Advanced Science and Technology Letters
Vol.34 (Business 2013), pp.50-57
http://dx.doi.org/10.14257/astl.2013.34.13

Understanding Information Flows among Individual Companies in Korean Stock Market

Ho-Yong Kim, Seok-Won Ahn, Gab-Jin Oh

Division of Business Administration, College of Business, Chosun University
Gwang-ju 501-759, Republic of Korea
E-mail: phecogjoh@gmail.com

Abstract. Systemic risk is the risk that negative effect that is caused by one company is propagated to other companies through a specific relationship channel. To measure systemic risk that is characterized by interconnected features among economic unit, we employ the generalized variance decomposition method (GVDM) with a volatility data set of 354 companies listed on the KOSPI index. We propose a novel approach to quantify systemic risk and to calculate the extent of systemic risk for the KOSPI market. We find that systemic risk is closely related to financial crises such as the Asian currency crisis and the subprime mortgage crisis.

1 Introduction

Systemic risk is the risk that is caused by either economical or operational activities of a company or a market, which is propagated to other companies or markets, and that its presence is gradually increased as propagation is successively progressed by its domino effect and snowball effect.

The representative case of systemic risk in a financial system is the sub-prime crisis in the US during the period from 2007 to 2008. The sub-prime crisis had occurred because of a complex linkage among the micro- and macro economy, derivatives and human psychology. The first default shock among the sub-prime mortgage banks was propagated to the investment banks, and the default of the investment banks subsequently affected the commercial banks. Consequently, the US economy collapsed because of the systemic risk prevailed in the financial system. This consecutive domino effect caused a liquidity crisis in the global economy that was induced by the aftermath of the sub-prime crisis.

A network model is often used to confirm the relationship individual companies because the most important concept in systemic risk is interconnection. The basic network model is an adjacency matrix that is filled with binary information and is characterized by the out-degree and the in-degree of companies. Billio, Monica, et al (2011) use a combined method composed of network and statistical models that is known as the Granger causality

ISSN: 2287-1233 ASTL

network. This method, however, has the weakness that the adjacency matrix of the granger causality network is filled with binary numbers; thus, it is difficult to strictly measure the systemic risk.

In this thesis, we employed the VAR model, which is able to analyze the contagion behavior. Contagion behavior is defined by how the shock of one variable affects other variables. We use the VAR model because it can simultaneously consider many endogenous variables. The VAR model can also analyze interactions among variables in VAR systems because it determines the relationships among variables with certain values. Additionally, the VAR model can be extended to the concept of systemic risk by approaching to the interactions of variables from a different perspective rather than that of earlier work[1].

We use the method to measure contagion effect in Korean stock market, KOSPI, analyze whether there is different aspect in specific periods.

2 Methods

2.1 Vector autoregressive model

The vector autoregression (VAR) model is a model that can estimate correlation and causality between variables by combining the features of time series and regression analysis. Financial time series data, such as the money supply, interest rate and the financial return of a company, is affected by past trends and fluctuations of other variables.

Therefore, Simultaneous analysis considered other related variables is needed to financial time series analysis, VAR model is able to coincidentally analyze time series data with more than one variable.

2.2 Generalized variance decomposition

The orthogonal impulse response function obtained by Cholesky factorization has the problem that it is sensitive to the order of the variables in the VAR system. Whereas the generalized impulse response function is not affected by the problem, this alternative

1 Diebold, Francis X., and Kamil Yilmaz. “On the network topology of variance decompositions: Measuring the connectedness of financial firms”(2011).

identification scheme can contain correlated errors and thus lose the advantage of orthogonalization. However, because the problem of reordering variants is quite critical, we apply the generalized variance decomposition method (GVDM) developed by Pesaran and Shin (1998).

The share of variable y_j in the forecast error of estimator $\hat{y}_{i,t+h}$ using the GVDM is

$$\omega^{g}{}_{ij,h} = \frac{\sigma_{jj}^{-1}\sum_{l=0}^{h-1}(\pi_i' B_l \Sigma \pi_j)^2}{\sum_{l=0}^{h-1}(\pi_i' B_l \Sigma B_l' \pi_i)}$$

where σ_{jj} is the jth diagonal element of the forecast error covariance matrix.

The traditional variance decomposition satisfies $\sum_{j=1}^{K}\omega_{ij} = 1$, but GVDM has $\sum_{j=1}^{K}\omega^{g}{}_{ij,h} \neq 1$. Therefore, we follow the normalized GVDM of Diebold and Yilmaz (2011) and Greenwood-Nimmo et al. (2012):

$$\tilde{\eta}_{ij} = \frac{\omega^{g}{}_{ij}}{\sum_{j=1}^{K}\omega^{g}{}_{ij}}$$

The normalized GVD satisfies

$$\sum_{j=1}^{K}\tilde{\eta}_{ij} = 1$$
$$\sum_{i=1}^{K}\sum_{j=1}^{K}\tilde{\eta}_{ij} = K.$$

2.3 Average information flow and contagion effect of shocks

We obtain the following matrix via the normalized GVD:

	y_1	y_2	⋯	y_j	From other
y_1	$\tilde{\eta}_{11}$	$\tilde{\eta}_{12}$	⋯	$\tilde{\eta}_{1j}$	$\sum_{j=1}^{K}\tilde{\eta}_{1j}=1$
y_2	$\tilde{\eta}_{21}$	$\tilde{\eta}_{22}$	⋯	$\tilde{\eta}_{2j}$	$\sum_{j=1}^{K}\tilde{\eta}_{2j}=1$
⋮	⋮	⋮	⋱	⋮	⋮
y_i	$\tilde{\eta}_{i1}$	$\tilde{\eta}_{i2}$	⋯	$\tilde{\eta}_{ij}$	$\sum_{j=1}^{K}\tilde{\eta}_{ij}=1$
To other	$\sum_{i=1}^{K}\tilde{\eta}_{i1}\neq 1$	$\sum_{i=1}^{K}\tilde{\eta}_{i2}\neq 1$	⋯	$\sum_{i=1}^{K}\tilde{\eta}_{ij}\neq 1$	$\sum_{i=1}^{K}\sum_{j=1}^{K}\tilde{\eta}_{ij}=K$

where $i, j = 1,2,\ldots,K$.

From the perspective of network theory, the NGVD matrix is an adjacency matrix filled with weights and not with the logical numbers 1 or 0. These weights are interpreted by Diebold and Yilmaz (2011) as connectedness. Because variance decomposition is a method that manages the forecast error extracted by the VAR system, these outputs are therefore the shocks that are unexplained by the relationships among the selected variables in the VAR system. We can also interpret these weights as the shocks.

Therefore, from this point on, we interpret each element of the normalized GVD matrix (NGVD matrix) $\tilde{\eta}_{ij}$ as the shock from company (variable) j company i. Because the diagonal term in the normalized GVD matrix (NGVD matrix) is the shock from the company onto itself and the row sum of the NGVD matrix is 1, the diagonal values in the results are ignored[2]. We also focus on the outflows of each company to confirm the contagion effect of shocks.

On an individual level, the outflow of a shock to another company from company y_j is the columned sum of company y_j as follows:

$$Out_{j,t} = \sum_{i=1}^{K}\tilde{\eta}_{ij,t}\ .$$

and the average information flow (AIF)[3] is

[2] i.e., the values of the diagonal terms are filled with zeros.

[3] AIF is equal to “Total connectedness”, Diebold and Yilmaz (2011).

$$\mathrm{AIF}_t = \frac{\sum_j^K Out_{jt}}{K}$$
$$for\ t = 1,2,\dots T.$$

AIF indicates the average information flow for all companies, which is equal to $\frac{\sum_{i=1}^{K}\sum_{j=1}^{K}\tilde{\eta}_{i,j,t}}{K}\quad for\ i \neq j$. The dynamics of AIF is determined using a rolling-window method with a window of one day.

3 Empirical results

3.1 Used Data

To calculate the primary result, we use the daily closing price for individual companies that are listed on the KOSPI stock index.

We use the mean and standard deviation of the normalized absolute log-return as a proxy of volatility from April 1 from April 1, 1991 to December 31, 2010. The volatility is defined as follows:

$$Vol_i(t) = \left|\frac{R_i(t) - \bar{R}_i}{\sigma_i}\right|,\quad i = 1, 2, \dots, N$$
$$R_i(\mathrm{t}) = \ln(\mathrm{p(t)}) - \ln(\mathrm{p(t-1)})$$

$Vol_i = normalized\ volatility$
$P(t) = closing - price - on\ day\ t$
$\bar{R}_i = average\ return\ of\ company\ i\ for\ entire\ period$
$\sigma_i = standard\ deviation\ of\ company\ i\ for\ entire\ period,$
where N is the number of companies.

Because the GVDM assumes that the forecast error obeys a multivariate normal distribution, the data must be appropriate for the nature of the normal distribution. Diebold and Yilmaz (2011) used the log-realized volatility for two reasons: volatility is valuable as a fear indicator and volatility is especially sensitive to crises. We therefore apply volatility data instead of a return time series.

Because the realized daily volatility is difficult to collect for many companies, we use the absolute standardized log-return as a proxy of daily volatility. Absolute return is more suitable for daily volatility than squared return[4], and the natural logarithm often obeys approximate normality.

For the entire period, we select 354 among all stocks listed on the KOSPI index

3.2 Results

Fig. 1. Average Information Flow (AIF)[5]

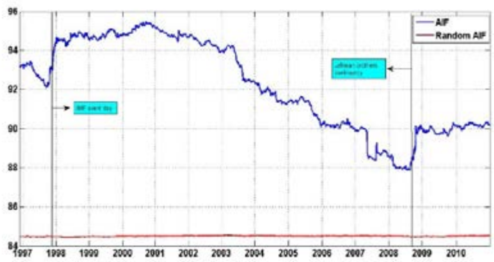


Figure 1 shows the result of AIF, which indicates contagion effect of KOSPI system, might be contained survival bias. Although we use so many historical data to extract useful error term due to many variables used in regression model, AIF is capturing major crisis events, IMF crisis and Lehman Brothers bankruptcy. The red line in Figure 1 is using shuffled data to eliminate historical relationships, showing whether it is meaningful result or not; it is not meaningful because it is not showing any patterns when compared with the blue line, which is using real data, so the result of red line is amply meaningful since it contains particular patterns and gives us definite information.

There are two meanings in AIF result. Firstly, the contagion effects among companies are rapidly increased, it is because the companies, which are reciprocally connected through their certain channels, are actively propagating negative shocks to their related partners by their financial or operational activities. Therefore, AIF indicates that activities of firms or market to avoid potential threats lead to domino effect of systemic risk and emphasize it when the negative event occurred.

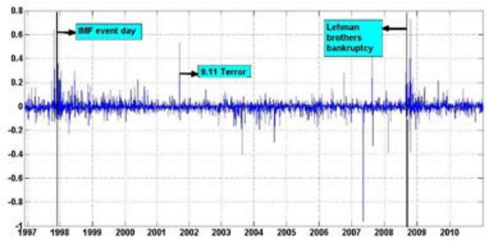
Secondly, there is the difference between domestic and foreign crisis. The contagion effect in IMF crisis is lasted high and long because IMF crisis had continued and

[4] Forsberg, Lars, and Eric Ghysels. "Why do absolute returns predict volatility so well?." *Journal of Financial Econometrics* 5.1 (2007): 31-67.

[5] The red line represents the randomized AIF, which is calculated using the average random normal returns of 130 random sets following the mean and variance of each company.

exacerbated Korea economy approximately 5 years and directly affecting it - The Asian currency crisis, equal to IMF crisis, lasted from November 21, 1997, when the relief loans were requested from the IMF, to August 23, 2001, when the repayments on the loans, which totaled 195 billion dollars, were completed - ,and subprime crisis as foreign crisis is indirectly effecting Korea economy through national or financial channel between US and Korea, so AIF result shows that its contagion effect is more smaller than that of domestic crisis.

Fig. 2. Difference of AIF



We also estimate the difference of the AIF values from Figure 2 that displays the difference of the AIF during entire period. The AIF increased during times of financial crisis, such as the Korean IMF event, the September 11 terror attacks and the sub-prime period. Differences values of the AIF following the aftermath of the shocks caused by the IMF event, the September 11th terror attacks and the subprime event were greatest near the day of the event.

Consequently, the contagion effects between companies should increase sharply in a financial crisis, whereas the systemic risk of a financial system will increase because of a number of events.

4 Conclusion

There are various channels that are associated with one company: lending channels that are connected to banks, industrial channels that are connected to other companies in the same industry and structural channels that are connected to subsidiaries. Systemic risk propagates the risk of one company to other companies through such channels.

The most important concept of systemic risk is connections (interactions) that are linked to other groups. Irrespective of the origins of negative feedback, a default of one company affects other industry sectors through its connections.

Many researchers have recognized the potentially serious impacts associated with systemic risk, and studies regarding this subject are ongoing. Most previous studies are related to the construction of networks of a certain system to analyze connections in that system.

Recent studies have measured systemic risk using incorporative methods such as the Granger causality network and variance decomposition network.

This study quantifies the contagion behavior among financial objects, such as an individual company and an industry sector, using a VAR model and a GVDM, which is regarded as an adjacency matrix in network theory. This method is used to measure the contagion effects of systemic risk and uses absolute normalized log-returns as a proxy of daily volatility for 354 survival companies listed on the KOSPI index.

The study demonstrates that shares values of other companies are of more significance when a significant financial event occurs and that for the Korean stock market, the deterioration of markets was sustained longer during the IMF crisis than the sub-prime crisis.

References

1. Allen, Franklin, Ana Babus, and Elena Carletti. "Financial Connections and Systemic Risk." European Banking Center Discussion Paper 2010-23S (2010).
2. Billio, Monica, et al. "Econometric measures of systemic risk in the finance and insurance sectors." Journal of Financial Economics (2011).
3. Diebold, Francis X., and Kamil Yilmaz. On the network topology of variance decompositions: Measuring the connectedness of financial firms. No. w17490. National Bureau of Economic Research, 2011.
4. Pesaran, H. Hashem, and Yongcheol Shin. "Generalized impulse response analysis in linear multivariate models." Economics letters 58.1 (1998): 17-29.
5. Koop, Gary, M. Hashem Pesaran, and Simon M. Potter. "Impulse response analysis in nonlinear multivariate models." Journal of Econometrics 74.1 (1996): 119-147.