The Lead-lag Relationships Among Stock Returns, Volatility Index And Sovereign CDS Spreads In Korea Market.

Jungsoon Hyun*
Naeyoung Kang†
Jungmu Kim ‡

College of Business, KAIST

July 16, 2012

Abstract

This study examines the lead-lag relationships among Korean equity, Sovereign CDS spreads and volatility index(measured by VKOSPI) based on VAR test and Granger-causality test. Moreover, using an impulse response function, we measure the time profile of the effect of a shock on the behavior of a series. Finally, based on the variance decomposition analysis, we show the contribution of each variable on another one. The empirical results implimented with sovereign data in this paper are consistent to those with corporate data.

In order to expand the research scope and overcome the limitation of previous researches that have focused on the lead-lag linkages only with an ordinary economic environment, our research takes into consideration the distinctive role of financial crisis by splitting the aggregate time horizon into three sub-periods in a proper way and then shows that the granger-causality has occurred more often during financial crisis due to a lack of liquidity for trasmitting information. Moreover, the overall lead-lag relationships seem to occur more frequently on the basis of daily data over the weekly data.

Keywords: sovereign credit risk, lead-lag relationship

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*Assistant Professor of Finance, Address: KAIST Business School, 87 Hoegiro, Dongdaemoon-gu, Seoul, 130-722, Korea, E-mail:*jshyun@business.kaist.ac.kr*

†Graduate student, Address: KAIST Business School, 87 Hoegiro, Dongdaemoon-gu, Seoul, 130-722, Korea, Phone: +82)10-9272-8382, E-mail:*jksk2922@business.kaist.ac.kr*

‡Graduate student, Address: KAIST Business School, 87 Hoegiro, Dongdaemoon-gu, Seoul, 130-722, Korea, Phone: +82)10-7461-8586, E-mail:*kimjungmu@business.kaist.ac.kr*

1 Introduction

1.1 *Motivation*

In 2007, subprime mortgage issues in the U.S. have a significant influence on the world economy as well as the domestic economy. This crisis results from undervaluing credit risk. As people have suffered from such crisis, the interest as a compensation for credit risk has been rising. So, in the markets, credit derivatives have been rapidly growing as a protection from credit risk and default risk. The definition of credit risk is the risk of loss resulting from failures of counterparties or borrowers to fulfill their obligations. Given that credit risk appears in almost all financial activities, it must be pivotal to measure, price and manage accurately. Credit derivatives can be one example of exciting innovations dealing with credit risk in financial markets. With them, it is possible for companies to trade and manage credit risks in much the same way as market risks.

For most recent years, credit derivatives markets have been sharply growing at an increasing rate as trading credit derivatives has been available in Korea as well as the United States and Europe. The most representative credit derivatives could be credit default swap(CDS). Credit default swap(CDS) is considered as an insurance in case a default by a particular company or sovereign entity occurs. The company is called as the reference entity and a default by the company is named as a credit event. The buyer of the insurance has an obligation to makes periodic payments to the seller and in return gets the right to sell a bond issued by the reference entity for its face value if a credit event occurs. The rate of payments made per year by the buyer is defined as the CDS spread.

Even if, only for less than 10 years, CDS has been traded, the research on CDS has been done so actively just because CDS spreads can be a better proxy for credit risk, compared to corporate bond spreads. Given that CDS is a more standardized contract rather than a corporate bond that is under the influence of coupon rate and priority etc. and, unlike corporate bonds, CDS does not require the information on risk free rate and so is not sensitive to the selection of risk free assets, there is no doubt that CDS can be a more appropriate representative of credit risk than corporate bond. Therefore, credit default swap spreads are an interesting alternative to bond prices in empirical research on credit ratings.

The subprime mortgage financial crisis during the 2007-2009 has made it hard for credit markets to function properly, causing spreads and volatility to surge and market liquidity to evaporate. The impact of these events on the pricing of credit risk is a matter of debate. In order to assess the impact of the financial crisis on the pricing of credit risk, we compare the results of pre-crisis, during-crisis and after-crisis period.

In this paper, we use sovereign CDS spreads instead of individual firms CDS spreads for mainly two reasons. First one is that sovereign credit instruments share exposure to systematic risk that financial crisis can be categorized as. The other reason is because sovereign CDS market is more liquid, which makes it possible to estimate credit spreads and returns accurately.

It is well known sovereign risk can have a negative impact on performance of stock index and furthurmore how volatile the movement of stock index should have very close links with sovereign risk and stock performance. Actually, it is found the empirical correlation patterns between sovereign CDS spreads and stock market performance. Nevertheless, there are barely confirmed researches on how those three variables are connected one another. For these reasons, the main purpose of this paper is to test how sovereign CDS spread, stock prices and volatility index are correlated.

At first, to make sure that the time series of each variable are stationary, we implement unit root test such as ADF(Augmented Dickey Fuller) test and cointegration test. Then, considering that the number of variables this paper covers exceeds two and we need to know multivariate model but not unitravatiate one, the vector autoregression model(VAR model) should be sutiable. This is because VAR model is considered as an extention of univariate autoregressive model and also provides us more useful information about the dynamic behavior of time series as well as superior forecasts. For further research, we investigate how long the impact of one variable to another lasts with impulse response analysis which measures how long the effect of a shock on the future values of a variable lasts. Considering the fact that in Korea, there is a rare research on these lead-lag relationships, this paper can be a pivotal role in the understanding on the movement among stock price, Sovereign CDS spreads and volatility index.

1.2 *Literature Review and Hypotheses*

Chan-Lau and Kim(2004) show that the majority of eight emerging countries do not have an equilibrium link. In contrasts, Zhu(2006) make use of corporate CDS spreads but not sovereign CDS spreads and insists that there is an equilibrium relationship between corporate CDS spreads and bond markets and also corporate CDS spreads lead bond markets. However, this paper is based on sovereign CDS spreads for expanding research scope as well as reflecting the effect of soveriegn risk resulting from fianancial crisis.

Longstaff et al.(2005) investigate the lead-lag relationship between the changes of CDS spread, bond spread and stock return on 68 North American companies with VAR(Vector Autoregressive) model. It is shown that any information relevant to credit risk affects the CDS market and stock market for the first time and then spread out to bond market. However, they fail to prove the lead-lag relationship between CDS market and stock market. In light of this literature, we propose the following hypotheses H1 and H2.

H1 : Positive stock return changes do not lead negative sovereign CDS spread changes.

H2 : Negative sovereign CDS spread changes do not lead Positive stock return changes.

Norden and Weber(2009) also has similar approaches with 58 companies from different countries and found results as the above but one difference from Longstaff et al.(2005) is that Norden and Weber(2009) points out that these lead-lag relationships are caused by liquidity. Additionally, they put new variable, that is implied stock volatility derived from at-the-time put options and then find out that there is a significantly negative influence of the implied stock volatility on stock returns and positive impact on corporate CDS spread changes. Here, since our goal in this paper includes verifying the role of the financial crisis on the lead-lag linkages of three variables(stock, sovereign CDS and volatility), we will make use of sovereign CDS spreads instead of corporate ones. As developing Norden and Weber research, we state the following hypotheses H3 through H6.

H3 : The changes of volatility index do not lead stock return changes.

H4 : Stock return changes do not lead the changes of volatility index.

H5 : The changes of volatility index do not lead sovereign CDS spread changes.

H6 : Sovereign CDS spread changes do not lead negative the changes of volatility index.

Norden and Weber(2004) conduct a research on the impact of events associated with credit rating on stock market and CDS market and find that those two markets reflect information on credit quality ahead of other markets. This is because those two markets are superior to predicting credit-related events. This implies that both stock prices and CDS spreads can play a pivotal role in measuring credit risk. However, they do not compare information asymmetry and the speed of transmitting information in stock market with those in CDS market. Stefan Ehlers and Marc G(2010) refer to Systematic risk information as the cause of lead-lag relationship between stock and CDS market and mention that this transfer widens during financial crisis. They take advantage of Granger-causal regression to analyze interaction between those two markets based on a larger subprime data of nearly 22 months in European markets. Kewei Hou(2007) point out that slow diffusion of information has a leading role in lead-lag relationship between those two markets. Moreover, this paper finds out due to Intra-industry lead-lag effect which means big firms lead small firms within the same industry, overall lead-lag effect start to appear. Reflecting these three suggestions, we endeavor to clear the importance of information transmision on lead-lag effects by splitting the whole sample periods into three sub-periods.

Gaiyan Zhang et al.(2008) try to make sure the role of stock market on CDS index or vice versa using VAR model. Moreover they focus on the lead-lag relationship between volatilities of CDS indices and stock market. These researches have been done by dividing CDS indices into two groups, investment-grade CDS indices (IG) and high-yield CDS indices (HY) with individual CDS names for the period from January 2001 to April 2004 based on the construction methodology of the CDX indices. The first finding is that stock market has an influence on CDS indices of both IG and HY but unlike IG, HY tends to more interact with stock markets as stock market condition become deteriorated. The second result is that volatilities of CDS indices for both IG and HY seem to lead stock market volatility but volatility of stock market has a feedback only to HY volatility. Thus, stock market functions as information transmitter in the pricing process and also the role of CDS market can be related to volatility spillover. These are consistent with the findings of Jorion and Zhang(2007) in that substantial jumps of CDS prices occur only in credit crunch and elsewhere CDS prices tend to be stabilized, and the movement of stock market leads that of CDS market.

The rest of the article is structured as follows. Section 2 describes data we use with descrpitive analysis. Then section 3 introduces the model we developed for verifying lead-lag effects. Section 4 illustates the methodology such as VAR test, Granger-Causality test, impulse response analysis and variance decomposition analysis. In section 5, the empirical results are exhibited depending on the time horizons of the whole sample periods. Finally, section 6 briefly summarizes our researches.

2 Data Description

2.1 *Data collection and sample composition*

In this section, we succinctly describe the three time series. Focusing on Korea markets, we use sovereign CDS spreads(quoted by KRW), KOSPI and VKOSPI time series data on a weekly(Wednesday) and daily basis. CDS data are provided by Markit and the maturity we mainly make use of for our research is 5 year. The final set of the time series periods covers January 2003 through August 2010.

One motivation for such a analysis starts from the empirical correlation patterns between sovereign CDS spreads and stock market performance : the lower the credit quality, the worse the stock returns.

Table 1: Correlation between sovereign CDS spreads and stock returns

	KOSPI	VKOSPI	5Y CDS
KOSPI	1		
(p-val)			
VKOSPI	-0.6441	1	
(p-val)	<.0001		
5Y CDS	-0.3525	0.1321	1
(p-val)	0.0012	0.2367	

The subprime mortgage crisis in 2007 to 2008 brought a huge global financial crisis that have critical impacts on all over the world. Given that this financial crisis can be catagorized as soveriegn risk that can be represented by CDS spreads, it is possible for us to get to know the inflence of the crisis by taking a close look at the sovereign CDS spreads. In this perspective, it is necessary to distiguish the crisis time horizon from the other among the whole periods. That's why we make three subperiods which covers before the crisis(till the end of the year 2006), during the turmoil period(the year 2007 to 2008) and lastly during stabilized horizon(from the first of 2009).

2.2 *Descriptive analysis*

As presented in Figure 1 through 3, the time series trends of three variables seem to have correlation each other. To be specific, in 2009 as CDS spreads swang upward rapidly, the KOSPI dropped dramatically and VKOSPI showed sharp increase.

Figure 1 about here

Figure 2 about here

Figure 3 about here

Table 2: Descriptive Analysis

	KOSPI	VKOSPI	5Y CDS
Mean	1270.05	26.34	0.01
Median	1333.23	23.67	0.01
Maximum	2064.85	89.30	0.07
Minimum	515.24	14.15	0.00
Std. Dev.	391.88	9.91	0.01
Skewness	-0.09	2.38	2.57
Kurtosis	1.87	10.93	10.60
Observations	1889.00	1889.00	1889.00

By taking natural logarithm to KOSPI variable, we obtain KORSPI return data. Then, for making the unit of individual variables unified, we apply natural logarithm to all three variables. Furthermore, considering that VAR test requires stationarity of time series data, to verify the stationarity of individual time series, we use ADF(Augmented Dickey Fuller) Test and PP(Philips Perron) Test. Table 3 shows the results of two tests. Since the majority of the raw data we collect has unit root problems, the solution to these issues is to get the level data to be one-differenced to each variable. Table 3 shows that the null hypothesis that level data have a unit root with 5 percent cannot be rejected while 1st differenced data are stationary.

Table 3 about here

3 Model

3.1 *Setup*

To perform Granger-causality test, we consider three equations below.

$$\Delta CDS_t = \alpha_1 + \sum_j \beta_{1,j}^{(stock)} \cdot \Delta R_{(t-j)} + \sum_j \gamma_{1,j}^{(cds)} \cdot \Delta CDS_{(t-j)} + \sum_j \delta_{1,j}^{(vkospi)} \cdot \Delta VOL_{(t-j)} + \epsilon_{1,t} \quad (1)$$

$$\Delta R_t = \alpha_2 + \sum_j \beta_{2,j}^{(stock)} \cdot \Delta R_{(t-j)} + \sum_j \gamma_{2,j}^{(cds)} \cdot \Delta CDS_{(t-j)} + \sum_j \delta_{2,j}^{(vkospi)} \cdot \Delta VOL_{(t-j)} + \epsilon_{2,t} \quad (2)$$

$$\Delta VOL_t = \alpha_3 + \sum_j \beta_{3,j}^{(stock)} \cdot \Delta R_{(t-j)} + \sum_j \gamma_{3,j}^{(cds)} \cdot \Delta CDS_{(t-j)} + \sum_j \delta_{3,j}^{(vkospi)} \cdot \Delta VOL_{(t-j)} + \epsilon_{3,t} \quad (3)$$

where ΔCDS_t:CDS spread change in t, ΔR_t: stock return change in t and ΔVOL_t: change of a Volatility index of Korea 200 Index.

To determine the optimal number m* of lags that has to be incorporated into the VAR model we use lag length criteria test which offer three well accepted procedures : AIC(Akaike information criterion), SC(Schwarz information criterion) and HQ(Hannan-Quinn information criterion). After applying both SC and HQ criteria, we decided to take the maximum of both quantities as the optimal lag length m* and denote the VAR model by VAR(m*). Note that only when both SC and HQ are zero, we use AIC as a lag length m*. After estimating the optimal lag length the Granger-causality test can be performed.

For testing hypothesis 1, the null hypothesis the time series ΔR_tdose not Granger-cause the time series ΔCDS_t is not rejected if all regression coefficients $\beta_{1,j}^{(stock)}$ of equation (1) are zero, i.e. the null hypothesis can also be represented as follows:

$$H_0 = \beta_{1,1}^{stock} = ... = \beta_{1,m_*}^{stock} = 0 \tag{4}$$

For testing hypothesis 5, the null hypothesis the time series ΔVOL_t dose not Granger-cause the time series ΔCDS_t is not rejected if all regression coefficients $\delta_{1,j}^{(vkospi)}$ of equation (1) are zero, i.e. the null hypothesis can also be represented as follows:

$$H_0 = \delta_{1,1}^{vkospi} = ... = \delta_{1,m_*}^{vkospi} = 0 \tag{5}$$

Analogously, according to equation (2), for testing hypothesis, the null hypothesis 2 the time series ΔCDS_t does not Granger-cause the time series ΔR_t can be transformed into

$$H_0 = \gamma_{2,1}^{cds} = ... = \gamma_{2,m_*}^{cds} = 0 \tag{6}$$

For testing hypothesis 3, the null hypothesis the time series ΔVOL_t dose not Granger-cause the time series ΔR_t is not rejected if all regression coefficients $\delta_{2,j}^{(vkospi)}$ of equation (2) are zero, i.e. the null hypothesis can also be represented as follows:

$$H_0 = \delta_{2,1}^{vkospi} = ... = \delta_{2,m_*}^{vkospi} = 0 \tag{7}$$

Analogously, according to equation (3), for testing hypothesis , the null hypothesis 6 the time series ΔCDS_t does not Granger-cause the time series ΔVOL_t can be transformed into

$$H_0 = \gamma_{3,1}^{cds} = ... = \gamma_{3,m_*}^{cds} = 0 \tag{8}$$

For testing hypothesis, the null hypothesis 4the time series ΔR_t dose not Granger-cause the time series ΔVOL_t is not rejected if all regression coefficients $\beta_{3,j}^{(stock)}$ of equation (3) are zero, i.e. the null hypothesis can also be represented as follows:

$$H_0 = \beta_{3,1}^{stock} = ... = \beta_{3,m_*}^{stock} = 0 \tag{9}$$

4 Methodology

4.1 *Granger-causality test*

The concept of Granger-causality helps us to analyze the interaction between the credit and stock markets. A series X is said to Granger-cause a series Y if X values provide statistically significant information about future values of Y. Note that Granger causality does not necessarily mean real causality.

A critical assumption that has to be fulfilled in the context of Granger-causality is the (trend-) stationarity of the underlying time series. To check the stationarity in each series, we use unit root tests, such as the Augmented Dickey-Fuller (ADF) test. In this paper, after implementing ADF test, we get to know that level time series has a unit root but one differenced time series do not have a unit root. From now on, one differenced time series will be used for VAR test.

After estimating the optimal lag length, VAR test and the Granger-causality test can be performed. When deciding optimal lag length, we choose the lag length that makes AIC, SC and HQ lower.

4.2 *Impulse Response test*

An impulse response function(IRF) contributes to discovering the dynamic relationship between variables within vector-autoregressive (VAR) models. It also measures how long the effect of a shock on the future values of a variable lasts. Impulse response analysis can be used for both linear and nonlinear multivariate models.

A VAR can be written in vector MA(∞) form as $y_t = \mu + \epsilon_t + \Phi_1 \cdot \epsilon_{t-1} + \Phi_2 \cdot \epsilon_{t-2} + \cdots$.

Thus, the matrix Φ_s has the interpretation $\frac{\partial y_{t+s}}{\partial \epsilon_t'} = \Phi_s$ that is, the row l, column j element of Φ_s identifies the consequences of one unit increase in the jth variable's innovation at date t(ϵ_{jt}) for the value of the ith variable at time t+s(y_{it+s}), holding all other innovations at all dates constant. $\frac{\partial y_{t+s}}{\partial \epsilon_t'}$ as a function of s is called the impulse response function. It describes the response of y_{it+s} to a one-time impulse in y_{it} with all other variables dated t or earlier held constant.

4.3 *Variance Decomposition Analysis*

Variance decomposition requires estimation of complete vector autoregressions(VAR). A VAR is a system of equations that treats the time path of each endogenous variable as a function of its own current and past realizations and the current and past realizations of the other variables in the system. The coefficients in the estimated VAR are of little use themselves. Instead, we look at variance decompositions of the system to draw implications about the dynamics of the data because this variance decomposition framework helps us to determine the proportin of the total variance in one variable that can be explained by other variables.

5 Empirical Results

5.1 *Analysis for the Complete Period*

The preceding procedure of VAR test is a test for selecting VAR lag order. Table 4 represents optimal lag depending on the time periods. Based on this standardized rule explained in section 3.1, Panel A reveals that lag 2(lag1) should be taked in the case of the weekly data(daily data). Panel B,C and D can be interpreted as the same way as Panel A.

Table 4 about here

Based on those optimal lags, we implement VAR test and Granger-causality test. The results of VAR test and Granger-causality test are attached[Table5,6].

Table 5 about here

Table 6 about here

Table 5 and 6 show us same interpretations on the lead-lag relationships between the three variables. Additionally, Panel B reveals that the results based on daily data are qualitatively similar and quantitatively even stronger compared to Panel A.

Panel A and B reveal that there are several intertemporal linkages between the three markets at the weekly level. On the basis of weekly data, it clearly turns out that lagged stock return changes have a significantly positive impact on sovereign CDS spread changes and so it is hard to reject H1 with Panel A. However, when using daily data, H1 can be rejected. In terms of H3, both Panel A and B can offer a clue to reject H3 since it is found that volatility index changes granger-cause stock return changes. In the perspective of H5, the rejection of H5 is strongly supported by the result that is volatility index changes tend to lead the sovereign CDS spread changes. Note that, unlike Panel A, Panel B offers us additional information on the lead-lag relationships. Not only H2 but also H6 can be rejected with daily data.

Here, we need to note that the quoting time of sovereign CDS spreads follows the UK local time which is almost one day ahead of Korea local time even when considering the market opening time of both Korea and UK. So, the rising sovereign risk that can be reflected by sovereign CDS spreads has a substantial influence on stock return one day later. That's why we can observe the lagged sovereign CDS spread changes lead stock return changes. In this perspective, the Granger-causality in the sense of sovereign CDS spreads granger-cause stock price should be taken for granted.

Moreover, by implementing impulse response analysis, we can be informed how long the impact of one variable on the other will last. The final graphs are attached below.

Figure 4 about here

Figure 4 exhibits impulse response based on weekly data. First, KOPSI return changes negatively correspond to one unit change of VKOSPI returns but the impact of VKOSPI on KOSPI disappear after one week. The Influence of CDS on KOSPI seems to be same as the effect of VKOSPI on KOSPI. Second, KOSPI return changes lead VKOSPI chagnes in the negative way but this relation seems to last at least for two weeeks. On the other hand, in the perspective of the power of CDS on VKOSPI, the increase of CDS causes VKOSPI to increase but this link does not exist no more than two week. As for CDS, KOSPI return changes have a negative relation with the sovereign CDS spread changes and this link can be shown for two weeks. In the case of role of VKOSPI, CDS spread changes are postiviely affected by the VKOSPI changes but this influence seems to be gone after one week.

Figure 5 about here

As appears in Figure 5, several differences are observed for daily data. First,positive KOPSI return changes are associated with positive VKOSPI returns but the impact of VKOSPI on KOSPI disappear after one day. The Influence of CDS on KOSPI seems to be negative only for three days. Second, KOSPI return changes lead VKOSPI chagnes to response in the negative way but this relation seems to last at least for 4 days. On the other hand, in the perspective of the power of CDS on VKOSPI, the increase of CDS causes VKOSPI to also increase but this link does not exist no more than 3 days. Lastly, the sovereign CDS spread changes negatively correspond to one unit change of KOSPI returns and this link can be shown for 4 days. Also, CDS spread changes are postiviely affected by the VKOSPI changes but this influence seems to be gone after 3 days.

Figure 6 about here

Figure 6 reveals the portion that each variable is explained by another one on the basis of weekly time series. The first row of the above graph implies that the change of VKOSPI returns can explains the approximate 2 percent change of KOSPI returns and approximate 1 percent changes of KOSPI changes is a portion illustrated by sovereign CDS spread changes. The second row exhibits that approximate 35 percent changes of VKOSPI returns can be from the KOSPI return changes whereas sovereign CDS spread changes barely have any explanation on VKOSPI changes. The third row shows that on the contrary of the case that less than 10 percent changes of that CDS spreads are illustrated by the VKOSPI changes, approximate 35 percent changes of the CDS spread changes result from KOSPI return changes.

Figure 7 about here

Overall, the results of variance decomposition analysis when making use of daily data look quite similar to those when with weekly data. However, in terms of quantity, there are minor differences between them. As shown in Figure 7, it is shown that the bare portion of KOSPI return changes are from the changes of VKOSPI returns as well as those of sovereign CDS spreads. Also, it is obvious that the majority parts of VKOSPI changes are explained by the KOSPI changes, but not by the CDS spread changes. Lastly, at most 20 percent changes of sovereign CDS spread changes result from stock return changes whereas it is hard to notice the power of VKOSPI changes to the CDS spread changes.

5.2 *Analysis for the Split-up Periods*

According to Kewei Hou(2007), the lead-lag effects result from the slow diffusion of common information, which can be considered as a type of information inefficiency. We can assume that in the middle of the world chaos over the year 2007 to 2008, it must be rare for any market participants to be fully informed of any available information. That is, there should exist the phenomena that is transmitting information quite slowly during those horizons. This is because there must be a interruption for trasmitting the common information to the public during the chaotic periods. That is why we can predict that the lead-lag linkages should be stronger during the crisis. This result is consistent with the information-delay interpretation of the lead-lag effect. Later on(after 2009), as soon as our economy has been stablized, the information has started to be trasmitted more efficiently. In other words, it is clear that various market frictions as well as investment restrictions have been relaxed and moreover the information disclosure has happened more frequently in the stablized periods. As a result, there have occured the improvement in information communication and market mechanisms. In these perspectives, we can assume that there will be observed less lead-lag effects for the stable horizons.

To verify our assumptions, we run VAR test and granger-causality test with three distinctive time horizons including 'before crisis' , 'during the global turmoil' and 'during the stable horizon after going through that crisis. Note that those three periods cover three different subperiods : before the year 2006, the year 2007 through 2008 and after 2009.

Table 7 and 8 exhibit the results of VAR test and Granger-causality test, respectively and the indications from both tables are almost same except that lead-lag effects have occured more frequently when based on daily series over weekly series. To put it briefly, it clearly turns out to be true because we observe 5 links in Panel A but 14 links in Panel B in both tables.

In the case of the financial crisis time periods from the year 2007 to 2008, there are found four linkages with Panel A and 5 ones with Panel B in both Table 6 and 7 and these numbers of lead-lag relationships are much higher than ones from the other two periods. Especially, during the crisis, the cross-autoregressions between the sovereign CDS spread changes and stock return changes seem to be more active compared to other periods and so for these reasons, both H1 and H2 can be mostly rejected at the 1 percent confidence level within that periods. From these testing results, we can empirically verify the critical roles of the slow diffusion of information to the lead-lag effect from the year 2007 to 2007 as Kewei Hou(2007) mentioned.

As shown in Panel A-3 in Table 7 and 8, with weekly time series, lead-lag relationships lowered in intensity and we do not find much evidence of Granger-causality.

Table 7 about here

Table 8 about here

6 Conclusion

Having thus far investigated the existence and the direction of lead-lag relationships between three time series(stock, CDS and volatility) in Korea markets, we find several interesting results. For these researches, our main tools are VAR test and Granger-causality test. For the further research, we implement impulse response analysis as well as variance decomposition analysis. The formor analysis helps us to measure the time profile of the effect of a shock on the behavior of a series whereas the latter analysis show us the portion that one unit change of each variable explain the other one.

We assume that sovereign CDS spreads and stock price have negative relationships and volatility index is negatively related to stock price. However, the empirical results from VAR test and Granger-causality test do not offer us strong evidence for our assumptions and the sign of the relationships between variables totally depends on the lag numbers. Additionally, these lead-lag relationships are stronger on the daily basis over weekly basis.

For the further research, we need to try to take a look at the contagion effect of volatility of each variable. This is because the fact that the volatility of a variable leads that of the other variable implies that, in terms of volatility, the lead variable reacts more efficiently to the lag variable and furthermore it will be valuable to do research on information efficiency.

References

Chan-Lau and Kim, 2004, "Equity prices, credit default swaps, and bond spreads in emerging markets", *International Money Fund*, PP 1-30.

Haibin Zhu, 2006, "An Empirical Comparison of Credit Spreads between the Bond Market and the Credit Default Swap Market", *Journal of Financial Services Research*, Vol 29, PP 211235.

Longstaff et al., 2005, "Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market", *The Journal Of Finance*, Vol. LX, NO. 5, PP2213-2253.

Norden and Weber, 2009, "The Co-movement of Credit Default Swap, Bond and Stock Markets: an Empirical Analysis" , *European Financial Management*, Vol. 15, No. 3, PP529-562.

Norden and Weber, 2004, "Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements", *Journal of Banking and Finance*, Vol 28, PP 2813-2843.

Stefan Ehlers and Marc Grtler and Sven Olboeter, 2010, "Financial Crises and Information Transfer - An Empirical Analysis of the Lead-Lag Relationship between Equity and CDS iTraxx Indices", *Social Science Research*, PP1-28.

Kewei Hou, 2007, "Industry information diffusion and the lead-lag effect in stock returns", *Review of Financial Studies*, Vol 20, PP 1113-1138.

Gaiyan Zhang et al, 2008, "Are the US stock market and credit default swap market related? Evidence from the CDX Indices", *Journal of Alternative*, Vol 11, PP 43-61.

Jorion and Zhang, 2007, "Good and bad credit contagion: Evidence from credit default swaps", *Journal of Financial Economics*, Vol 84, PP 860-883.

Francis A. Longstaff, Jun Pan, Lasse H. Pedersen, And Kenneth J. Singleton, 2011, "How Sovereign Is Sovereign Credit Risk? By , American Economic Journal: Macroeconomics", *American Economic Journal: Macroeconomics*, Vol 3, Number 2, PP 75-103(29).

Mara Coronado Vaca and M Teresa Corzo Santamara and Laura Lazcano Benito1, 2011, " A Case for Europe: the Relationship between Sovereign CDS and Stock Indexes", Working Paper, PP 1-28.

Hans Bystrom, 2005, "Credit Default Swaps and Equity Prices : The iTRAXX CDS Index Market", Working Paper, PP1-14.

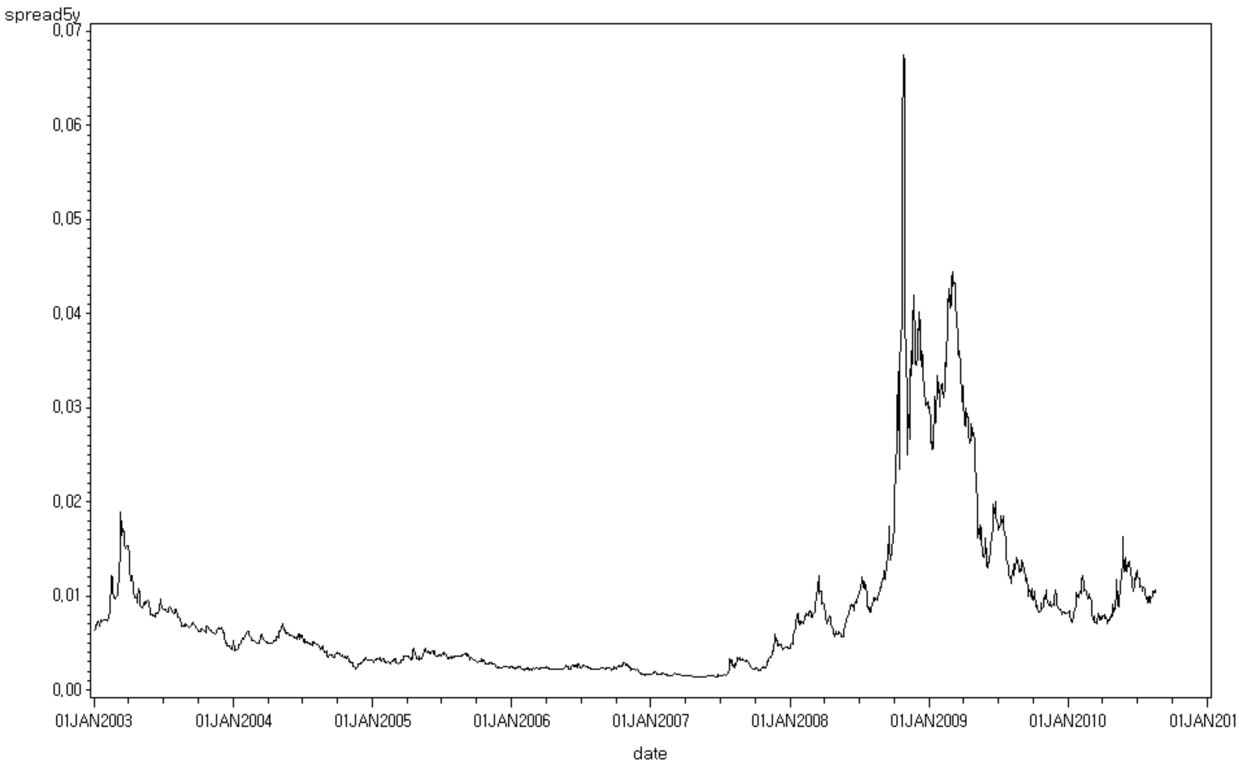

Figure 1: Time series of Soveriegn CDS 5Y spreads

Figure 1,2 and 3 display time seires of daily cross-sectional time series of raw data to each variable. Missing data are eliminated.

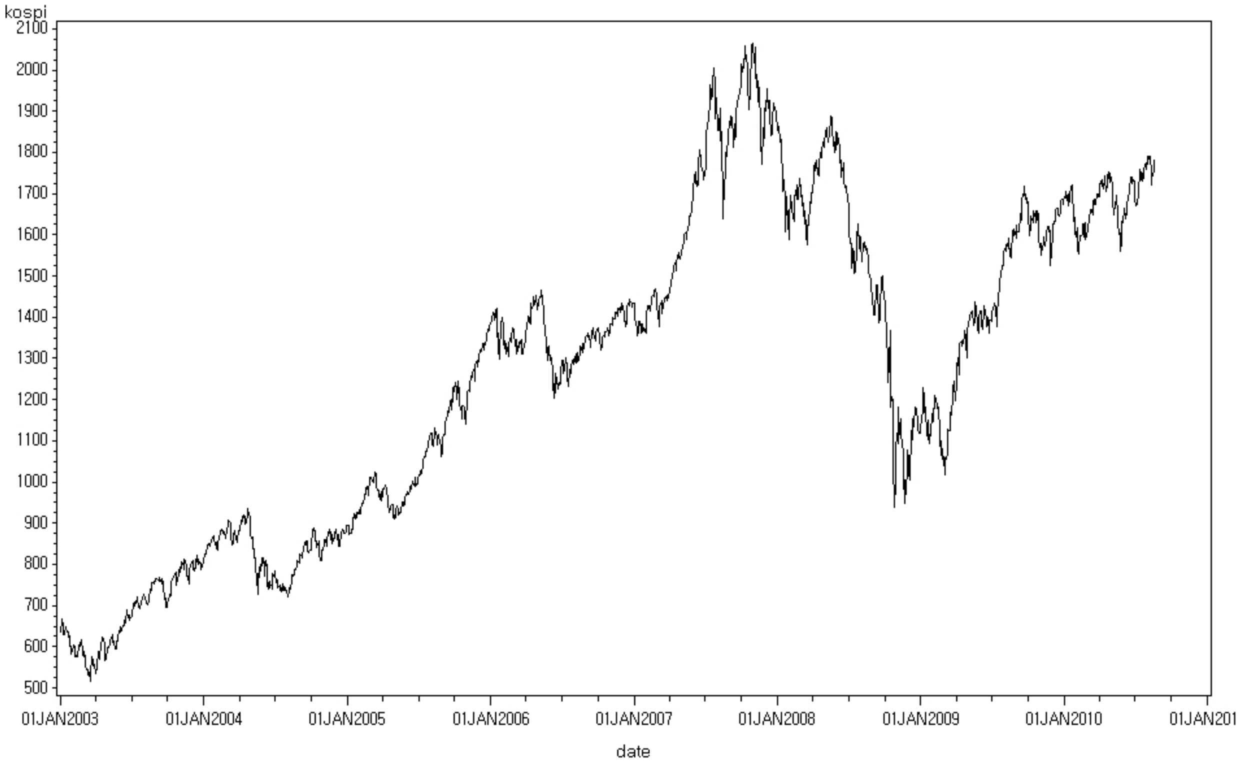

Figure 2: Time series of Kospi Index

Table 3: Unit Root Test

For weekly(daily) data, test critical values of 90 percent, 95 percent and 99 percent are -3.4416, -2.8664, and -2.5694(-3.4327, -2.8625 and -2.5673) respectively. The values in Table 2 are all t-statistics. It is clear that level data have a unit root whereas 1st-differenced data are stationary.

Panel A : ADF Test				
	Weekly data		Daily data	
	level	1st difference	level	1st difference
log(KOSPI)	-1.2749	-28.2869	-1.0036	-49.6340
log(VKOSPI)	-3.2659	-28.8884	-3.9201	-49.1500
log(5YCDS)	-1.8973	-24.0900	-1.6764	-42.7345
Panel B : Philips Perron Test				
	Weekly data		Daily data	
	level	1st difference	level	1st difference
log(KOSPI)	-1.3335	-28.3480	-0.9780	-49.6399
log(VKOSPI)	-3.8486	-28.9593	-3.3223	-51.4842
log(5YCDS)	-1.8399	-24.0504	-1.7302	-43.0342

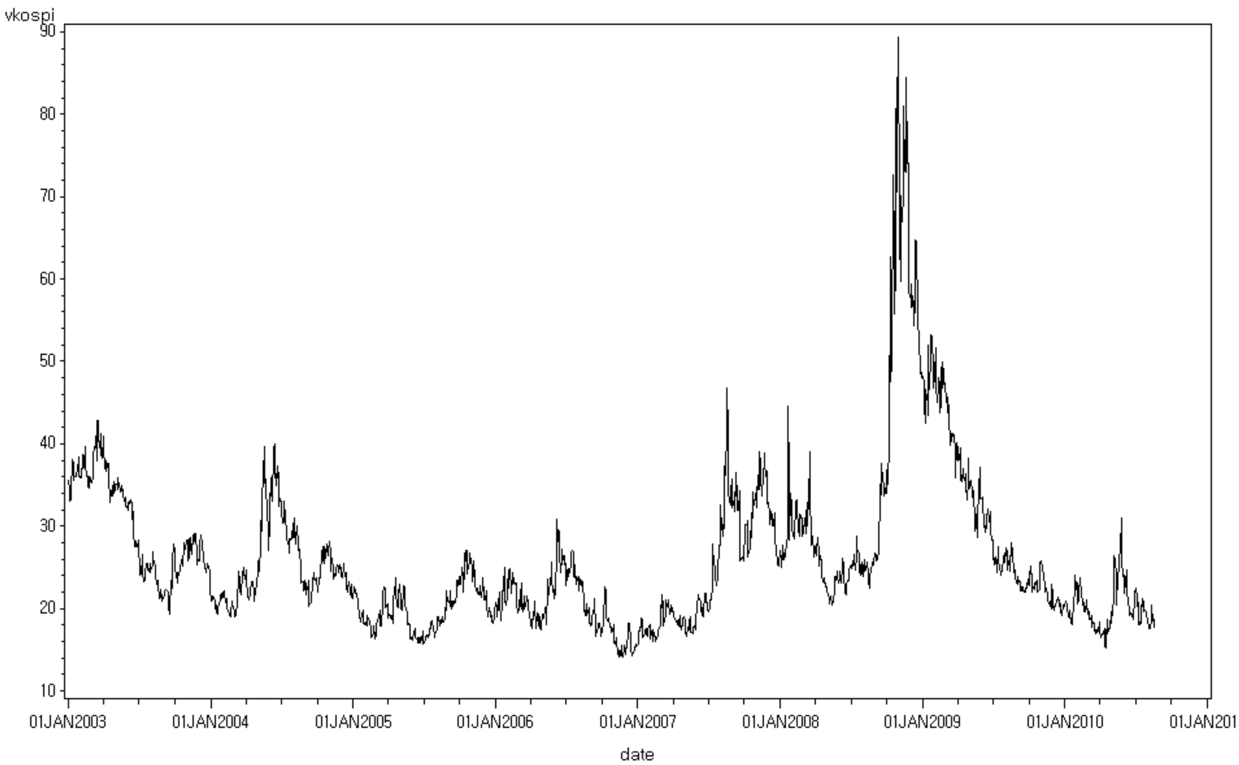

Figure 3: Time series of VKospi index

Table 4: VAR Lag Order Selection Criteria

There are usded three criteria for fiding optimal lag number : that is, AIC(Akaike Information Criterion), SC(Schwarz Information Criterion) and HQ(Hannan-Quinn Information Criterion). Here are rules we are based on when determining the optimal lag : After applying both SC and HQ criteria, we decided to take the maximum of both quantities as the optimal lag length. Note that only when both SC and HQ are zero, we use AIC as a lag length.

Panel A : The Aggregate Set

	Weekly data			Daily data		
	AIC	SC	HQ	AIC	SC	HQ
optimal lag	3	1	2	1	1	1

Panel B : Before Crisis

	Weekly data			Daily data		
	AIC	SC	HQ	AIC	SC	HQ
optimal lag	1	1	1	4	1	1

Panel C : During Crisis

	Weekly data			Daily data		
	AIC	SC	HQ	AIC	SC	HQ
optimal lag	3	0	0	6	1	1

Panel D : After Crisis

	Weekly data			Daily data		
	AIC	SC	HQ	AIC	SC	HQ
optimal lag	1	0	1	1	0	1

Table 5: Aggregate lead-lag analysis with Vector Autoregression Test

For each times series(stock, CDS, volatility), we estimate a vector autoregression to study aggregate lead-lag relationships across markets for different frequencies(weekly and daily data). We report coefficients and t-statistics from VAR model. Weekly data refers to the Wednesday-Wednesday interval. Note that the degree of freedom is determined by optimal lag numbers multiplied by the number of independent variables in one equation. For the weekly data, due to the degree of freedom of 4, the absolute value of t that is greater than 2.132(2.776 and 4.604) is significant at 90(95 and 99) percent confidence level. Also, For the daily data, the degree of freedom of 2 indicates that the absolute value of t that is greater than 2.92(4.303) is significant at 90(95) percent confidence level.

Panel A : Weekly data

Dep.Var.	R(t)		VOL(t)		CDS(t)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
R(t-1)	-0.2187	-3.1085	0.0281	0.1447	0.0430	0.1878
R(t-2)	-0.2190	-3.1208	0.2607	1.3458	0.7769	3.4038
VOL(t-1)	0.0052	0.2331	-0.3399	-5.4835	0.0673	0.9208
VOL(t-2)	-0.0593	-2.6453	-0.0059	-0.0954	0.3391	4.6551
CDS(t-1)	-0.0155	-0.8336	0.0992	1.9347	-0.1126	-1.8640
CDS(t-2)	-0.0344	-1.8487	0.0834	1.6259	0.0525	0.8681
Const.	0.0037	1.8213	-0.0034	-0.6030	-0.0034	-0.0930

Panel B : Daily data

Dep.Var.	R(t)		VOL(t)		CDS(t)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
R(t-1)	0.0165	0.5151	0.1430	1.3902	-0.5393	-5.9369
VOL(t-1)	0.0272	2.8721	-0.1191	-3.9118	-0.1659	-6.1717
CDS(t-1)	-0.0474	-5.2493	0.1571	5.4069	0.1304	5.0813
Const.	0.0006	1.6903	-0.0013	-1.1064	-0.0004	-0.3473

Table 6: VAR Granger Causality/Block Exogeneity Wald Tests based on the aggregate data

The granger-causality test provides chi-square statistics. Considering the null hypothesis in this paper are based on two-tale test, Chi-square statistics are significant at the 90(95 and 99) percent confidence level as long as the p-value is less than 0.05(0.025 and 0.005).

Panel A : Weekly data

Dep.Var.	R(t)				VOL(t)				CDS(t)		
	Chi-sq.	df	Prob		Chi-sq.	df	Prob		Chi-sq.	df	Prob
VOL(t)	8.1708	2	0.0168	R(t)	1.8250	2	0.4015	R(t)	11.8156	2	0.0027
CDS(t)	3.7523	2	0.1532	CDS(t)	5.6102	2	0.0605	VOL(t)	21.9303	2	0.0000
All	11.9771	4	0.0175	All	6.9096	4	0.1407	All	23.6648	4	0.0001

Panel B : Daily data

Dep.Var.	R(t)				VOL(t)				CDS(t)		
	Chi-sq.	df	Prob		Chi-sq.	df	Prob		Chi-sq.	df	Prob
VOL(t)	8.2489	1	0.0041	R(t)	1.9327	1	0.1645	R(t)	35.2468	1	0.0000
CDS(t)	27.5547	1	0.0000	CDS(t)	29.2347	1	0.0000	VOL(t)	38.0898	1	0.0000
All	33.6154	2	0.0000	All	29.3209	2	0.0000	All	46.2983	2	0.0000

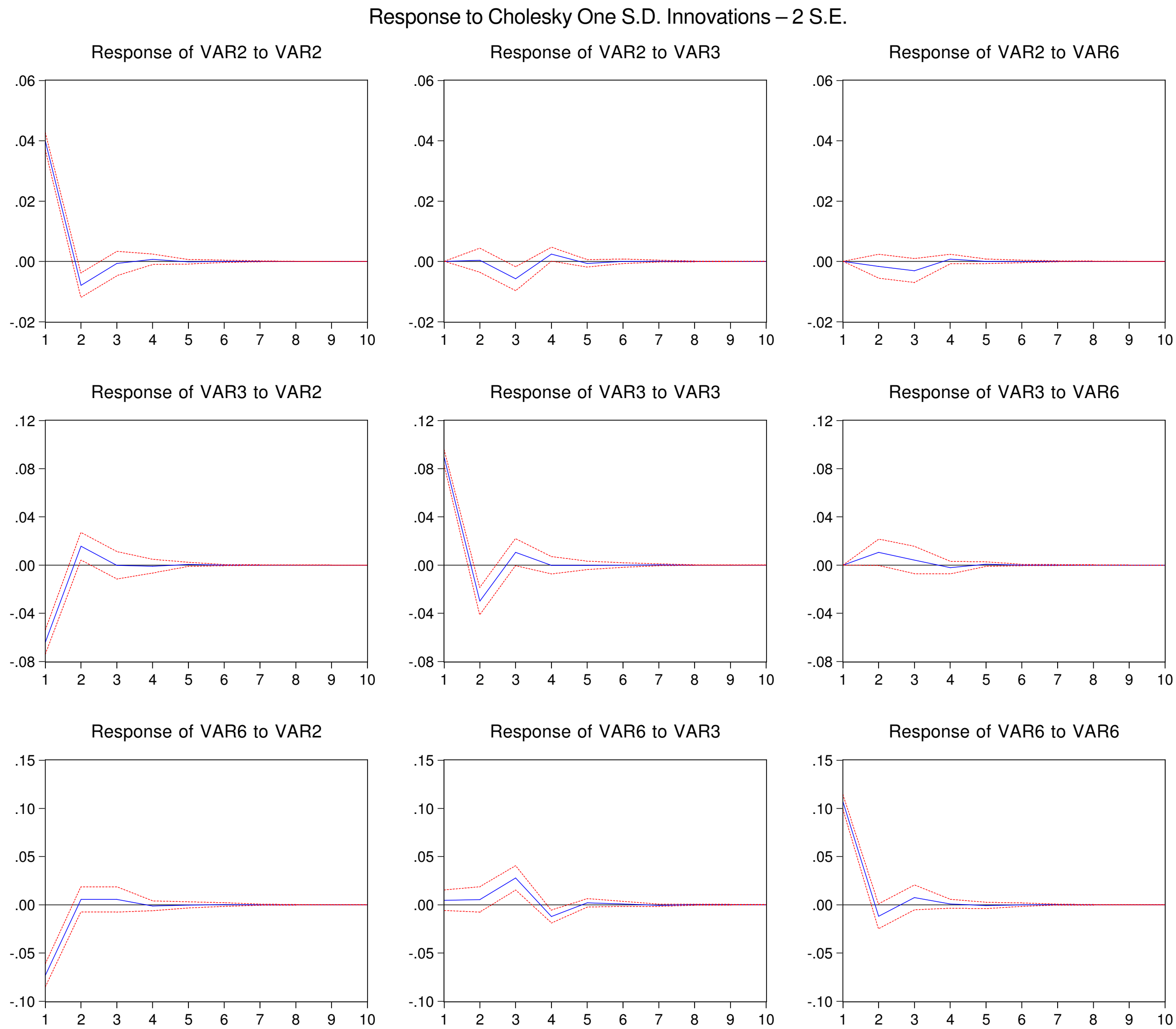

Figure 4: Impulse Response Analysis on the basis of weekly data

Note that VAR2(VAR3, VAR6) stands for stock return changes(volatility index changes, 5Y sovereign CDS spread changes). The dotted line indicates the range of 95 percent confidence level. The X axis stands for lag number and the Y axis shows the impulse response as decimal values.

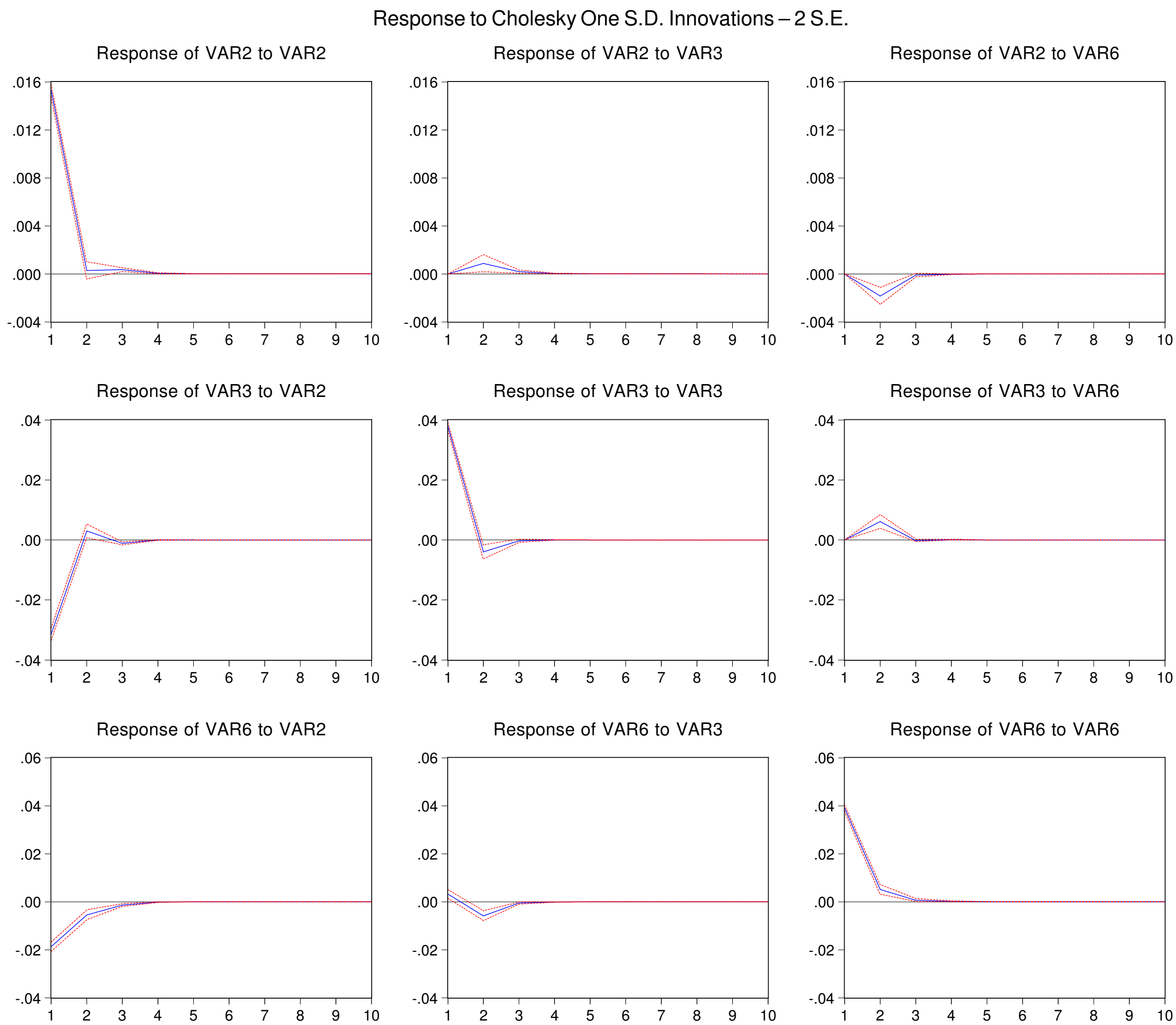

Figure 5: Impulse Response Analysis on the basis of daily data

Note that VAR2(VAR3, VAR6) stands for stock return changes(volatility index changes, 5Y sovereign CDS spread changes). The dotted line indicates the range of 95 percent confidence level. The X axis stands for lag number and the Y axis shows the impulse response as decimal values.

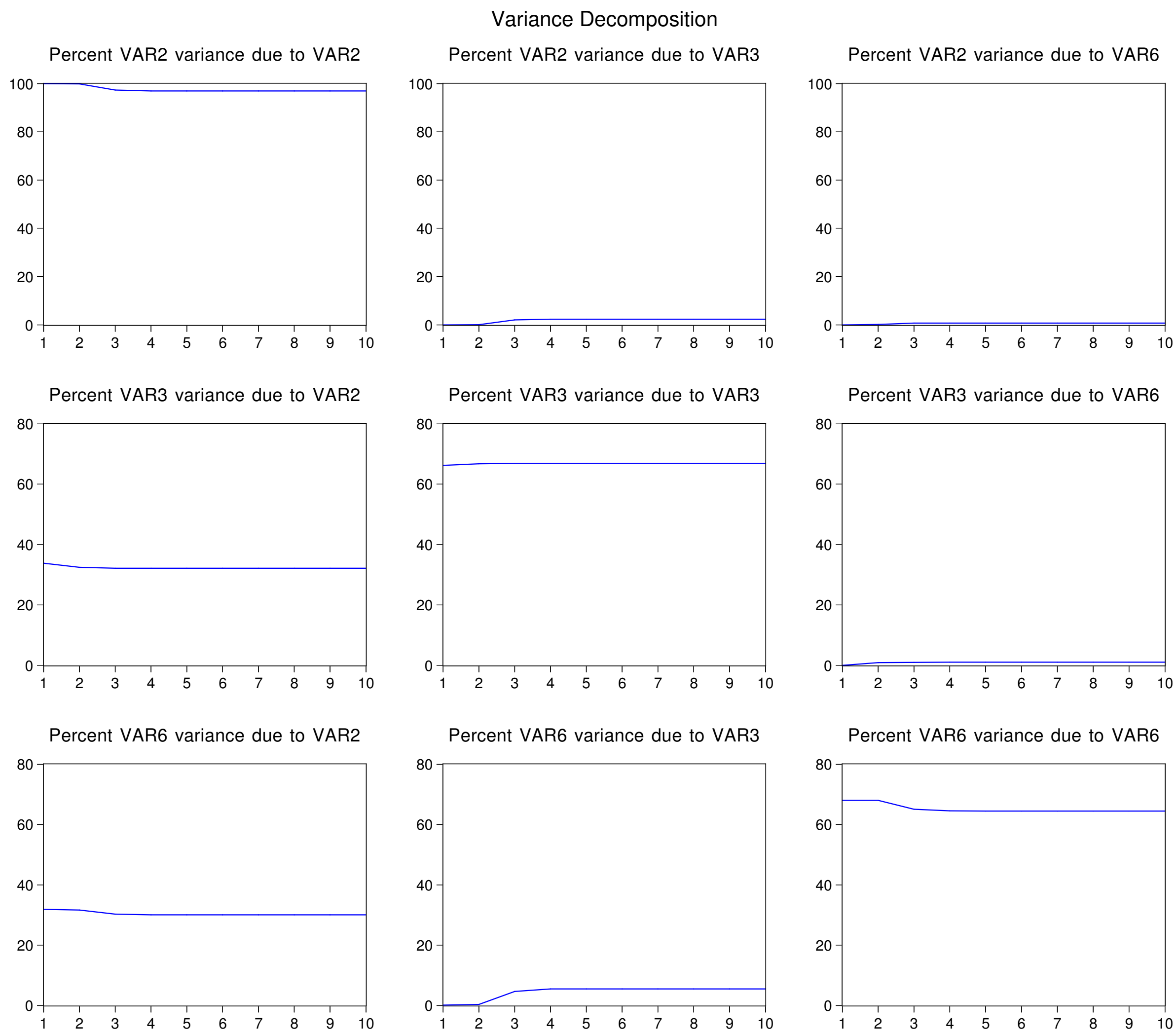

Figure 6: Variance Decomposition Analysis on the basis of weekly data

Note that VAR2(VAR3, VAR6) stands for weekly stock return changes(volatility index changes, 5Y sovereign CDS spread changes). Based on impulse analysis in Figure4, it seems that 10 lags(which means 10 weeks) are enough for any impacts to disappear. So we apply 10 lags to the variance decomposition analysis.

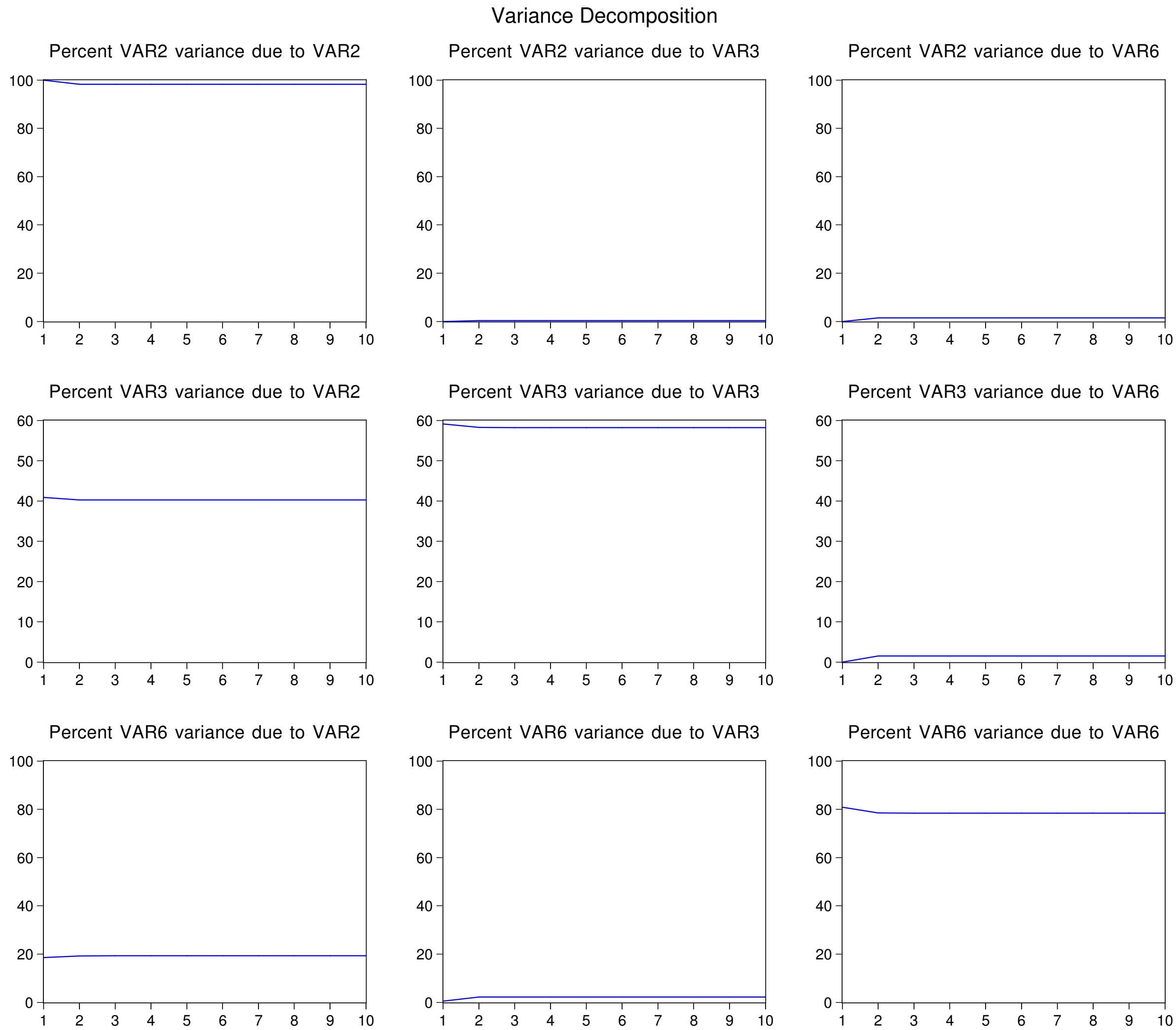

Figure 7: Variance Decomposition Analysis on the basis of daily data

Note that VAR2(VAR3, VAR6) stands for stock return changes(volatility index changes, 5Y sovereign CDS spread changes). Based on impulse analysis in Figure4, it seems that 10 lags(which means 10 weeks) are enough for any impacts to disappear. So we apply 10 lags to the variance decomposition analysis.

Table 7: Sub-periodic lead-lag analysis with a VAR model

For each times series(stock, CDS, volatility), we estimate a vector autoregression to study sub-periodic lead-lag relationships across markets for different frequencies(weekly and daily data). We report coefficients and t-statistics from VAR model. weekly data refers to the Wednesday-Wednesday interval. Note that the degree of freedom is determined by optimal lag numbers multiplied by the number of independent variables in one equation. For the weekly data, we need to use the degree of freedom of 2 and 6 : Firstly, the degree of freedom of 2 indicates that the absolute value of t that is greater than 2.92(4.303) is significant at 90(95) percent confidence level. Secondly, the degree of freedom of 6 indicates that the absolute value of t that is greater than 1.943(2.447 and 3.707) is significant at 90(95 and 99) percent confidence level.Also, For the daily data, the degree of freedom of 2 should be applied.

Panel A : Weekly data

A-1: Before Crisis

Dep.Var.	R(t)		VOL(t)		CDS(t)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
R(t-1)	-0.1981	-2.1308	-0.2007	-0.7507	-0.1657	-0.6293
VOL(t-1)	0.0200	0.6628	-0.4016	-4.6364	0.0282	0.3306
CDS(t-1)	0.0272	1.0568	-0.0335	-0.4518	-0.1450	-1.9868
Const.	0.0050	2.0412	-0.0059	-0.8381	-0.0074	-1.0712

A-2: During Crisis

Dep.Var.	R(t)		VOL(t)		CDS(t)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
R(t-1)	-0.2503	-1.7091	0.0981	0.2669	0.5207	1.0664
R(t-2)	-0.3137	-2.0554	0.5125	1.3379	1.6451	3.2328
R(t-3)	-0.3860	-2.4535	0.9869	2.4994	1.3440	2.5620
VOL(t-1)	-0.0004	-0.0092	-0.2225	-1.9664	0.0519	0.3455
VOL(t-2)	-0.0990	-2.1839	-0.0572	-0.5027	0.6331	4.1868
VOL(t-3)	0.0125	0.2531	0.1512	1.2230	0.0911	0.5550
CDS(t-1)	-0.0095	-0.2105	0.0539	0.4752	-0.0787	-0.5221
CDS(t-2)	-0.0497	-1.1644	0.2090	1.9493	0.1545	1.0846
CDS(t-3)	-0.1637	-3.7999	0.3931	3.6357	0.3301	2.2979
Const.	0.0040	0.7604	-0.0049	-0.3736	0.0148	0.8475

A-3: After Crisis

Dep.Var.	R(t)		VOL(t)		CDS(t)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
R(t-1)	0.0748	0.4734	0.3461	0.7230	-0.7411	-1.1833
VOL(t-1)	0.0851	1.9916	-0.4804	-3.7094	-0.2492	-1.4708
CDS(t-1)	-0.0424	-1.2293	0.1995	1.9078	-0.1616	-1.1811
Const.	0.0050	1.4174	-0.0157	-1.4606	-0.0118	-0.8415

Table 7
Continued.

Panel B : Daily data

B-1: Before Crisis

Dep.Var.	R(t)		VOL(t)		CDS(t)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
R(t-1)	-0.0380	-0.9115	0.3290	2.4516	-0.4455	-4.0989
VOL(t-1)	-0.0283	-2.2001	0.0025	0.0607	-0.0240	-0.7160
CDS(t-1)	-0.0288	-2.3058	0.0742	1.8492	0.0932	2.8650
Const.	0.0008	1.7133	-0.0018	-1.2685	-0.0016	-1.4162

B-2: During Crisis

Dep.Var.	R(t)		VOL(t)		CDS(t)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
R(t-1)	0.0143	0.2147	0.1457	0.6871	-0.4562	-2.3959
VOL(t-1)	0.0794	4.2920	-0.2328	-3.9413	-0.2321	-4.3770
CDS(t-1)	-0.1000	-4.9405	0.2909	4.5038	0.2270	3.9144
Const.	0.0004	0.3953	0.0000	0.0024	0.0036	1.3998

B-3: After Crisis

Dep.Var.	R(t)		VOL(t)		CDS(t)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
R(t-1)	-0.0084	-0.1165	0.0681	0.2786	-0.6490	-2.7195
VOL(t-1)	0.0409	1.9739	-0.1756	-2.5147	-0.3722	-5.4605
CDS(t-1)	-0.0348	-1.9761	0.1489	2.5056	0.1573	2.7106
Const.	0.0009	1.2892	-0.0028	-1.2397	-0.0025	-1.1437

Table 8: VAR Granger Causality/Block Exogeneity Wald Tests based on sub-periodic data

The granger-causality test provides chi-square statistics. Considering the null hypothesis in this paper are based on two-tale test, Chi-square statistics are significant at the 90(95 and 99) percent confidence level as long as the p-value is less than 0.05(0.025 and 0.005).

Panel A : Weekly data

A-1: Before Crisis

Dep.Var.	R(t)				VOL(t)				CDS(t)		
	Chi-sq.	df	Prob		Chi-sq.	df	Prob		Chi-sq.	df	Prob
VOL(t)	0.4393	1	0.5074	R(t)	0.5636	1	0.4528	R(t)	0.3960	1	0.5292
CDS(t)	1.1169	1	0.2906	CDS(t)	0.2041	1	0.6514	VOL(t)	0.1093	1	0.7409
All	1.4377	2	0.4873	All	0.6236	2	0.7321	All	1.3632	2	0.5058

A-2: During Crisis

Dep.Var.	R(t)				VOL(t)				CDS(t)		
	Chi-sq.	df	Prob		Chi-sq.	df	Prob		Chi-sq.	df	Prob
VOL(t)	5.6970	3	0.1273	R(t)	7.3065	3	0.0627	R(t)	15.6461	3	0.0013
CDS(t)	15.2406	3	0.0016	CDS(t)	16.1767	3	0.0010	VOL(t)	18.2878	3	0.0004
All	23.9969	6	0.0005	All	16.2636	6	0.0124	All	30.0281	6	0.0000

A-3: After Crisis

Dep.Var.	R(t)				VOL(t)				CDS(t)		
	Chi-sq.	df	Prob		Chi-sq.	df	Prob		Chi-sq.	df	Prob
VOL(t)	3.9664	1	0.0464	R(t)	0.5227	1	0.4697	R(t)	1.4003	1	0.2367
CDS(t)	1.5111	1	0.2190	CDS(t)	3.6398	1	0.0564	VOL(t)	2.1631	1	0.1414
All	4.8364	2	0.0891	All	3.6547	2	0.1608	All	2.4323	2	0.2964

Table 8
Continued.

Panel B : Daily data

B-1: Before Crisis

Dep.Var.	R(t)				VOL(t)				CDS(t)		
	Chi-sq.	df	Prob		Chi-sq.	df	Prob		Chi-sq.	df	Prob
VOL(t)	4.8404	1	0.0278	R(t)	6.0103	1	0.0142	R(t)	16.8009	1	0.0000
CDS(t)	5.3165	1	0.0211	CDS(t)	3.4194	1	0.0644	VOL(t)	0.5127	1	0.4740
All	9.8883	2	0.0071	All	8.3138	2	0.0157	All	22.1241	2	0.0000

B-2: During Crisis

Dep.Var.	R(t)				VOL(t)				CDS(t)		
	Chi-sq.	df	Prob		Chi-sq.	df	Prob		Chi-sq.	df	Prob
VOL(t)	18.4214	1	0.0000	R(t)	0.4721	1	0.4920	R(t)	5.7402	1	0.0166
CDS(t)	24.4084	1	0.0000	CDS(t)	20.2843	1	0.0000	VOL(t)	19.1584	1	0.0000
All	37.9960	2	0.0000	All	23.1141	2	0.0000	All	19.2153	2	0.0001

B-3: After Crisis

Dep.Var.	R(t)				VOL(t)				CDS(t)		
	Chi-sq.	df	Prob		Chi-sq.	df	Prob		Chi-sq.	df	Prob
VOL(t)	3.8961	1	0.0484	R(t)	0.0776	1	0.7805	R(t)	7.3958	1	0.0065
CDS(t)	3.9051	1	0.0481	CDS(t)	6.2779	1	0.0122	VOL(t)	29.8171	1	0.0000
All	6.5559	2	0.0377	All	6.5561	2	0.0377	All	30.1646	2	0.0000