Lead-lag relationship between macroeconomic variables: evidence from Korea

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Abstract

This study seeks evidence supporting the existence of theoretical relationships and possible directions of causality between call money rates, exchange rates, industrial production index (IPI) and stock market movements from the perspective of Korea. We apply standard time series techniques including long run structural modelling (LRSM), vector error correction modelling (VECM) and variance decomposition (VDC). Our findings tend to suggest that IPI is the most leading factor among our variables for the long-term, and exchange rates is the most follower. It can be explained since the real economy is expected to lead monetary policy, stock markets and exchange rates in the long run. Findings of this study are meaningful for the investors and policy makers since a very few studies have been carried out examining the causal relationships of the above variables with the above techniques in Korea. This paper may help fill the gap for policy makers, practitioners and investors.

Key words: Direction of causality, Macroeconomic variables, Stock markets

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1. Introduction: Objective and motivation

After experiencing the global financial crisis, there has been increasing attention on the relationship between macroeconomic variables and stock market movements. As all of us witnessed, macroeconomic factors and financial markets are closely interacting, thus bad operations in financial markets may strike the whole economic system and any failing to deal with the real economy sector can cause deep depression in financial market. Therefore, these causal relationships between macroeconomic factors and stock markets are getting more spotlight.

Economic theories demonstrate that interest rates, exchange rates, money supply, inflation and other economic factors such as industrial productions are important variables in understanding the movement of stock prices. Rationally, interest rates and stock market movements are negatively correlated. It means that a higher interest rate monetary policy usually affects stock market negatively. This is because higher interest rates make fixed income securities more attractive than holding stocks considering the returns and risks. Exchange rates and stock market movements have more bidirectional causalities. Profits on foreign investment in a country's stock market are converted into foreign currencies. When the local currency depreciates, the adjusted profit rates are decreasing and when the local currency appreciates, the adjusted profit rates are increasing. Thus, foreign investors always closely pay their attention to exchange rate movements to decide a investment timing. In a different way, increasing foreign investments in a country’s stock market may cause the local currency to appreciate because of the increasing demand of the currency. Industrial productions also support stock market performance as an economic indicator.

Empirically, after Granger (1986), Johansen and Juselius (1990) proposed a cointegration analysis to examine the economic variables and stock market relationship, there has been a number of literature proving relations of macroeconomic variables and stock markets in different countries (J.J. Choi et al 1999, Nasseh and Strauss 2000, Fifield et al. 2000, Muradoglu et al. 2001, Lovatt and Ashok 2000, Maysami 2006 and Gupta 2013). Among them, Maysami et al (2006) show a cointegrating vector among returns on the Singapore Exchange and macroeconomic variables by applying the vector error correction model (VECM). Similarly, Gupta et al (2013) identifies that call money rates and exchange rates cause changes in stock returns, and did not find reverse causality from stock returns to call money and exchange rates. J.J. Choi et al (1999) finds industrial production and real stock prices are cointegrated in all G-7 countries. However, we could not find the causal relationship between these variables from the study.

Given these empirical and theoretical research, this paper wants to examine causalities between call money rates, exchange rates, IPI and stock market movements in Korean Exchange (KOSPI) by using monthly data for 22 years starting from January 1991. We assume that exchange rates as a determinant of investment decisions of foreign investors, call money rates as a monetary policy of a central bank as well as one of considerations of investment activities of institutional investors, and industrial production index as a real economy indicator. The reason we decide to take Korea as a case study is that Korean market is attracting more and more global investors with its growing market size, increasing openness, and the country has strong industrial production.

Our finding is that IPI is the most leading factor among our variables for the long-term, and exchange rates are the most follower. It can be interpreted as the real economy leads Korean stock market as well as call money rates and exchange rates in the long run. Findings of this study are meaningful for the investors and policy makers since a few studies have been carried out examining the causal relationships of the above variables in Korea. This paper may help fill the gap for policy makers and investors.

In this paper, we discuss empirical evidence in part 2 by doing literature review from previous studies, after that we support our theoretical findings with statistical results by applying time series techniques in part 3. In part 4, we make conclusions of findings and discuss limitations of this study as well as further improvements in future studies.

2. Literature Review

The findings from the empirical testing of relationships between macroeconomic variables and stock markets provide evidence that there are relationships among them. Fama (1981) as a pioneer, finds a positive correlation between stock returns and real economic variables such as industrial production, interest rates, money supply etc. Chen, Roll and Ross (1986) insist that the changes in aggregate production, the short-term interest rates and inflation explain changes in stock prices. Further, Mukherjee and Naka (1995) apply the VECM to analyze the relationship between the Japanese Stock Market and macroeconomic variables including exchange rates, call money rates, real economic activity, inflation, money supply and long-term government bond rate. They concludes that a cointegrating relation exist and stock prices indeed contribute to this relation. Similarly, Maysami and Koh (2000) examine that changes in short- and long-term interest rate, exchange rate and money supply form a cointegrating relation with changes in Singapore's stock market returns. Following that, Maysami and Sims employ the VECM technique to examine the relationship between macroeconomic variables and stock returns in Malaysia and Thailand (2001a), Japan and Korea (2001b), Hong Kong and Singapore (2002b). The results confirm the influence of macroeconomic variables on the stock market indices in six countries. Further, Maghyereh (2002) investigates the long-run relationship between the Jordanian stock prices and macroeconomic variables by using Johansen's cointegration analysis. The study shows that macroeconomic variables were reflected in stock prices in the Jordanian capital market. Based on these prior empirical studies, we tend to assume that there are causal relationships between macroeconomic variables and stock market movements.

The relationship between each macroeconomic variable and stock market movements has also received considerable attention in the literature. For interest rates, Zhou (1996) finds that interest rates have a prominent impact on stock returns, especially on long horizons. In addition, Arango (2002) insists that the nonlinear and inverse relationship between the share prices on the Bogota stock market and the interest rate as measured by the interbank money rate. Aggarwal (1981) attempts to explore the relationship between changes in the dollar exchange rates and changes in indices of stock prices for the period from 1974 to 1978, shows a positive correlation and this relationship is stronger in the short term than in the long term. Ajayi and Mougoue (1996) investigate the short-and long- run relationship between stock prices and exchange rates in eight advanced economies. They find different direction from Aggarwal (1981), that is, an increase in stock prices causes currency depreciations for both the U.S. and the U.K. since a rising stock market is an indicator of an expanding economy with higher inflation expectations. Foreign investors see higher inflation negatively, therefore the demand for the currency drops and it result in currency depreciation. This is in line with our hypothesis that a decline in stock prices makes foreign investors sell the financial assets in the currency and this leads to currency depreciation. There are also some empirical works for supporting relations between IPI and stock indices. Canova and De Nicolo (1995) investigate linkages between domestic output growth and domestic stock returns. Loflund and Nummelin (1997) also find the interaction between asset returns and industrial production growth for Finland and Sweden.

On the contrary, some studies argue that there is no evidence of long-run relationship among these variables. For example, Rahman and Uddin (2008) conclude that there is no long-run relationship between stock prices and exchange rates based on the case of Bangladesh for the period of June 2003 to March 2008. Bahmani and Sohrabian (1992) also confirm that there is just a short run relationship between the exchange rates and stock prices. Lee (1997) conducts a research on the Standard & Poor 500 index with the call money rate, and finds that the relationship is not stable over time, even it gradually changes from a significantly negative to no relationship. Moreover, J.J.Choi (1999) shows the result that real stock returns has significant short-run causality for the growth rate of industrial production in the US, UK, Japan, Canada and Germany.

So far, we have reviewed a number of literatures on relationships between macroeconomic variables and stock market movements. As different research shows mixed results, this study examine causal relationships among our variables and then whether these variables have a long run relationship by applying LRSM technique. Further, we are going to show that lead-lag relationships among our variables with VECM method, and finally conduct VDCs to check the relative exogeneity and endogeneity of the variables.

3. Data, Methodology and Empirical results

This research employs a time series technique including cointegration, long run structural modelling, error correction modelling and variance decomposition. These tests help this study to find theoretical relationships among variables; stock markets, exchange rates, interest rates and industrial productions. The reasons why we prefer to use a time series other than a regression model are as follows:

Firstly, the time-series techniques based on cointegration with vector error correction model and variance decomposition methods for testing granger causality of relationships among variables. It means that cointegration techniques does not assume theory and causality before it is proven by the data. On the other hand, in a regression model, the endogeneity and exogeneity of variables are predetermined by the researcher based on theories.

Secondly, when we test finance variables, generally the results could be statistically invalid because of the non-stationarity of variables. Using time series techniques, we can solve this problem by transforming variables to I(1) form with the differenced form of variables. However, traditional regression models assume that all variables are stationary. This assumption is not realistic in real markets, and the results could possibly mislead the conclusion as the statistical tests are not statistically valid when non-stationary variables are applied.

This research uses monthly data in the period of January 1991 to December 2012 from DataStream. The total observations is 263.

3.1 Stationarity tests

To test the unit roots of all the variables, we conducted both the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) Test. For the first stage, we tested whether these variables are I(1) which non-stationary in their level form and stationary in their differenced form. The differenced form for exchange rates and KOSPI are made by taking a difference of their log forms ($DEXCHGE = LEXCHGE - LEXCHGE_{t-1}$; $DKOSPI = LKOSPI - LKOSPI_{t-1}$), for call money rates and IPI are made by taking a difference of their original form ($DCALLMO = CALLMO - CALLMO_{t-1}$; $DIPI = IPI - IPI_{t-1}$) since these variables are already in percentage forms.

The results as shown below in table 1, all the variables we are using for this study are I(1). The results were determined by comparing test statistics with the 95% critical value for the ADF statistic. We chose the test statistics for each variable based on the highest computed value of AIC and SBC. In some cases, AIC and SBC gave us different orders but both results were consistent, thus it was not an issue here.

[Table 1. Stationarity test results]

Variables in level form			
Variable	Critical value	Test statistics	Results
LEXCHGE	-3.4286	-2.2335	Non-stationary
LKOSPI		-2.5243	Non-stationary
CALLMO		-3.4205	Non-stationary
IPI		-3.0427	Non-stationary
Variables in differenced form			
Variable	Critical value	Test statistics	Results
DEXCHGE	-2.8729	-10.9836	Stationary
DKOSPI		-10.9564	Stationary
DCALLMO		-10.3008	Stationary
DIPI		-6.5398	Stationary

The Phillips-Perron (PP) test also gave us the same results. In the PP test, the null hypothesis is 'The variable is non-stationary', and we can reject the null when the p-value of the test result is smaller than the selected significance level. We set the critical value here as 1%. It means that, the p-values of LEXCHGE, LKOSPI, CALLMO and IPI should be greater than 0.01; the p-values of DEXCHGE, DKOSPI, DCALLMO and DIPI should be smaller than 0.01. As tested all the variables, we were able to get the results that all our variables are I(1).

3.2. Determination of the order of the VAR

Prior to doing cointegration test, we needed to determine order of the VAR which helps us to select how many lags we are going to use for cointegration test. In VAR test, the results gave us AIC(0) and SBC(5), and the result made us think for a while. If we follow AIC and choose zero lag, serial correlation is the problem, and even we will face difficulties later since Microfit will not show us the result completely. However, if we choose 5 lags based on SBC, the result possibly will have an over-parameterisation risk. Therefore, we decided that testing for the serial correlation of variables first.

[Table 2. Serial correlation tests]

Variables	Chi-Sq P-values	Results (at 5%)
DEXCHGE	0.112	No serial correlation
DKOSPI	0.915	No serial correlation
DCALLMO	0.016	Serial correlation
DIPI	0.468	No serial correlation

As the above results, there is autocorrelation for one variable among four variables. Thus, if we adopt a lower order, we may encounter the effects of serial correlation. Therefore, we decided to choose higher lags since we have 263 observations which is relatively long time period. However, actually 5 lags are a bit high, we decided to experiment with 2 or 3 lags and if the number gives us the same result as 5 lags, then we use the number of lags instead of 5 lags. Therefore we are going to try the VAR order of 2, 3 and 5 lags in following cointegration test.

3.3. Cointegration tests

For testing cointegration, we applied both Johansen and Engle-Granger methods. As we mentioned in previous section, we looked at optimal VAR order by comparing number of cointegrating vectors of 2, 3 and 5 lags. In Johansen cointegration test with 5 lags, we found one cointegrating vector at 95% significance level on the basis of maximal Eigen value and trace statistics, whereas according to AIC, HQC and SBC, there are zero and 4 cointegration vectors respectively[1]. We did the same test for VAR order of 2 and 3 as well, and found that the test for 3 lags gives us the same results as 5 lags (table 3), therefore decided adopting 3 lags for our testing instead of 2 or 5 lags.

[1] In the case of maximal eigenvalue and trace, if the test statistic for null of 'r = 0' is greater than the 95% critical value, we can reject the null. For AIC, SBC and HQC, the number of cointegrating vectors is selected by based on the highest numbers.

[Table 3. Cointegration test result]

Criteria	No. of cointegrating vectors		
	5 lags	2 lags	3 lags
Maximal Eigen value	1	2	1
Trace	1	2	1
AIC	0	0	0
SBC	4	4	4
HQC	0	0	0

Table 4 below shows us the outcome of Johansen cointegration test with 3 lags. From the results, we selected one cointegrating vector based on the eigen value and trace statistics at 95% level.

[Table 4. Johansen cointegration test with 3 lags]

Maximum eigen value statistics				
H0	H1	Statistic	95% Crit.	90% Crit.
r=0	r=1	35.59	31.79	29.13
r≤1	r=2	20.61	25.42	23.10
Trace statistics				
H0	H1	Statistic	95% Crit.	90% Crit.
r=0	r≥1	76.49	63.00	59.16
r≤1	r≥2	40.90	42.34	39.34

We also conducted Engel-Granger test whether the test results consistent with Johansen method. In E-G test, we assumed an OLS regression based on theories and empirical studies; 'LKOSPI = $\alpha + \beta_1$ LEXCHGE + β_2 CALLMO + β_3 IPI + e_t'. Again, we found one cointegration from E-G test as in Johansen test as table 5 below[2].

[2] The result was made by comparing test statistics of the highest value of AIC and SBC with DF critical value at 95%. In this result, we assume that there is on cointegration among variables based on SBC value (-4.91) which is greater than DF critical value(-4.14).

[Table 5. Engle-Granger test result]

	Test statistics	DF critical value at 95%
AIC	-4.02	-4.14
SBC	-4.91	

Based on both Johansen and Engel-Granger cointegration test, we can insist that there is a theoretical relationship among stock market, exchange rate, call money rate and industrial production. It means that they affect each other, and in equilibrium in the long term.

This result is in line with our expectations during our literature review stage. As many other prior research results, we were also able to prove a cointegration among our variables. Next stage, we will find long run relationships among our variables with the long run structural modelling. We expect that the test could give us a result whether the variables have long-run relationships each other which had arguments in other empirical studies.

3.4. Long Run Structural Modelling (LRSM)

Using the Long Run Structural Modelling (LRSM), we can quantify the theoretical information among variables. First, we applied a normalising restriction of KOSPI at the exact-identifying stage, obtained the results as below (Panel A of table 6).

[Table 6. Exact and over identifying restrictions on the cointegrating vector]

	Panel A	Panel B(1)	Panel B(2)
EXCHNGE	2.821* (1.316)	1.801* (0.459)	3.087* (1.300)
KOSPI	1.000 (*None*)	1.000 (*None*)	1.000 (*None*)
CALLMO	0.139 (0.111)	0.00 (*None)	0.145 (0.120)
IPI	-0.010 (0.030)	0.004 (0.020)	-0.000 (*None)
Trend	0.002 (0.012)	-0.008 (0.007)	-0.001 (0.004)
Log-Likelihood	40.634	34.425	40.579
Chi-Square	None	12.417 [0.000]	0.101 [0.741]

By calculating the t-ratios manually, we found that only EXCHGE was significant, other variables such as CALLMO, IPI were insignificant. These results were surprising since we already found theoretical relationships in earlier stages. Therefore, we decided to verify the significance of these variables by doing over-identifying restrictions.

When we imposed the over-identifying restrictions of CALLMO, the null hypothesis 'CALLMO is insignificant' was rejected. It means that the restriction was incorrect, in other words, CALLMO is significant (Panel B(1) of table 6). On the contrary, when we made the over-identifying restrictions for IPI, we were not able to reject the null hypothesis (Panel B(2) of table 6), it means that IPI is still insignificant.

However, based on our intuition, we would like to believe that IPI is a significant variable here. The reason is that, the IPI has been used as an indicator of economic health since it is closely related to the business cycle. Business cycles show the up and down movements of industrial productions which illustrate the condition of the economy, and a stock market normally reflect those conditions of economy.

3.5. Vector Error Correction Model (VECM)

Based on our analysis, we have established that our variables EXCHGE, KOSPI, CALLMO and IPI are cointegrated to a certain significant degree. However, the cointegration cannot tell us the direction of the causality, that is, which variables are exogenous and which are endogenous. Therefore we employed VECM model to examine the lead-lag relationships of the variables.

The error correction model tells us the differences between the short-term and long-term Granger causality. Granger-causality is a form of temporal causality among variables and long-term relations 'e_{t-1}'. The error correction term 'e_{t-1}' explains the long-term relations among the variables, and tells us how long it will take to get back to long term equilibrium if the variable is shocked. Equations for each variable are as below.

$$\Delta LEXCHGE = \alpha_t + \Delta LEXCHGE_{t-1} + \Delta LKOSPI_{t-1} + \Delta CALLMO_{t-1} + \Delta IPI_{t-1} + e_{t-1} + \varepsilon_t$$

$$\Delta LKOSPI = \alpha_t + \Delta LKOSPI_{t-1} + \Delta LEXCHGE_{t-1} + \Delta CALLMO_{t-1} + \Delta IPI_{t-1} + e_{t-1} + \varepsilon_t$$

$$\Delta CALLMO = \alpha_t + \Delta CALLMO_{t-1} + \Delta LEXCHGE_{t-1} + \Delta LKOSPI_{t-1} + \Delta IPI_{t-1} + e_{t-1} + \varepsilon_t$$

$$\Delta IPI = \alpha_t + \Delta IPI_{t-1} + \Delta LEXCHGE_{t-1} + \Delta LKOSPI_{t-1} + \Delta CALLMO_{t-1} + e_{t-1} + \varepsilon_t$$

By checking the error correction term 'e_{t-1}' for each variable whether it is significant, we found **one exogenous variable, IPI**, as table 7 below.

[Table 7. Vector error correction model]

Variables	ECM(-1) t-ratio [p-value]	Implications
LEXCHGE	- 2.330 [0.021]	Endogenous
LKOSPI	-2.348 [0.020]	Endogenous
CALLMO	-4.230 [0.000]	Endogenous
IPI	-0.468 [0.640]	Exogenous

This result means that, as the exogenous variable, when IPI receives market shocks, other factors including the stock market (KOSPI), exchange rates (EXCHGE) and call money rates (CALLMO) will be affected by the shocks. This tends to indicate that the real economy activities lead other macroeconomic factors as well as stock market movements. In this sense, when researchers or policy makers analyse a market system, they would be interested to monitor the changes of IPI as it will affect exchange rates, interest rates and stock prices.

3.6. Variance Decompositions (VDC)

Although VECM results showed us IPI is the leader among our variables, but we have not got the relative endogeneity of remaining variables. VDC test will helps us to ascertain the relative degree of endogeneity among those variables. The relative exogeneity or endogeneity of a variable can be determined by the proportion of the variance explained by its own past. If a variable is mostly explained by itself, it is the most exogenous variable. Whereas, the most endogenous variable is mostly explained by others. The relative endogeneity and exogeneity of the variables are important for policy makers. If the causality runs from economic variables to stock markets, the appropriate policies for developing financial markets will be controlling the economic factors. On the other hand, if the causality runs from changes in stock market indices to other macroeconomic variables, then policy makers may need to keep their stock market stable in order to control the economic volatility.

We applied both orthogonalised and generalised VDCs, and compared the exogeneity / endogeneity of variables for 12 months, 36 months and 60 months. The table 8 below is the results of orthogonalised VDCs.

[Table 8. Orthogonalised Variance Decompositions]

No.	Time horizons		
	12 months	36 months	60 month
1	LEXCHGE	LEXCHGE	LEXCHGE
2	LKOSPI	IPI	IPI
3	IPI	LKOSPI	LKOSPI
4	CALLMO	CALLMO	CALLMO

This results gave us confusion. According to VECM analysis, IPI was the only exogenous one among our variables, but in VDCs, it was only ranked third for 12 months and second for 36, 60 months. Here, we need to discuss about limitations of orthogonalised VDCs. Firstly, it assumes that when a particular variable is shocked, all other variables are switched off. Secondly, it is dependent on a particular ordering of variables thus, the first variable would report as the highest percentage.

Because of above reasons, we decided to rely on generalised VDCs. Generalised VDCs is more reliable than orthogonalised VDCs, since it does not make such a restrictive assumption and independent on a particular ordering of variables. However, when interpret the numbers generated by the Generalised VDCs, we need to be careful and perform additional computations to make the numbers add up to 100% for a specified horizon (the numbers add up to 100% in the case of orthogonalised VDCs). Based on generalised VDCs, the forecast error variance of each variable are as table 9 below.

[Table 9. Generalised Variance Decompositions]

Forecast at Horizon = 12 months

	LEXCHGE	LKOSPI	CALLMO	IPI
LEXCHGE	55.7%	33.8%	6.1%	4.4%
LKOSPI	9.6%	67.6%	18.8%	4.0%
CALLMO	13.2%	10.2%	75.9%	0.7%
IPI	6.0%	18.1%	3.1%	72.8%

Forecast at Horizon = 36 months

	LEXCHGE	LKOSPI	CALLMO	IPI
LEXCHGE	52.6%	37.8%	4.7%	4.9%
LKOSPI	13.4%	59.3%	23.4%	3.9%
CALLMO	23.4%	7.8%	64.8%	4.0%
IPI	7.4%	19.5%	4.3%	68.8%

Forecast at Horizon = 60 months

	LEXCHGE	LKOSPI	CALLMO	IPI
LEXCHGE	51.8%	38.9%	4.3%	5.0%
LKOSPI	14.1%	57.8%	24.2%	3.8%
CALLMO	29.9%	6.4%	57.9%	5.8%
IPI	7.7%	19.8%	4.5%	68.0%

We depicted above result tables into the table 10 below. The variable relative exogeneity / endogeneity of our variables are as table 10 below.

[Table 10. relative exogeneity / endogeneity]

No.	**Time-horizons**		
	12 months	**36 months**	**60 months**
1	CALLMO	IPI	IPI
2	IPI	CALLMO	CALLMO
3	LKOSPI	LKOSPI	LKOSPI
4	LEXCHGE	LEXCHGE	LEXCHGE

These results tend to indicate that there were some difference orders for different time horizons.

The call money rate leads other variables for 12 months, and IPI is the leader for 36 months and 60 months. We were curious why the result order was different by time horizons. Practically, it could be explained as call money rates more exogenous than IPI for short or mid-term, and for the long-term, IPI affects call money rates as well as other variables.

However, we also would like to know statistical reasons, therefore checked diagnostic tests results for each variable in VECM test since diagnostic tests can tell us how reliable our results are. From the scanning, we found some abnormal factors such as serial correlation, functional form, normality and heteroscedasticity problems of our variables as table 11 below[3].

[Table 11. Diagnostic test results]

Variables	Diagnostic tests (at 5%)
EXCHGE	Normality, Heteroscedasticity
KOSPI	Functional form, Normality
CALLMO	Serial correlation, Normality
IPI	Functional form, Normality, Heteroscedasticity

After we looked at the diagnostic tests results, we noticed that our VECM results could be a bit biased because of above problems of variables. Thus, we wanted to try one more time horizon to check whether the VDC results can show us comparatively constant result. We added 24 months, and the results gave us that the same ordering for 12 months and 24 months, 36 months and 60 months (Table 12).

[Table 12. relative exogeneity / endogeneity]

No.	Time-horizons			
	12 months	24 months	36 months	60 months
1	CALLMO	CALLMO	IPI	IPI
2	IPI	IPI	CALLMO	CALLMO
3	LKOSPI	LKOSPI	LKOSPI	LKOSPI
4	LEXCHGE	LEXCHGE	LEXCHGE	LEXCHGE

Finally, we decided to rely the results of generalised VDCs, which our variables have different

[3] Diagnostic test results are based on p-value of chi-square at 5% significant level. When the p-value is smaller than 0.05 (5%), we reject the null hypothesis (i.e. there is no serial correlation)

relative exogeneity / endogeneity depend on time horizons. In sum, call money rates is the most leading variable for short and mid-term, but in the long term, the IPI affects call money rates, stock market movements, exchange rates.

3.7. Impulse Response Functions (IRF)

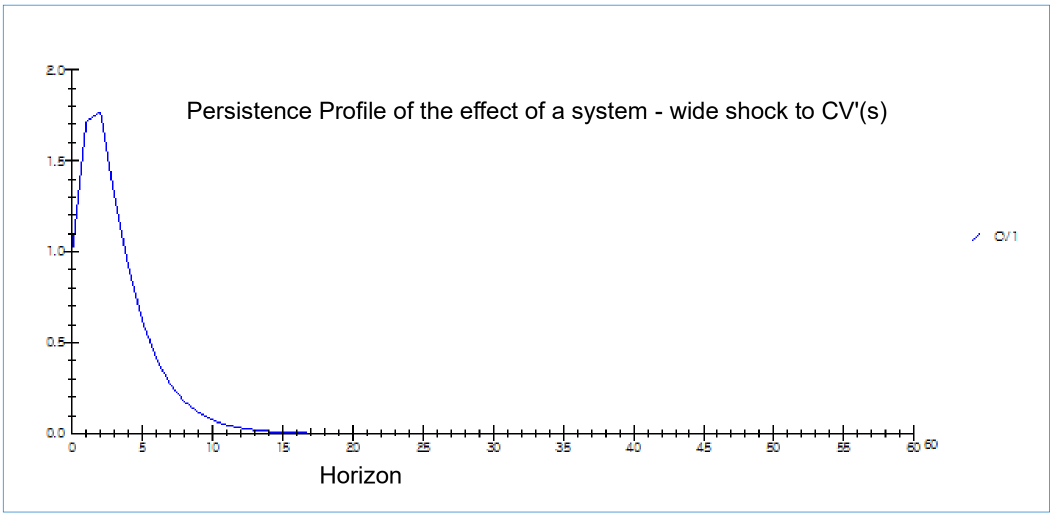
The IRFs presents the same information as the VDCs with graphical form. We applied both the orthogonalised IRFs and generalised IRFs, found similar results from both. We have attached the various graphs of IRFs in appendix 7A to 7H.

3.8. Persistence Profile

While VDCs and IRFs indicate variable-specific shocks, the persistence profile shows us a system wide shocks that if the whole system is shocked, how long it will take to get back to the equilibrium.

The chart below illustrates that the persistence profile for the cointegrating equation of this study. According to our result as figure 1 below, it will take about 15 months for the cointegrating relationship to get back to equilibrium.

[Figure 1. Persistence Profile]



4. Conclusions and Suggestions for future research

This study attempts to test possible causal relationships between stock markets (KOSPI) and macroeconomic variables (call money rates, exchange rates, IPI) in Korea by employing the standard time series techniques including LRSM, VECM and VDCs.

We found a cointegration among our variables as other previous studies but different causal relationships. Gupta (2011) insists that call money rates and exchange rates affect stock markets but cannot find inverse direction relationship. However, in our generalised VDCs, exchange rates is the most endogenous variable in both short- and long-term.

We also had some inconsistencies during the test. Firstly, IPI was an insignificant variable for both exact-identifying and over-identifying in LRSM, however we concluded that IPI is the significant variable based on our intuition. Even though we could not statistically support our theoretical hypothesis at the stage, however, the VECM and the VDCs showed that IPI is the most leader for the long term among the variables. Secondly, the VECM and the VDCs gave us different results. The VECM told us that IPI is the only exogenous variable but in VDCs it did not rank first all the time. Therefore, we checked our diagnostic test and then made a conclusion as there could be different directions of causality in different time horizons. That is, call money rates affect other variables most for short- and mid-term, and IPI as a real economy indicator, leads other macroeconomic factors as well as stock markets in the long-term.

Our research results tend to suggest that in the short- and the mid-term, call money rates which is a mean of monetary policies could move economic activities as well as affect the stock market and exchange rates. It means that proper monetary policy affects economy and stock markets in the short and the mid-term. In the same sense, real economic sector activities such as industrial production influence other economic factors as well as the stock market in the long term, therefore policies for promoting real economy activities could encourage stock market developments also affect exchange rates which is one of the crucial factors for export. It is an important suggestion for export driven countries like Korea. An active economy brings good financial market performances, and it results in stable exchange rates, also increase exports.

We admit that there are some limitations of our study. There are many other factors that affect financial markets and economic conditions such as employment, inflations, disposal income, social equality etc. In addition, nowadays, a country's stock market is closely affected by other countries' markets as well. Therefore, using just exchange rates, interest rate and IPI may not be enough to explain those movements of stock markets and macroeconomic variables. In addition, even though we proved the lead-lag relations among variables by time series techniques, there are always possibilities that these variables have bidirectional relationships depending on situations, since these are all linked and affecting each other. Future studies could be conducted with more variables with different countries.

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