are originated from 5 different financial indexes converges to 6 traders' network measures. Assuming a shock is given to that centrality, systemic risk can be contagious to other traders' net trading volumes. Those increased (or decreased) abnormal trading behaviors are spilled over to other traders as seen in above figures.

7.3 Discussion

With the results the channels of systemic risk transfer from the financial indexes through network centrality to traders can be assessed.

This can provide a few implication to financial policy makers and regulators. In particular under extremely stressed conditions, a certain type of traders which have high centrality or sensitivity to others can be restricted or incentivize to trade or not. Korean government gave the counter incentive to foreign investors to invest in Korean bond market when excessive fund flowed into Korea, while it waived the interest income tax for foreign investors to invest in bond market when the fund flowed out.

8 Conclusion

I forecast traders' net trading volumes in capital market with machine learning technique, which has better performance compared to traditional econometric method. This is consistent with other previous literature. With the forecasted values the expectation forecasting to reflect real trading decision is modelled, which leads to network estimation in capital markets. Foreign investors are found to have much influence within the network structure. This is an proving evidence that foreign investors play a role of leading indicator to local traders with the information superiority on global financial markets.

With the wider scope of analysis and released assumption, dynamic network structures are estimated. Foreign investors' influence is still found critical based on the OUT degree centrality and impulse response analysis. However, given the shock of financial indexes foreign investors' influence decreased, while OUT degree centralities of foreign investors are shown diverse at the shock of macro variables.

Systemic risk spillover channels are also found with the 3-stages impulse response analysis. The top 3 responses at the shock of 5 different financial indexes converge to 6 types of traders' network measures out of 40. Based on the results of the impulse response analyses with the shocks of those network measures and central traders' net trading volumes, foreign investors, mutual funds and individual traders are found to play central roles within the network structures in capital markets.

This paper has a few contributions to previous research and policy makers including financial regulators. First of all, a methodology reflecting real trading decision process is used to estimate a network structure in capital markets. Utilising the network structures I enlarge the understanding of relationships among traders and further investigate systemic risk spillover channels in capital markets. The inter-relations among financial indexes, network measures and net trading volumes of traders can provide the implication for policy makers and financial regulators to enact a new regulation.

There are still a few further research topics. Enhancement of forecasting precision with newly developed machine learning techniques can be possible for recently the machine learning area is one of the most actively studied. Research on systemic risk spillover structure more in depth can be implemented. Reverse impulse relationship between net trading volume, network measure, and financial indexes can be also one of the examples.

References

Adamic, L., Brunetti, C., Harris, J. H. & Kirilenko, A. (2017), 'Trading networks', *The Econometrics Journal* .

Atsalakis, G. S. & Valavanis, K. P. (2009), 'Surveying stock market forecasting techniquespart ii: Soft computing methods', *Expert Systems with Applications* **36**(3), 5932–5941.

Billio, M., Getmansky, M., Lo, A. W. & Pelizzon, L. (2012), 'Econometric measures of connectedness and systemic risk in the finance and insurance sectors', *Journal of Financial Economics* **104**(3), 535–559.

Box, G. E. & Jenkins, G. M. (1976), 'Time series analysis, control, and forecasting', *San Francisco, CA: Holden Day* **3226**(3228), 10.

Chen, H., Xiao, K., Sun, J. & Wu, S. (2017), 'A double-layer neural network framework for high-frequency forecasting', *ACM Transactions on Management Information Systems (TMIS)* **7**(4), 11.

De Faria, E., Albuquerque, M. P., Gonzalez, J., Cavalcante, J. & Albuquerque, M. P. (2009), 'Predicting the brazilian stock market through neural networks and adaptive exponential smoothing methods', *Expert Systems with Applications* **36**(10), 12506–12509.

Forero, F. J. P. & Vega, M. (2016), Asymmetric exchange rate pass-through: Evidence from nonlinear svars, Report.

Ghulam, Y. & Doering, J. (2017), 'Spillover effects among financial institutions within germany and the united kingdom', *Research in International Business and Finance* .

Granger, C. W. (1969), 'Investigating causal relations by econometric models and cross-spectral methods', *Econometrica: Journal of the Econometric Society* pp. 424–438.

Guidolin, M. & Pedio, M. (2017), 'Identifying and measuring the contagion channels at work in the european financial crises', *Journal of International Financial Markets, Institutions and Money* **48**, 117–134.

He, F., Billings, S. A., Wei, H.-L. & Sarrigiannis, P. G. (2014), 'A nonlinear causality measure in the frequency domain: Nonlinear partial directed coherence with applications to eeg', *Journal of neuroscience methods* **225**, 71–80.

Hochreiter, S. & Schmidhuber, J. (1997), 'Long short-term memory', *Neural computation* **9**(8), 1735–1780.

Koop, G., Pesaran, M. H. & Potter, S. M. (1996), 'Impulse response analysis in nonlinear multivariate models', *Journal of econometrics* **74**(1), 119–147.

Leung, H., Schiereck, D. & Schroeder, F. (2017), 'Volatility spillovers and determinants of contagion: Exchange rate and equity markets during crises', *Economic Modelling* **61**, 169–180.

Majhi, R., Panda, G. & Sahoo, G. (2009), 'Efficient prediction of exchange rates with low complexity artificial neural network models', *Expert Systems with Applications* **36**(1), 181–189.

Maknickien, N., Rutkauskas, A. V. & Maknickas, A. (2011), 'Investigation of financial market prediction by recurrent neural network', *Innovative Technologies for Science, Business and Education* **2**(11), 3–8.

Pei, X. & Zhu, S. (2017), *Measurements of Financial Contagion: A Primary Review from the Perspective of Structural Break*, Springer, pp. 61–84.

Pesaran, H. H. & Shin, Y. (1998), 'Generalized impulse response analysis in linear multivariate models', *Economics letters* **58**(1), 17–29.

Potter, S. M. (2000), 'Nonlinear impulse response functions', *Journal of Economic Dynamics and Control* **24**(10), 1425–1446.

Rahimi, A., Lavoie, M. & Chu, B. (2016), 'Linear and nonlinear granger-causality between short-term and long-term interest rates during business cycles', *International Review of Applied Economics* pp. 1–15.

Sims, C. A. (1972), 'Money, income, and causality', *The American economic review* **62**(4), 540–552.

Son, Y., Byun, H. & Lee, J. (2016), 'Nonparametric machine learning models for predicting the credit default swaps: An empirical study', *Expert Systems with Applications* **58**, 210–220.

Song, X. & Taamouti, A. (2016), 'Measuring nonlinear granger causality in mean', *Journal of Business and Economic Statistics* (just-accepted), 1–37.

Tsay, R. S. (2000), 'Time series and forecasting: Brief history and future research', *Journal of the American Statistical Association* **95**(450), 638–643.

Wang, Y.-H. (2009), 'Nonlinear neural network forecasting model for stock index option price: Hybrid gjrgarch approach', *Expert Systems with Applications* **36**(1), 564–570.

Zhang, Y. & Wu, L. (2009), 'Stock market prediction of sp 500 via combination of improved bco approach and bp neural network', *Expert systems with applications* **36**(5), 8849–8854.

Table 3: 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

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

Table 4: Prediction performance

		Level				1st Diff.			
		RMSE	MAE	MAPE	NMSE	RMSE	MAE	MAPE	NMSE
Stock market									
Train	ARIMA	0.75	0.58	17,809.46	1.47	0.52	0.43	217.58	0.73
	ANN	0.55	0.43	21,775.49	0.79	0.52	0.43	214.53	0.73
	LSTM	0.51	0.41	68,441.74	0.68	0.50	0.42	160.23	0.68
Test	ARIMA	0.77	0.59	275.64	1.00	0.54	0.44	202.03	1.00
	ANN	0.55	0.43	235.05	1.00	0.53	0.45	189.26	1.00
	LSTM	0.51	0.42	342.24	1.00	0.51	0.43	169.54	1.00
Stock derivative market									
Train	ARIMA	0.96	0.80	17,647.47	0.80	0.73	0.67	106.59	0.99
	ANN	0.90	0.76	40,549.59	0.70	0.73	0.67	108.19	0.99
	LSTM	0.87	0.74	48,163.37	0.67	0.73	0.67	116.69	0.98
Test	ARIMA	0.91	0.75	229.29	1.00	0.74	0.67	101.69	1.00
	ANN	0.87	0.72	432.56	1.00	0.74	0.68	104.74	1.00
	LSTM	0.84	0.71	329.38	1.00	0.74	0.68	110.09	1.00
Bond market									
Train	ARIMA	0.18	0.13	277.03	0.78	0.44	0.37	2,553.82	6.20
	ANN	0.18	0.13	300.55	0.77	0.17	0.11	655.42	0.90
	LSTM	0.18	0.13	178.33	0.75	0.16	0.11	501.59	0.84
Test	ARIMA	0.17	0.12	185.92	1.00	0.45	0.39	1,538.81	1.01
	ANN	0.17	0.12	198.09	1.00	0.14	0.10	333.45	1.00
	LSTM	0.17	0.12	163.52	1.00	0.14	0.10	363.33	1.00
Bond derivative market									
Train	ARIMA	0.77	0.61	14,853.81	0.98	0.66	0.54	262.10	1.06
	ANN	0.69	0.55	82,559.83	0.77	0.62	0.54	160.50	0.93
	LSTM	0.70	0.55	29,420.44	0.80	0.61	0.52	151.78	0.89
Test	ARIMA	0.87	0.69	132.49	1.00	0.73	0.60	187.86	1.00
	ANN	0.78	0.63	411.67	1.00	0.68	0.59	140.58	1.00
	LSTM	0.78	0.63	241.14	1.00	0.67	0.58	127.71	1.00
FX derivative market									
Train	ARIMA	0.64	0.52	25,525.28	0.68	0.53	0.44	171.29	0.99
	ANN	0.64	0.52	22,328.05	0.68	0.52	0.44	187.36	0.98
	LSTM	0.58	0.48	18,580.26	0.57	0.52	0.44	145.47	0.98
Test	ARIMA	0.83	0.68	880.72	1.00	0.64	0.56	111.95	1.00
	ANN	0.82	0.68	1,090.18	1.00	0.63	0.56	115.94	1.00
	LSTM	0.74	0.62	2,547.00	1.00	0.63	0.56	104.23	1.00

[Note]
RMSE = Root Mean Square Error, MAE = Mean Absolute Error,
MAPE = Mean Absolute Percentage Error, NMSE = Normalized Mean Squared Error

Table 5: Traders' reactions on forecast of foreign investors with level data

	IND	BANK	FI	CIS	OTH	INS	GOV	FOR
Reactions on forecast of foreign investors in stock market								
SU	0.005	0.005	0.009**	0.028***	0.005	0.010**	0.006	–
SD	0.006	0.005	0.005	0.009**	0.006	0.006	0.005	0.004
BU	0.006	0.006	0.005	0.005	0.006	0.005	0.005	0.008*
BD	0.005	0.005	0.006	0.005	0.005	0.004	0.006	0.006
FXD	0.006	0.005	0.005	0.006	0.005	0.006	0.005	0.005
Reactions on forecast of foreign investors in stock derivative market								
SU	0.002**	0.002	0.002***	0.003***	0.001	0.002*	0.002**	0.003***
SD	0.002	0.002	0.002	0.003***	0.002	0.002	0.001	-
BU	0.002	0.002	0.002	0.001	0.001	0.002	0.002	0.002**
BD	0.002	0.001	0.002	0.002*	0.002**	0.002	0.002	0.002
FXD	0.001	0.002	0.002	0.002**	0.002	0.002*	0.001	0.002
Reactions on forecast of foreign investors in bond market								
SU	0.002**	0.001	0.002***	0.002***	0.001	0.001*	0.002**	0.002***
SD	0.001	0.001	0.001***	0.003	0.001	0.001	0.001	0.001
BU	0.001	0.001	0.001	0.001	0.001	0.001	0.001	-
BD	0.002*	0.001***	0.001***	0.001***	0.002**	0.001	0.001	0.001
FXD	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.001
Reactions on forecast of foreign investors in bond derivative market								
SU	0.003	0.003	0.004**	0.004**	0.003	0.003	0.003	0.004***
SD	0.003	0.003	0.003	0.004**	0.003	0.003	0.003	0.003
BU	0.003***	0.004*	0.003	0.005**	0.002*	0.003	0.003	0.004*
BD	0.003	0.003	0.004	0.003	0.003	0.003	0.003	-
FXD	0.002	0.003	0.003	0.003	0.003	0.003	0.002	0.003
Reactions on forecast of foreign investors in FX derivative market								
SU	0.003***	0.003***	0.004***	0.004***	0.003***	0.003***	0.003***	0.004***
SD	0.003***	0.003***	0.003***	0.004***	0.003***	0.003***	0.003***	0.003***
BU	0.003***	0.004***	0.003***	0.005***	0.002***	0.003***	0.003***	0.004***
BD	0.003***	0.003***	0.004***	0.003***	0.003***	0.003***	0.003***	0.004***
FXD	0.002***	0.003***	0.003***	0.003***	0.003***	0.003***	0.002***	-

[Note]
Each number means that logarithmic ratio of restricted model's forecast error over unrestricted model's forecast error. In unrestricted model, a rational expectation on foreign investors' trading volumes in each market is included as an independent variable.
1%=***, 5%=**, 10%=*, significance level

Table 6: Traders' reactions on forecast of foreign investors with 1st difference data

	IND	BANK	FI	CIS	OTH	INS	GOV	FOR
Reactions on forecast of foreign investors in stock market								
SU	0.023*	0.017	0.017	0.022*	0.018	0.022*	0.021*	-
SD	0.019	0.020	0.019	0.020	0.018	0.016	0.020	0.018
BU	0.020	0.019	0.023*	0.019	0.018	0.019	0.019	0.018
BD	0.021	0.019	0.018	0.020	0.024**	0.020	0.020	0.018
FXD	0.018	0.019	0.018	0.018	0.020	0.014	0.025	0.018
Reactions on forecast of foreign investors in stock derivative market								
SU	0.037**	0.031	0.027	0.037*	0.035	0.032	0.029	0.031
SD	0.032	0.031	0.043**	0.031	0.026	0.024**	0.034	-
BU	0.028	0.032	0.033	0.031	0.029	0.029	0.030	0.031
BD	0.031	0.028	0.029	0.030	0.030	0.031	0.027	0.033
FXD	0.028	0.028	0.028	0.025*	0.029	0.026	0.052**	0.028
Reactions on forecast of foreign investors in bond market								
SU	0.009*	0.007	0.008	0.009*	0.008	0.009*	0.009*	0.008
SD	0.008	0.008	0.009*	0.009**	0.007	0.007*	0.008	0.008
BU	0.008	0.008	0.009**	0.008	0.007	0.008	0.007	-
BD	0.009*	0.008	0.008	0.008	0.009	0.008	0.007	0.008
FXD	0.008	0.008	0.008	0.007	0.008	0.006*	0.011	0.008
Reactions on forecast of foreign investors in bond derivative market								
SU	0.013	0.012	0.012	0.013*	0.013	0.014*	0.014*	0.013
SD	0.012	0.012	0.013	0.013*	0.011	0.010**	0.013	0.011
BU	0.013	0.013	0.015**	0.01	0.011	0.011	0.012	0.012
BD	0.014**	0.013*	0.013	0.013	0.014	0.013	0.011	-
FXD	0.011	0.012	0.011	0.011	0.013	0.010	0.018*	0.018*
Reactions on forecast of foreign investors in FX derivative market								
SU	0.013***	0.012***	0.012***	0.013***	0.013***	0.014***	0.014***	0.013***
SD	0.012***	0.012***	0.013***	0.013***	0.011***	0.010***	0.013***	0.011***
BU	0.013***	0.013***	0.015***	0.012***	0.011***	0.011***	0.012***	0.012***
BD	0.014***	0.013***	0.013***	0.013***	0.014***	0.013***	0.011***	0.015***
FXD	0.011***	0.012***	0.011***	0.011***	0.013***	0.010***	0.018***	-

[Note]
Each number means that logarithmic ratio of restricted model's forecast error over unrestricted model's forecast error. In unrestricted model, a rational expectation on foreign investors' trading volumes in each market is included as an independent variable.
1%=***, 5%=**, 10%=*, significance level

Table 7: In degree centrality at positive shock

		Positive			Negative		
		$1st$	$2nd$	$3rd$	$1st$	$2nd$	$3rd$
Finance	Kospi	GOV_{fxd}	CIS_{fxd}	GOV_{bu}	CIS_{su}	FOR_{su}	ETC_{bd}
	Krw/usd	IND_{bu}	GOV_{su}	INS_{bu}	CIS_{su}	FOR_{su}	ETC_{bd}
	S&P	IND_{bu}	CIS_{fxd}	GOV_{su}	CIS_{su}	FOR_{su}	ETC_{bd}
	Nikkei	IND_{bu}	GOV_{su}	IND_{bd}	CIS_{su}	ETC_{su}	FOR_{su}
	Hangseng	CIS_{fxd}	GOV_{su}	GOV_{bu}	CIS_{su}	ETC_{bd}	FOR_{su}
Macro	Current account	ETC_{bd}	INS_{su}	FI_{su}	ETC_{su}	CIS_{fxd}	GOV_{bu}
	Cap.&Fin. account	ETC_{bd}	INS_{su}	FI_{su}	ETC_{su}	CIS_{fxd}	GOV_{bu}
	Inflation rate	CIS_{fxd}	GOV_{bu}	$BANK_{su}$	ETC_{bd}	CIS_{su}	FI_{su}
	Unemployment rate	FI_{su}	FI_{bu}	$BANK_{bu}$	GOV_{fxd}	FOR_{bd}	$BANK_{su}$
	Base interest rate	GOV_{fxd}	GOV_{bu}	CIS_{bu}	ETC_{bd}	FI_{su}	INS_{bu}

[Note] Trader_*market*
(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
(market)
su = stock, *sd* = Stock derivative, *bu* = Bond, *bd* = Bond derivative, *fxd* = FX derivative

Table 8: In degree centrality at negative shock

		Positive			Negative		
		$1st$	$2nd$	$3rd$	$1st$	$2nd$	$3rd$
Finance	Kospi	GOV_{fxd}	CIS_{fxd}	GOV_{bu}	CIS_{su}	FOR_{su}	ETC_{bd}
	Krw/usd	CIS_{su}	ETC_{bd}	FOR_{su}	GOV_{su}	IND_{bu}	INS_{bu}
	S&P	CIS_{su}	FOR_{su}	ETC_{bd}	CIS_{fxd}	IND_{bu}	GOV_{su}
	Nikkei	CIS_{su}	ETC_{su}	FOR_{su}	IND_{bu}	GOV_{su}	IND_{bd}
	Hangseng	CIS_{su}	ETC_{bd}	FOR_{su}	CIS_{fxd}	GOV_{su}	GOV_{bu}
Macro	Current account	ETC_{su}	CIS_{fxd}	GOV_{bu}	ETC_{bd}	INS_{su}	FI_{su}
	Cap.&Fin. account	CIS_{fxd}	ETC_{su}	GOV_{bu}	ETC_{bd}	INS_{su}	FI_{su}
	Inflation rate	ETC_{bd}	CIS_{su}	FI_{su}	CIS_{fxd}	GOV_{bu}	$BANK_{su}$
	Unemployment rate	GOV_{fxd}	FOR_{bd}	$BANK_{su}$	FI_{su}	FI_{bu}	$BANK_{bu}$
	Base interest rate	ETC_{bd}	FI_{su}	INS_{bu}	GOV_{fxd}	GOV_{bu}	CIS_{bu}

[Note] Trader_*market*
(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
(market)
su = stock, *sd* = Stock derivative, *bu* = Bond, *bd* = Bond derivative, *fxd* = FX derivative

Table 9: Out degree centrality at positive shock

		Positive			Negative		
		$1st$	$2nd$	$3rd$	$1st$	$2nd$	$3rd$
Finance	Kospi	GOV_{fxd}	CIS_{fxd}	GOV_{bu}	CIS_{su}	FOR_{su}	ETC_{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	Current account	FOR_{sd}	IND_{fxd}	FI_{sd}	IND_{sd}	$BANK_{fxd}$	CIS_{su}
	Cap.&Fin. account	FOR_{sd}	IND_{fxd}	FI_{sd}	$BANK_{fxd}$	IND_{sd}	IND_{su}
	Inflation rate	$BANK_{fxd}$	IND_{su}	IND_{sd}	FOR_{sd}	FI_{sd}	FOR_{bd}
	Unemployment rate	$BANK_{bd}$	FOR_{fxd}	$BANK_{fxd}$	IND_{fxd}	FOR_{su}	FOR_{bd}
	Base interest rate	IND_{sd}	$BANK_{fxd}$	FI_{fxd}	FOR_{sd}	FI_{sd}	$BANK_{bd}$

[Note] Trader_*market*
(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
(market)
su = stock, *sd* = Stock derivative, *bu* = Bond, *bd* = Bond derivative, *fxd* = FX derivative

Table 10: Out degree centrality at negative shock

		Positive			Negative		
		$1st$	$2nd$	$3rd$	$1st$	$2nd$	$3rd$
Finance	Kospi	GOV_{fxd}	CIS_{fxd}	GOV_{bu}	CIS_{su}	FOR_{su}	ETC_{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	Current account	IND_{sd}	$BANK_{fxd}$	CIS_{su}	IND_{fxd}	FOR_{sd}	FI_{sd}
	Cap.&Fin. account	IND_{sd}	$BANK_{fxd}$	IND_{su}	FOR_{sd}	IND_{fxd}	FI_{sd}
	Inflation rate	FOR_{sd}	FI_{sd}	FOR_{bd}	$BANK_{fxd}$	IND_{su}	IND_{sd}
	Unemployment rate	IND_{fxd}	FOR_{su}	FOR_{bd}	$BANK_{bd}$	FOR_{fxd}	$BANK_{fxd}$
	Base interest rate	FOR_{sd}	FI_{sd}	$BANK_{bd}$	$BANK_{fxd}$	IND_{sd}	FI_{fxd}

[Note] Trader_*market*
(Trader)
IND = Individual trader, BANK = Bank, FI = Financial investment(securities companies)
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(market)
su = stock, *sd* = Stock derivative, *bu* = Bond, *bd* = Bond derivative, *fxd* = FX derivative

Table 11: Network measure change at the shock of financial indexes

Centrality		Shock Kospi	Krw/usd	S&P	Nikkei	Hangseng
Positive response	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 response	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] Trader_*market*
(Trader)
IND = Individual trader, BANK = Bank, FI = Financial investment(securities companies)
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(market)
su = stock, *sd* = Stock derivative, *bu* = Bond, *bd* = Bond derivative, *fxd* = FX derivative

Table 12: Trading volume change at the shock of OUT degree centrality

Trading		Positive Shock			Negative Shock		
		IND_{su}	CIS_{fxd}	CIS_{su}	FOR_{bd}	IND_{fxd}	FOR_{su}
Positive response	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 response	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}

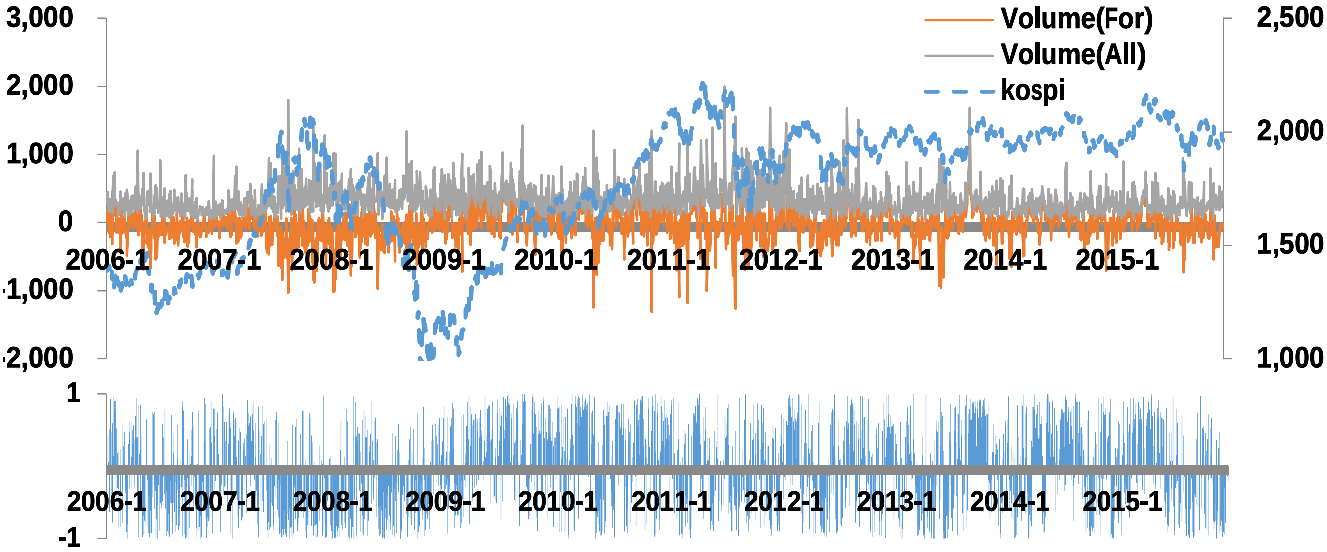
[Note] Trader_*market*
(Trader)
IND = Individual trader, BANK = Bank, FI = Financial investment(securities companies)
CIS = Collective Investment Scheme, OTH = others (small financial companies)
INS = Insurance companies, GOV = Government, FOR = Foreign investment
(market)
su = stock, *sd* = Stock derivative, *bu* = Bond, *bd* = Bond derivative, *fxd* = FX derivative

Table 13: Trading volume change at the shock of trading volume change

Trading		Positive Shock			Negative Shock		
		CIS_{fxd}	$BANK_{fxd}$	FOR_{bd}	FOR_{su}	FOR_{fxd}	$BANK_{fxd}$
Positive response	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 response	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] Trader_*market*
(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
(market)
su = stock, *sd* = Stock derivative, *bu* = Bond, *bd* = Bond derivative, *fxd* = FX derivative

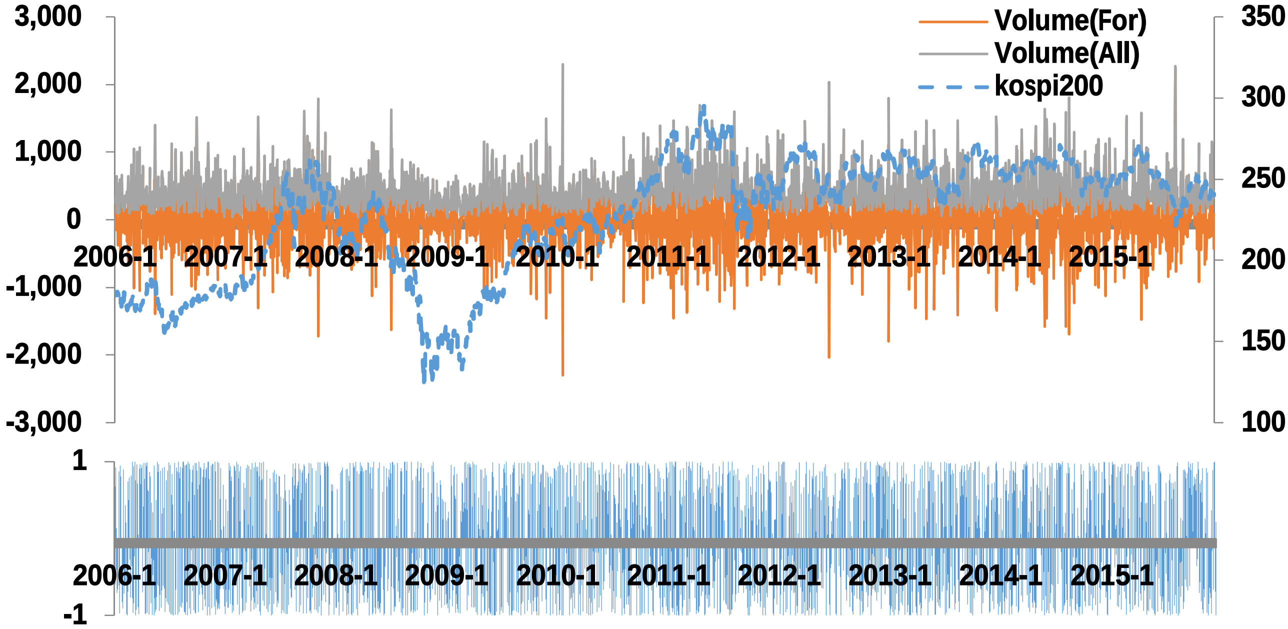
Figure 4: Foreign investors' trading volume in stock market



Notes:
(Upper) Left : billion KRW, Right : KOSPI index
(Lower) Foreign investors' daily net trading / (All investors' absolute daily net trading/ 2)

Source : KRX (www.krx.co.kr)

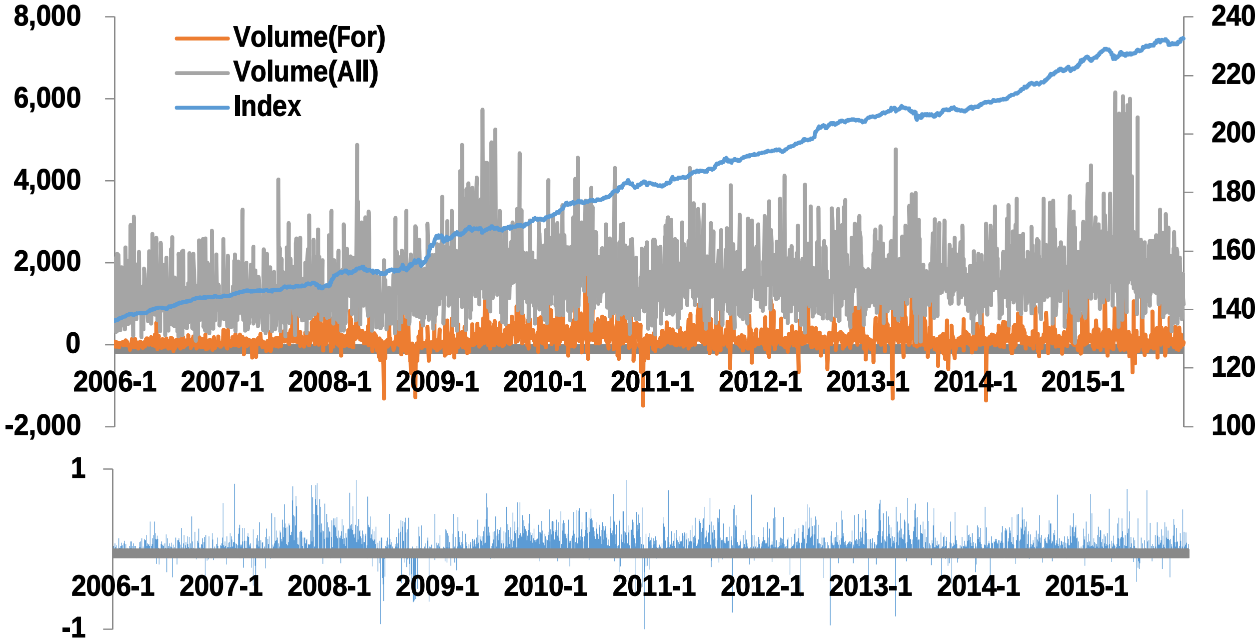
Figure 5: Foreign investors' trading volume in stock derivative market



Notes:
(Upper) Left : billion KRW, Right : KOSPI200 index
(Lower) Foreign investors' daily net trading / (All investors' absolute daily net trading/ 2)

Source : KRX (www.krx.co.kr)

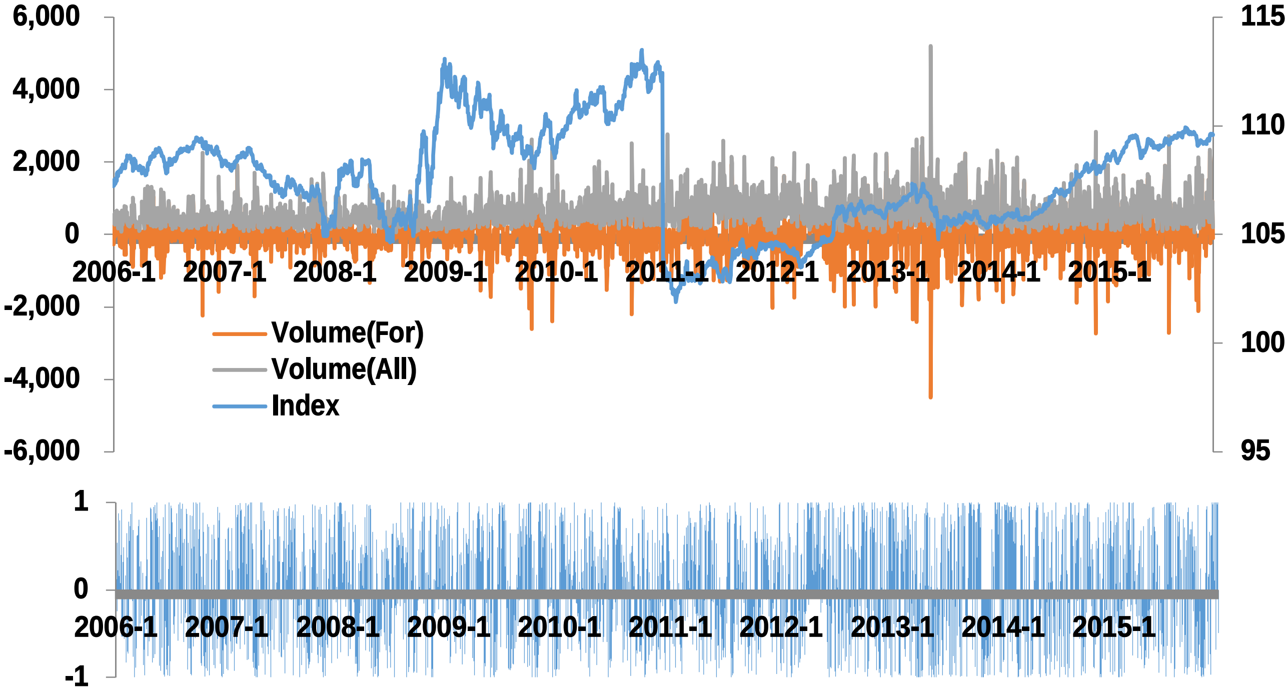
Figure 6: Foreign investors' trading volume in bond market



Notes:
(Upper) Left : billion KRW, Right : Korean bond composite index (KIS)
(Lower) Foreign investors' daily net trading / (All investors' absolute daily net trading/ 2)

Source : Korea Investors Service(www.kisrating.com)
Korean Financial Investment Association (www.kofia.or.kr)

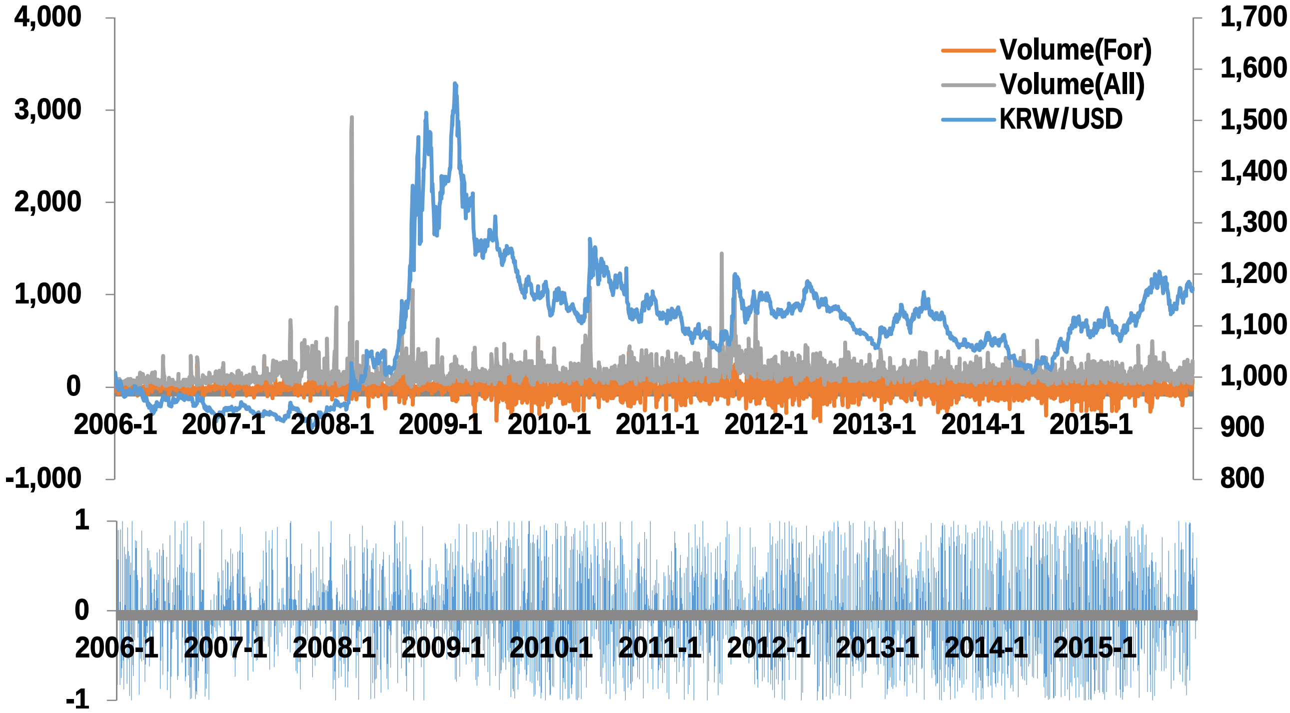
Figure 7: Foreign investors' trading volume in bond derivative market



Notes:
(Upper) Left : billion KRW, Right : Korean treasury bond (3yr) futures index
(Lower) Foreign investors' daily net trading / (All investors' absolute daily net trading/ 2)

Source : KRX (www.krx.co.kr)

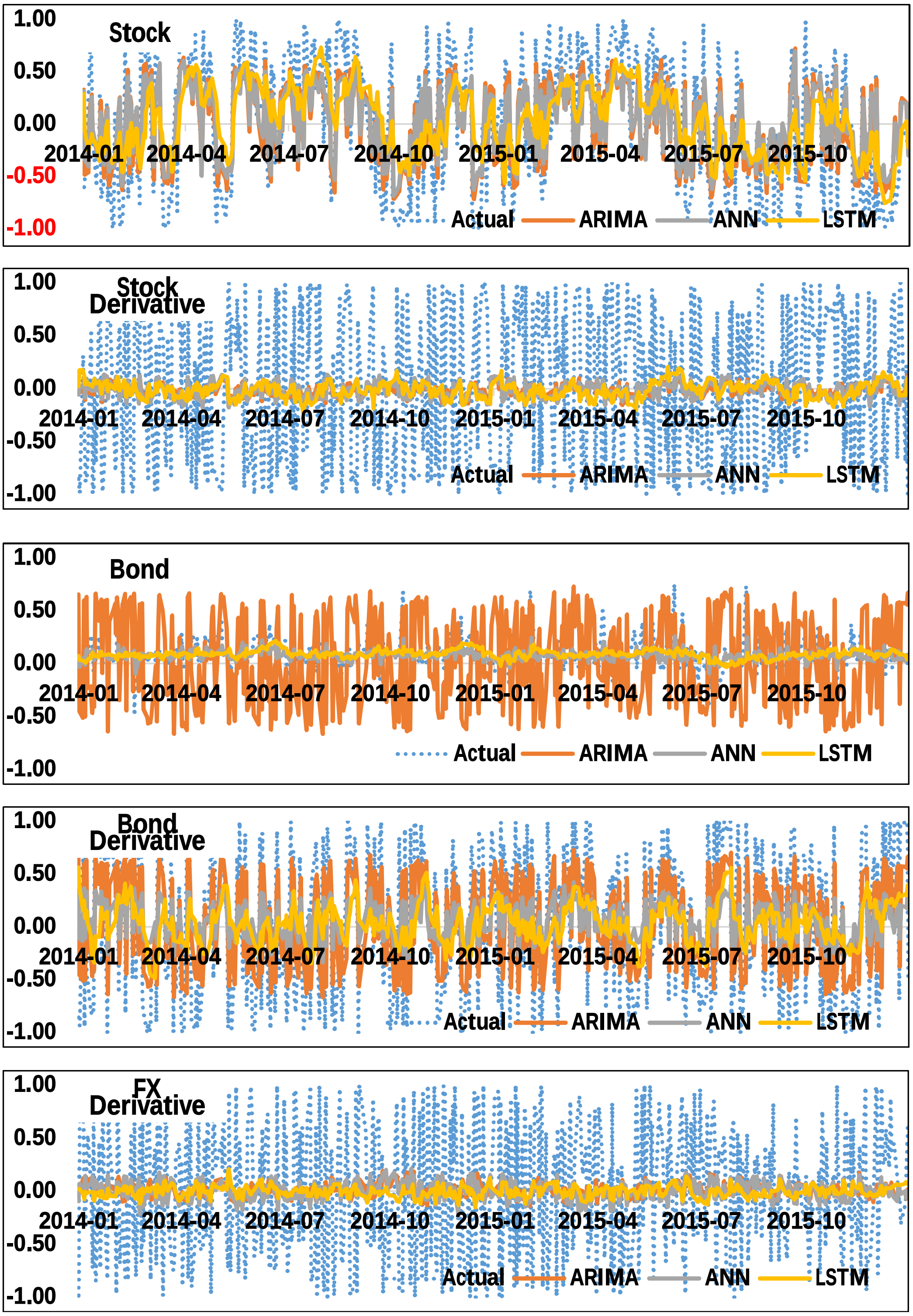
Figure 8: Foreign investors' trading volume in FX derivative market



Notes:
(Upper) Left : billion KRW, Right : KRW/USD
(Lower) Foreign investors' daily net trading / (All investors' absolute daily net trading/ 2)

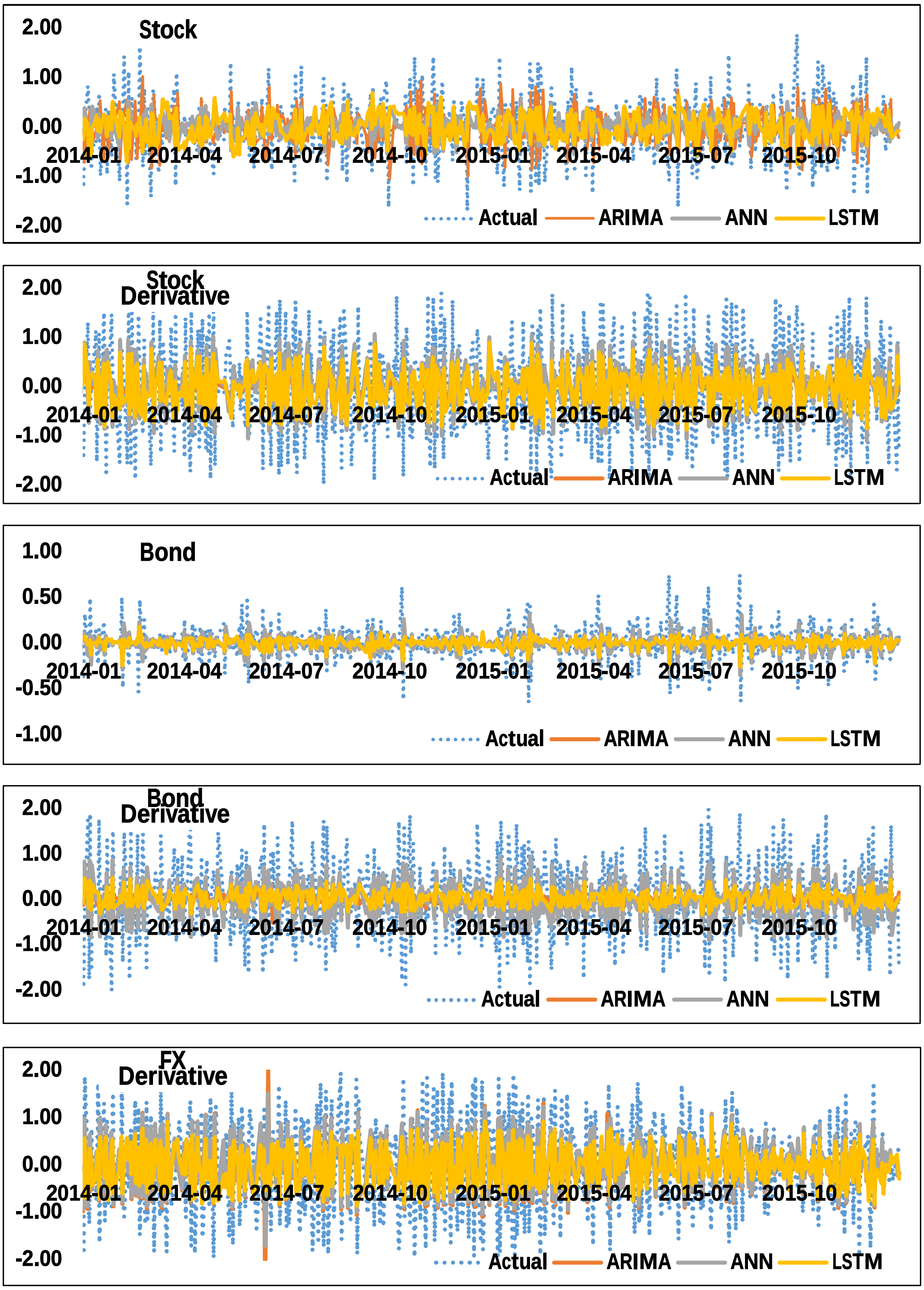
Source : KRX (www.krx.co.kr)

Figure 9: Forecasting result with level data



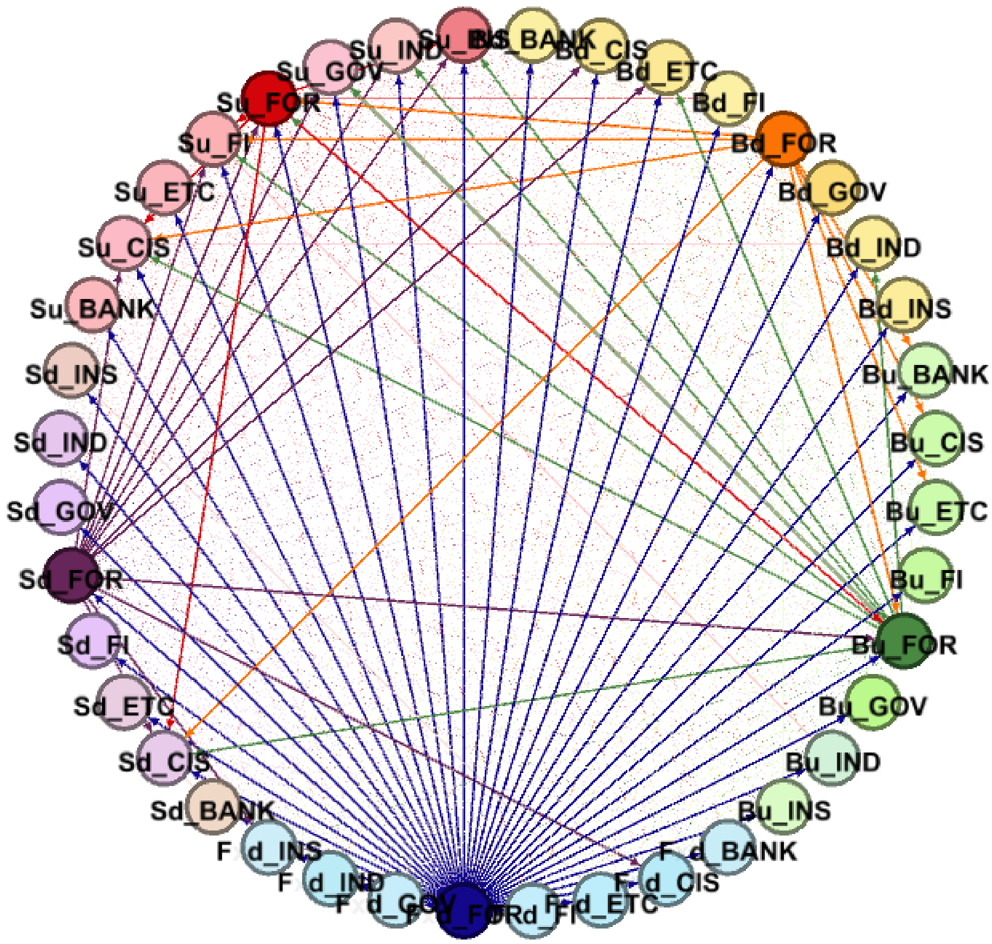
Notes:
Foreign investors' daily net trading / (All investors' absolute daily net trading/ 2)

Figure 10: Forecasting result with 1st difference data



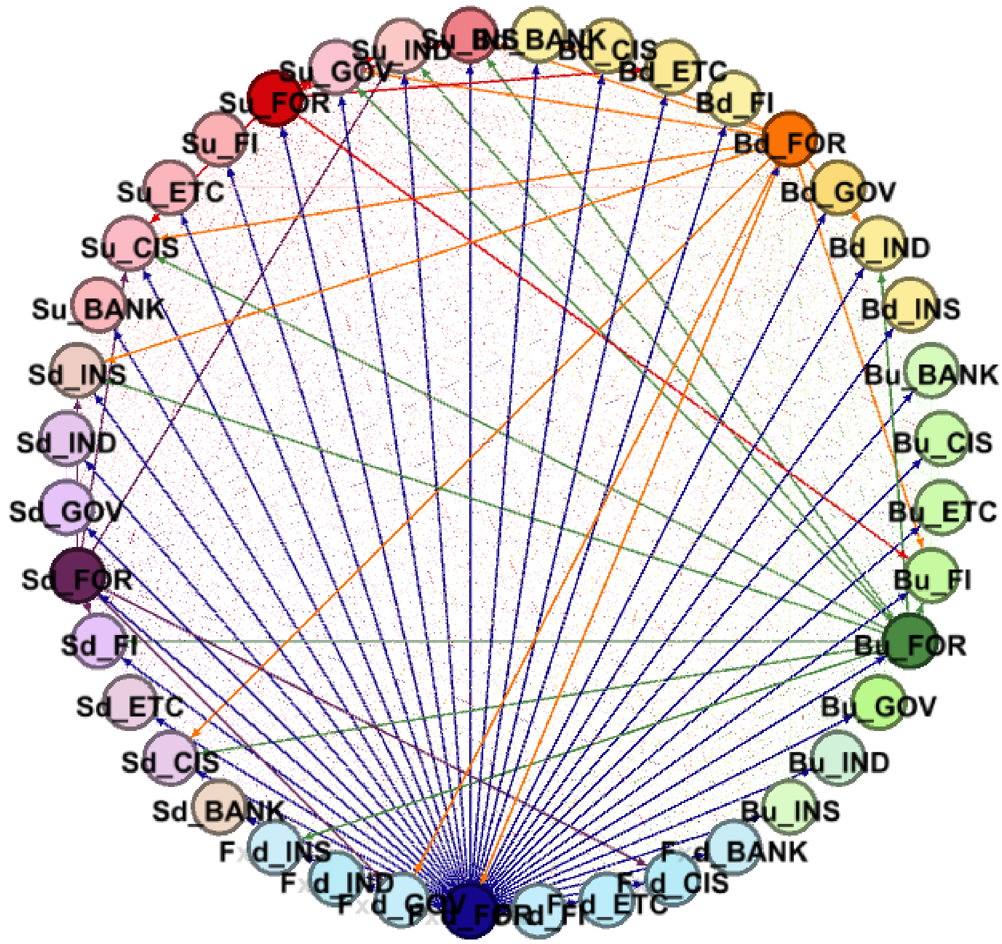
Notes:
Foreign investors' daily net trading / (All investors' absolute daily net trading/ 2)

Figure 11: Network structure with rational expectation on foreign investors with level data



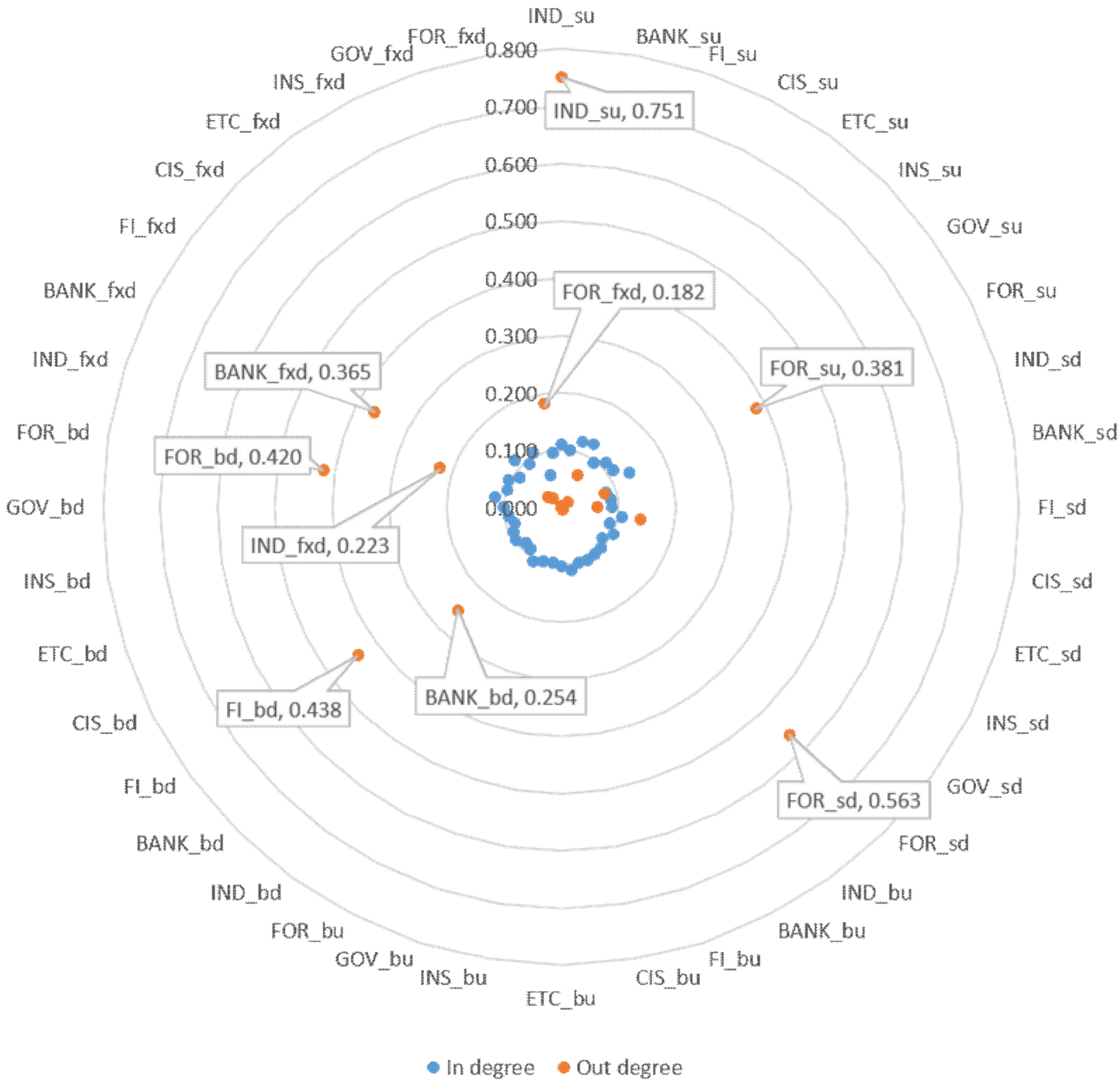
Notes: An arrow means foreign investors in a certain market have influence on the trader with 10% significance level.

Figure 12: Network structure with rational expectation on foreign investors with 1st differential data



Notes: An arrow means foreign investors in a certain market have influence on the trader with 10% significance level.

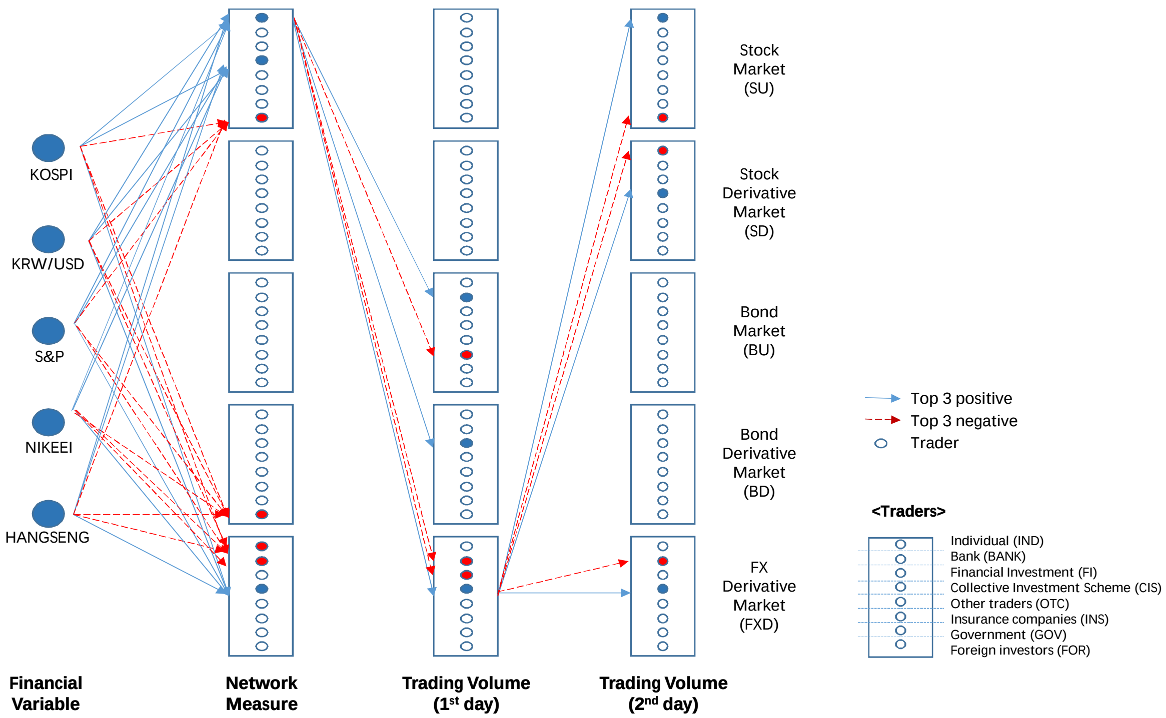
Figure 13: Average monthly OUT/IN degree centrality



Notes: Trader_market

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

Figure 14: System risk spillover structure from IND in stock market



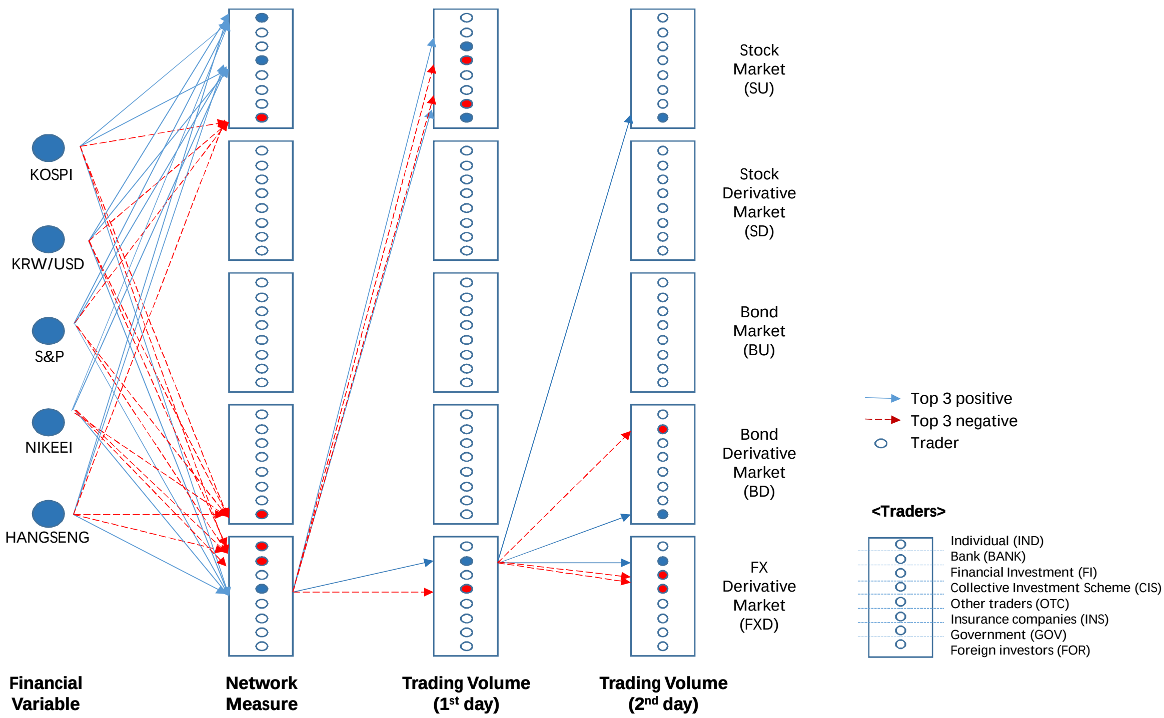
Notes:

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

(**2st phase**)
Impulse : one positive standard deviation shock on the daily centrality of IND_su
Response :
Top 3 positive to BANK_bu, FI_bd, CIS_fxd
Top 3 neagtive to INS_bu, BANK_fxd, FI_fxd

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

Figure 15: System risk spillover structure from CIS in FX derivative market

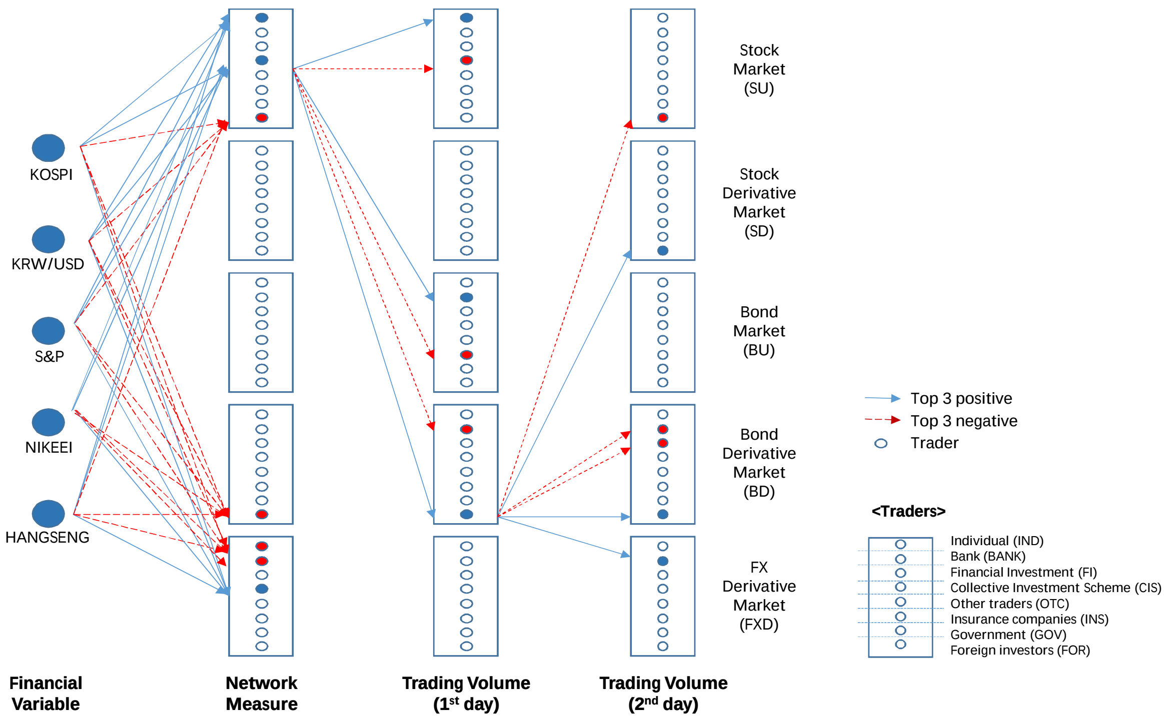


Notes:
(**1st phase**)
Impulse : one standard deviation shock on KOSPI, KRW/USD, S&P, NIKKEI, HANGSENG
Response :
Top 3 positive to IND_su, CIS_su and CIS_fxd
Top 3 neagtive to FOR_su, FOR_bd, IND_fxd

(**2st phase**)
Impulse : one positive standard deviation shock on the daily centrality of CIS_fxd
Response :
Top 3 positive to FI_su, FOR_su, BANK_fxd
Top 3 neagtive to CIS_su, GOV_su, CIS_fxd

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

Figure 16: System risk spillover structure from CIS in stock market



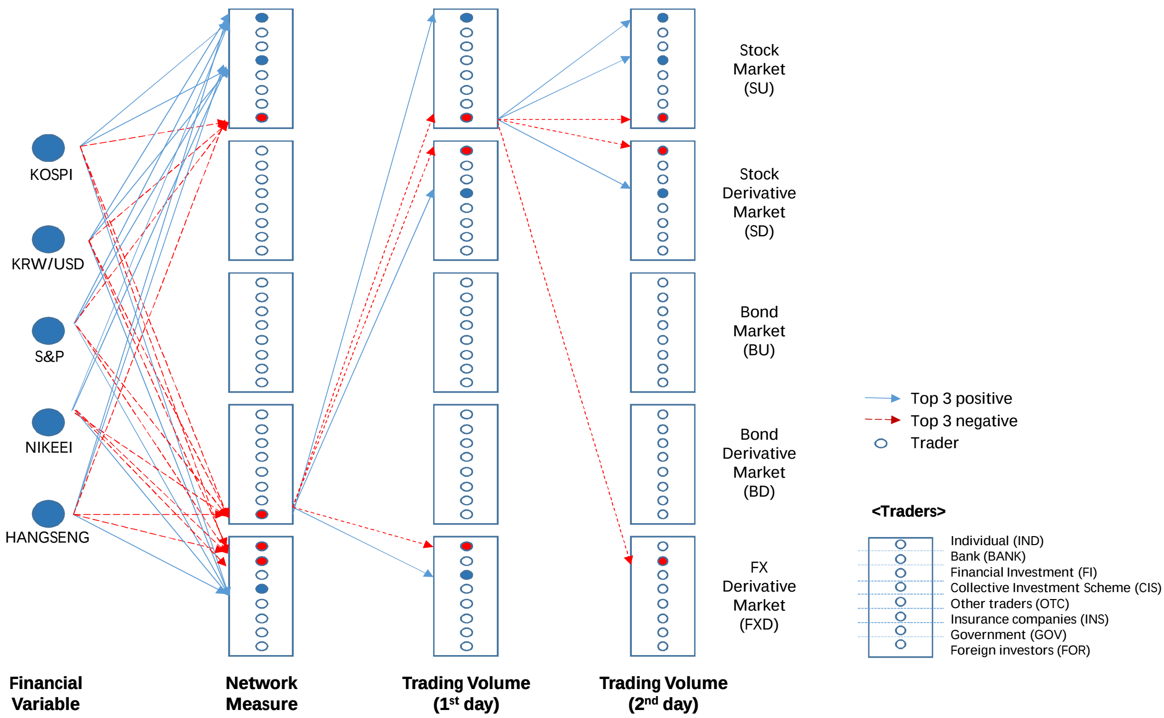
Notes:

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

(**2st phase**)
Impulse : one positive standard deviation shock on the daily centrality of CIS_su
Response :
Top 3 positive to IND_su, BANK_bu, FOR_bd
Top 3 neagtive to CIS_su, INS_bu, BANK_bd

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

Figure 17: System risk spillover structure from FOR in bond derivative market



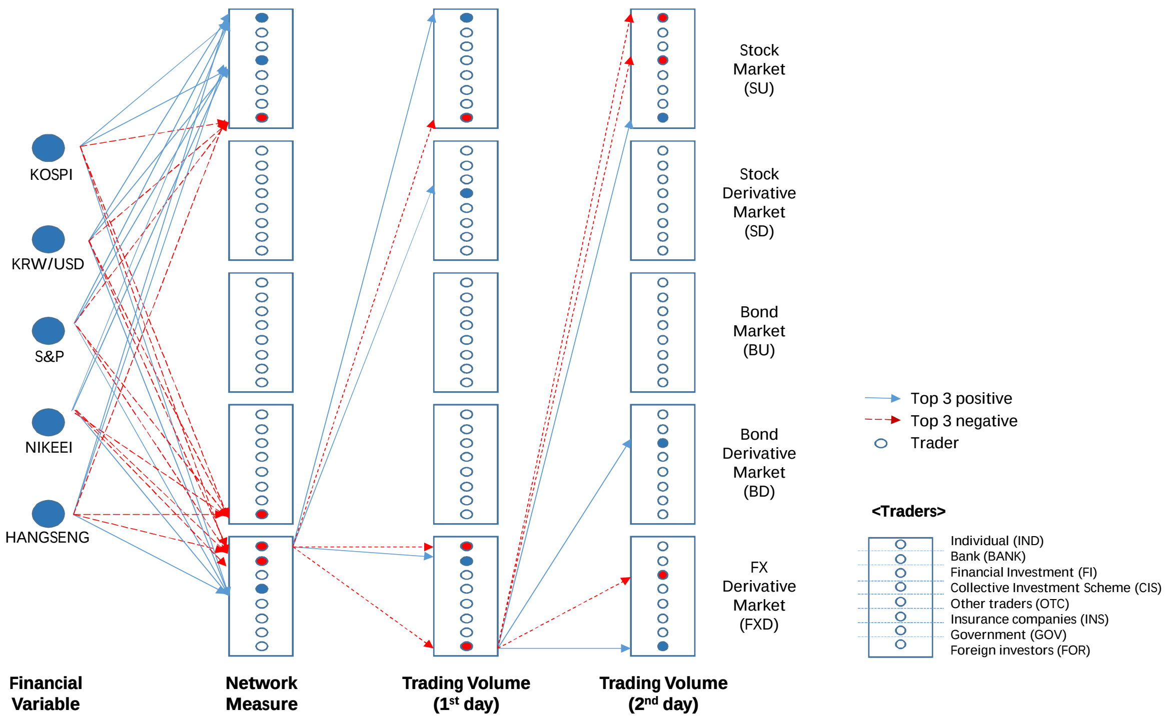
Notes:

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

(**2st phase**)
Impulse : one negative standard deviation shock on the daily centrality of FOR_bd
Response :
Top 3 positive to IND_su, CIS_sd, FI_fxd
Top 3 neagtive to FOR_su, IND_sd, IND_fxd

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

Figure 18: System risk spillover structure from IND in FX derivative market

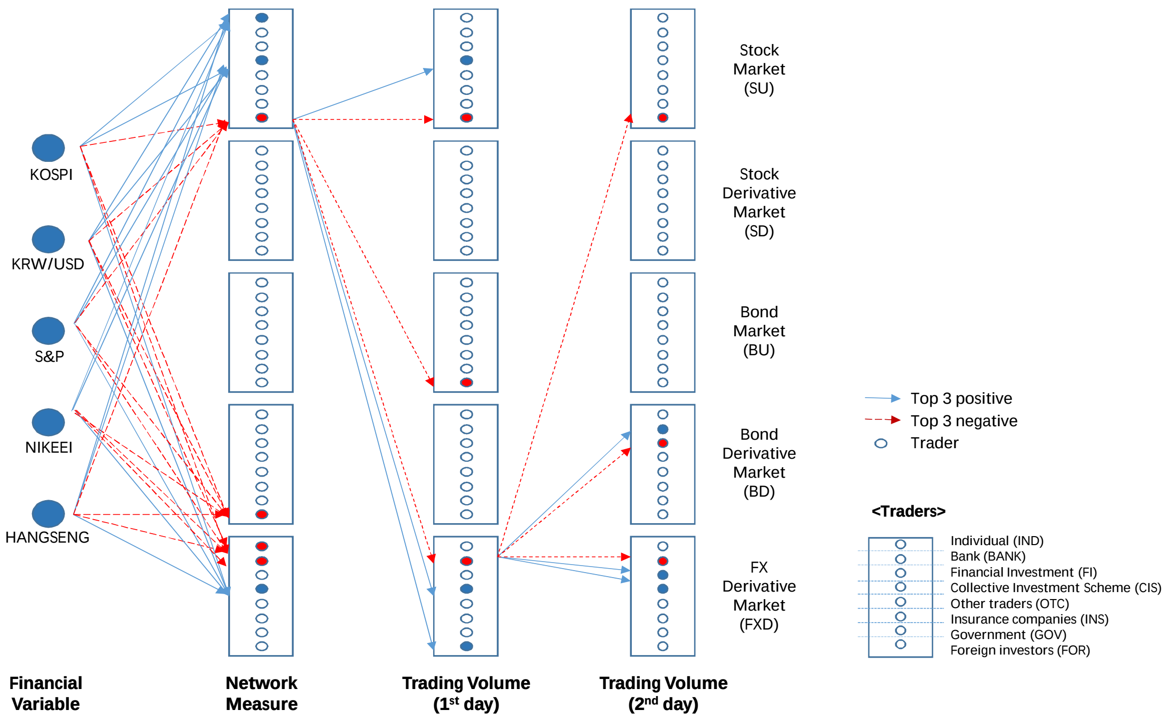


Notes:
(**1st phase**)
Impulse : one standard deviation shock on KOSPI, KRW/USD, S&P, NIKKEI, HANGSENG
Response :
Top 3 positive to IND_su, CIS_su and CIS_fxd
Top 3 neagtive to FOR_su, FOR_bd, IND_fxd

(**2st phase**)
Impulse : one negative standard deviation shock on the daily centrality of IND_fxd
Response :
Top 3 positive to IND_su, CIS_sd, BANK_fxd
Top 3 neagtive to FOR_su, IND_fxd, FOR_fxd

(**3rd phase**)
Impulse : one negative standard deviation shock on the daily net trading volume of FOR_fxd
Response :
Top 3 positive to FOR_su, FI_bd, FOR_fxd
Top 3 neagtive to IND_su, CIS_su, FI_fxd

Figure 19: System risk spillover structure from FOR in stock market



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

(**2st phase**)
Impulse : one negative standard deviation shock on the daily centrality of FOR_su
Response :
Top 3 positive to CIS_su, CIS_fxd, FOR_fxd
Top 3 neagtive to FOR_su, FOR_bu, BANK_fxd

(**3rd phase**)
Impulse : one negative standard deviation shock on the daily net trading volume of BANK_fxd
Response :
Top 3 positive to BANK_bd, FI_fxd, CIS_fxd
Top 3 neagtive to FOR_su, FI_bd, BANK_fxd