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ISSN: 0193-4120 Page No. 2352 - 2361

# A Study on the Causal Relationship between Economic Variable Using VAR Model

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***Article Info***
***Volume 81***
***Page Number: 2352 - 2361***
***Publication Issue:***
***November-December 2019***

***Abstract***

In this study, we analyzed the causal relationship among the Korean Won to US Dollar exchange rate (ER) and the consumer price index (CPI) provided by the Bank of Korea, and the KOSDAQ index provided by the Korea Exchange (KRX). The sample data were monthly data from January 1, 2005 to December 31, 2018. As the research model, we used the vector autoregressive model (VAR model), which is a vector time series model, to perform Cointegration Test, Granger Causality Test, Impulse Response Function Analysis, and Variance Decomposition Analysis. The results are as follows. The cointegration test of the economic time series variables CPI, KOSDAQ, and ER shows that there is no cointegration relationship between Trace and Maximum Eigenvalue statistics. In the Granger causality test, each of the variables shows that the significance probability of the chi-square statistic is smaller than the significance level of 0.05, indicating that there is a bidirectional linear dependency respectively, which is influenced by the past values of the self and the other two variables. The analysis of whether it affects volatility shows that the significance probability of the F-statistic is smaller than the significance level of 0.05, and therefore the model has predictive power. The results of impulse response function analysis to see how long the predictive power persists shows that the impulse of the CPI on the KOSDAQ negatively affects up to time lag 4 and disappears, and on the ER up to the time lag 2. In addition, the variance decomposition analysis of prediction error was performed to estimate the extent to which the changes in the CPI, the KOSDAQ, and the ER interact with each other. The result shows that, after the sixth lead, the CPI has an explanatory power of about 97% for itself, the KOSDAQ has an explanatory power of about 98% for itself, and other variables do not affect the CPI and the KOSDAQ. The ER does not affect the CPI, has an explanatory power of about 12% for the KOSDAQ, and about 87% for itself.

***Article History***
***Article Received:*** *5 March 2019*
***Revised:*** *18 May 2019*
***Accepted:*** *24 September 2019*
***Publication:*** *12 December 2019*

***Keywords****: Cointegration Test, Impulse Response Function Analysis, Variance Decomposition Analysis, VAR.*

## 1. INTRODUCTION

Korea's economy is maintaining a good growth rate of exports, but the economy is weakening mainly on domestic demand, as investment, employment, and economic indicators are slowing down or declining. Externally, in the course of normalizing US monetary policy, economic uncertainties such as capital outflows and sharp depreciation of currencies of some of the vulnerable emerging economies are growing. In the midst of this, as the trade disputes between the US and China are intensifying, concerns about the contraction in world trade and the sustainability of global economic growth are

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rising. Recently, as the Korean stock market has been sensitive to changes in overseas economic variables such as the US interest rate and the Won-Dollar exchange rate as well as the domestic economy such as the price and the economic situation, there is a growing need to analyze how stock prices react to changes in macroeconomic variables at home and abroad.

In particular, the consumer price index (CPI) is expected to climb due to the continued rise in agricultural product prices and the termination of electric charge reduction. The exchange rate (ER) is expected to rise compared to the previous year due to the surge of US long-term Treasury bond rate according to inflation concerns, and monetary policy differentiated among major countries. The KOSDAQ index is expected to continue to decline due to lack of corporate and financial restructuring and stable demand. The purpose of this study is to provide useful information on monetary policy and economic policy formulation by analyzing the relationship between economic time series variables. The preceding studies on the relationships among economic time series variables are as follows. In a study on the relationship between travel stock index and macroeconomic variables using time series analysis, consumer price and money supply were the causal variables of the stock index [1]. A study on the correlation between the rice index and the price index based on the VAR model suggested that producer prices consistently affected consumer prices [2]. Darbar and Deb analyzed the correlation among exchange rates, stock prices, interest rates, and raw materials using a bivariate GARCH model, and found that there was volatility transfer effect between bonds and exchange rate, bonds and stocks, exchange rate and raw material market respectively [3]. Aloui analyzed the average, volatility, and causal relationships between stocks and foreign exchange markets in the US and European markets, and found that there was a causal relationship between averages and fluctuations of exchange rate and stock price respectively [4]. And Kanas analyzed the interdependence between stock returns and exchange rate fluctuations using EGARCH models of six industrial countries such as the US, UK, Japan, Germany, France, and Canada and found that the effect of stock returns on exchange rate fluctuations had been increasing [5]. This study analyzes the causal relationship between the Won-Dollar exchange rate, the consumer price index, and the KOSDAQ index in the extension of previous studies.

## 2. RESEARCH MODEL

### 2.1 Vector Autoregressive Model

The p-order vector autoregressive model, in which the k-dimensional multivariate time series $Z_t = (Z_{1t}, Z_{2t}, \cdots, Z_{kt})'$ returns from the past p multivariate time series $Z_{t-1}, Z_{t-2}, \cdots, Z_{t-p}$ at time t, is called the VAR(p) model and can be expressed as follows.

$$\begin{aligned} Z_t &= \delta + \Phi_1 Z_{t-1} + \cdots + \Phi_p Z_{t-p} + \varepsilon_t \\ &= \delta + \sum_{i=1}^{p} \Phi_i Z_{t-i} + \varepsilon_t \end{aligned} \tag{1}$$

namely,

$$\begin{bmatrix} z_{1,t} \\ z_{2,t} \\ \vdots \\ z_{k,t} \end{bmatrix} = \begin{bmatrix} \delta_1 \\ \delta_2 \\ \vdots \\ \delta_k \end{bmatrix} + \sum_{i=1}^{p} \begin{bmatrix} \phi_{11} \phi_{12} \cdots \phi_{1k} \\ \phi_{21} \phi_{22} \cdots \phi_{2k} \\ \vdots \quad \vdots \quad \cdots \quad \vdots \\ \phi_{k1} \phi_{k2} \cdots \phi_{kk} \end{bmatrix} \begin{bmatrix} z_{1,t-i} \\ z_{2,t-2} \\ \vdots \\ z_{k,t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{k,t} \end{bmatrix} \tag{2}$$

Where,

$\delta$: $k \times 1$constant vector

$\Phi_i$ :$k \times k$timeseries regression coefficient matrix between current and differential variables

$\varepsilon_t$: multivariate white noise process

### 2.2 Selecting Order of the VAR Model

There are various information criteria used for model selection using the covariance matrix$\sum_\varepsilon$ for the estimation error of the VAR model, but

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the statistics used in this study are as follows [6].

$$SBC = \log\left|\hat{\Sigma}\right|_{\varepsilon} + r\log(T)\ /\ T \quad (3)$$

$$HQC = \log\left|\hat{\Sigma}\right|_{\varepsilon} + 2r(\log(T))\ /T \quad (4)$$

Where,

$\hat{\Sigma}_{\varepsilon}$ is the maximum likelihood estimator of $Var(\varepsilon_t)$,ris the estimated number of parameters, and Tis the number ofobservations.

### 2.3 Cointegration Test

if we put $\Phi_i^* = -\sum_{j=i+1}^{p-1}\Phi_j$in the VAR(p) model of (Equation 1), the VAR(p) model

$$\nabla Z_t = -(I_k - \Phi_1 - \Phi_2 - \cdots - \Phi_p)Z_{t-1} + \sum_{i=1}^{p-1}\Phi_i^*\nabla Z_{t-i} + \varepsilon_t \quad (5)$$

If we let $\alpha$and $\beta$be a matrix of size $k \times k(k \geq r)$ and rank r respectively, and put $(\alpha\beta)' = -(I_k - \Phi_1 - \Phi_2 - \cdots - \Phi_k)$, then (Equation 5) is expressed as follows.

$$\nabla Z_t = \delta + \Pi Z_{t-1} + \sum_{i=1}^{p-1}\Phi_i^*\nabla Z_{t-i} + \varepsilon_t \quad (6)$$

This is called a vector error correction model, where $\nabla Z_t = Z_t - Z_{t-1}$ , $\Pi = \alpha\beta'$ , $\alpha$ and $\beta$ are $k \times r$ matrix respectively, $\Phi_j$ is $k \times k$ matrix, $\delta = \delta_0 + \delta_1 t$ is deterministic trend term, and $\delta_0$ and $\delta_1$ are $k \times 1$ matrix. $\beta' Z_{t-1}$ is called a cointegration relation or a long-term equilibrium, and $\alpha$ is a rate-determining parameter that measures how sensitive the data are when they are out of long-term equilibrium relation of $\beta' Z_{t-1}$. If $0 < rank(\Pi) = r < k$in (Equation 6), there exist r mutually independent linear combination equations. The test for determining the number of columns that are linearly independent of $\Pi = \alpha\beta'$, i.e., the value of the cointegration coefficient, r , is called the cointegration test. The method of testing the cointegration is follows [7], [8], [9].

The trace statistic for testing the null hypothesis with r cointegration vectors is given as in (Equation 7),

$$\lambda_{trace} = -T\sum_{i=r+1}^{k}\log(1 - \lambda_i) \quad (7)$$

The maximum eigenvalue statistic for testing the hypothesis with maximum rcointegration vector is given as in (Equation 8).

$$\lambda_{max} = -T\log(1 - \lambda_{r+1}) \quad (8)$$

Where, Tis the number of observations, and $\lambda_i$is the eigenvalues.

### 2.4 Granger Causality Test

Assuming that $Z_t$follows the VAR(p) model and the coefficient matrix $\Phi(B)$can be partitioned into $\Phi_{ij}(B)$,$i, j = 1,2$,the VAR(p) model can be expressed as follows.

$$\begin{bmatrix}\Phi_{11}(B)\Phi_{12}(B)\\ \Phi_{21}(B)\Phi_{22}(B)\end{bmatrix}\begin{bmatrix}Z_{1t}\\ Z_{2t}\end{bmatrix} = \begin{bmatrix}\delta_1\\ \delta_2\end{bmatrix} + \begin{bmatrix}\varepsilon_{1t}\\ \varepsilon_{2t}\end{bmatrix} \quad (9)$$

In (Equation 9), if $\Phi_{12} = 0$, vector $Z_{1t}$affects $Z_{2t}$, but $Z_{2t}$does not affect $Z_{1t}$. That is, the future value of $Z_{1t}$can be explained by the past value of $Z_{1t}$, but is nothing to do with past value of $Z_{2t}$, while the future value of $Z_{2t}$is affected by the past values of $Z_{1t}$and $Z_{2t}$. In this case, $Z_{2t}$is not a Granger cause of $Z_{1t}$ . In this study, we, performed a modified Wald test in which the Chi-square test was performed only for the first p coefficients that were optimal time lags [10], [11].

### 2.5 Impulse Response Function Analysis

In the vector autoregressive model, the impulse response function is a moving average model derived from the model, which shows how all the variables in the model respond to impulse over time, given the unexpected impulse in the economy.

The vector autoregressive model can be converted to the $MA(\infty)$ model if the AR(p) model of (Equation 1) satisfies the invertibility condition [12], [13]. In other words, if all the eigenvalues of $\Phi$are time series in the unit circle, $Z_t$can be expressed as vector moving average (VMA(∞)model)by $\varepsilon_t$.

$$Z_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \cdots = \mu + \sum_{s=0}^{\infty} \Psi_s \varepsilon_{t-s}$$
$$= \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_k \end{bmatrix} + \sum_{s=0}^{\infty} \begin{bmatrix} \phi_{11}\phi_{12} \cdots \phi_{1k} \\ \phi_{21}\phi_{22} \cdots \phi_{2k} \\ \vdots \quad \vdots \quad \cdots \quad \vdots \\ \phi_{k1}\phi_{k2} \cdots \phi_{kk} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-s} \\ \varepsilon_{2,t-s} \\ \vdots \\ \varepsilon_{k,t-s} \end{bmatrix} \quad (10)$$

(Equation 10) is expressed using a backshift operator as follows.

$$Z_t = \mu + \Psi(B)\varepsilon_t \quad (11)$$

where, the coefficient $\Phi(B)$ represents the effect of $Z_1$ on the impact of $\varepsilon_t$ as a function of times, which is called the impulse response function. The individual element of $\Phi(B), \Phi_{ij}(s)$ is the impact multiplier or innovation coefficient for a period of at time s affecting on the $i$ th variable$Z_i$when$\varepsilon_j$ changes by one unit.

### 2.6 Variance Decomposition Analysis

The variance decomposition analysis of prediction error is a method of describing the relational characteristics of variables, along with the impulse response function analysis. While the impulse response function analysis tracks the impact of endogenous variables on the variables in the vector autoregressive model, variance decomposition analysis is a method of decomposing changes in endogenous variables for the impact of each component on the endogenous variables in the vector autoregressive model. Prediction errors for a particular variable include a number of impulse factors for other variables. The method of decomposing these by each factor is variance decomposition analysis of prediction error. In other words, through the variance decomposition of prediction error, relative importance of endogenous variable variation in the error terms of the vector autoregressive model is identified.

## 3. RESULT ANALYSIS

### 3.1 Unit Root Test

The results of the Augmented Dickey-Fuller Unit Root Tests (ADF-Unit Root Test) on the CPI, KOSDAQ, and ER variables show that the p-value of the Tau statistic is greater than the significance level of 0.05, indicating that the model is nonstationary time series with unit root. Therefore, to check the stability of each time series variable, the unit root test was performed again after the first differencing (∇). The results show that all the p-values of the Tau statistics are smaller than the significance level of 0.05, which confirms that the model is stationary time series with no unit root, that is, each time series variable follows I(1) (Table 1).

**Table 1:**ADF-Unit Root Test

| Level Variable | Type | Pr<Tau | ∇Variable | Pr<Tau |
|---|---|---|---|---|
| CPI | Zero Mean | 0.9999 | ∇CPI | <.0001 |
| | Single Mean | 0.3172 | | <.0001 |
| | Trend | 0.9503 | | <.0001 |
| KOSDAQ | Zero Mean | 0.7571 | ∇KOSDAQ | <.0001 |
| | Single Mean | 0.1458 | | <.0001 |
| | Trend | 0.2889 | | <.0001 |
| ER | Zero Mean | 0.7512 | ∇ER | <.0001 |
| | Single Mean | 0.1736 | | <.0001 |
| | Trend | 0.3830 | | <.0001 |

Checking the results of first differencing in a graph, we confirmed that it is a horizontal and

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*ISSN: 0193-4120 Page No. 2352 - 2361*

stable time series with no trend as shown in (Figure 1).

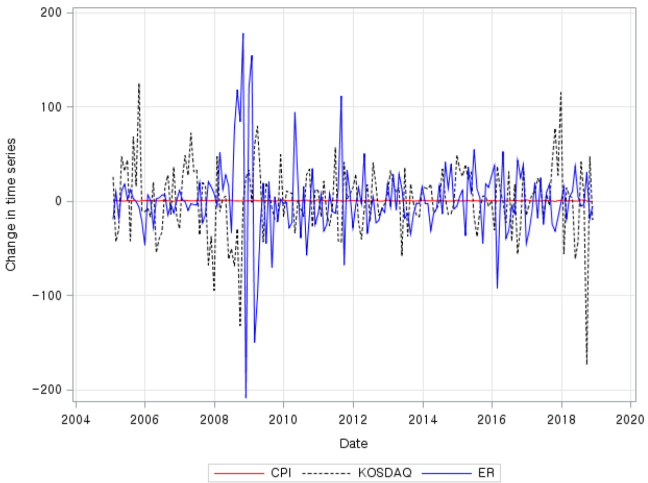


**Figure1:**Time Series Graph after the First Differencing

### 3.2 VAR Model Setup

Some studies show that the optimal order p=2 of the VAR(p) model explains the dynamic structure of multivariate time series well. However, in this study, we decided the order p by the minimum information criterion based on schwarz bayesian criterion (SBC) statistic and hannan-quinn criterion (HQC) statistic. As the result, when AR is 1, SBC = -23.5170 and HQC = -23.6501 are the smallest, so the VAR(1) model is selected (Table 2).

**Table 2:**Setting VAR(1) Model

| **Minimum Information Criterion Based on SBC** | | | | | |
|---|---|---|---|---|---|
| Lag | MA0 | MA1 | MA2 | MA3 | MA4 |
| AR 0 | -13.5145 | -13.5421 | -13.5852 | -13.6653 | -13.8865 |
| AR 1 | -23.5170 | -23.4205 | -23.2921 | -23.2638 | -23.2259 |
| AR 2 | -23.3853 | -23.2711 | -23.1419 | -23.1416 | -23.0744 |
| AR 3 | -23.3026 | -23.2211 | -23.0972 | -22.9742 | -22.9237 |
| AR 4 | -23.1527 | -23.1848 | -23.0134 | -22.8940 | -22.7040 |
| **Minimum Information Criterion Based on HQC** | | | | | |
| Lag | MA0 | MA1 | MA2 | MA3 | MA4 |
| AR 0 | -13.5477 | -13.6520 | -13.7443 | -13.8799 | -14.0371 |
| AR 1 | -23.6501 | -23.6249 | -23.6131 | -23.6451 | -23.6069 |
| AR 2 | -23.6192 | -23.6276 | -23.5377 | -23.5806 | -23.6141 |
| AR 3 | -23.6381 | -23.6377 | -23.6352 | -23.6112 | -23.5682 |
| AR 4 | -23.5906 | -23.6037 | -23.5941 | -23.5629 | -23.4826 |

### 3.3Cointegration Test

The results of the time series change of the variables (CPI, KOSDAQ, ER) show that they all have clear trend. Thus, the cointegration test was performed using Johansen's trace statistic of cointegration test and maximum eigenvalue statistic.A and B in Table 3 are trace statistics, and the null hypothesis$H_0$is adopted indicating that there is no cointegration relationship with A's trace = 29.8371 < 5% Critical Value = 34.56 and B's trace = 33.1916 < 5% Critical Value = 42.20, when $H_0: r = 0$ vs. $H_1: r > 0$. C and D in Table 3 are Maximum Eigenvalue statistics, and the null hypothesis$H_0$ is adopted indicating that there is also no cointegration relationship with C's Maximum of 20.8919 <

5% Critical Value = 23.78 and D's Maximum = 21.0570 < 5% Critical Value = 25.54, when$H_0: r = 0$ vs. $H_1: r > 0$ (Table 3).

**Table 3:**Cointegration Test

| **Cointegration Rank Test Using Trace - A** | | | | |
|---|---|---|---|---|
| $H_0$: Rank $= r$ | $H_1$: Rank $> r$ | Eigenvalue | Trace | 5% Critical Value |
| 0 | 0 | 0.1183 | 29.8371 | 34.56 |
| 1 | 1 | 0.0487 | 8.9472 | 18.15 |
| 2 | 2 | 0.0040 | 0.6596 | 3.84 |
| **Cointegration Rank Test Using Trace Under Restriction - B** | | | | |

| $H_0$: Rank = r | $H_1$: Rank > $r$ | Eigenvalue | Trace | 5% Critical Value |
|---|---|---|---|---|
| 0 | 0 | 0.1191 | 33.1916 | 42.20 |
| 1 | 1 | 0.0489 | 12.1347 | 25.47 |
| 2 | 2 | 0.0227 | 3.8162 | 12.39 |
| **Cointegration Rank Test Using Maximum Eigenvalue - C** | | | | |
| $H_0$: Rank = r | $H_1$: Rank > $r$ | Eigenvalue | Trace | 5% Critical Value |
| 0 | 0 | 0.1183 | 20.8919 | 23.78 |
| 1 | 1 | 0.0487 | 8.2856 | 16.87 |
| 2 | 2 | 0.0040 | 0.6596 | 3.74 |
| **Cointegration Rank Test Using Maximum Eigenvalue Under Restriction** - D | | | | |
| $H_0$: Rank = r | $H_1$: Rank > $r$ | Eigenvalue | Trace | 5% Critical Value |
| 0 | 0 | 0.1191 | 21.0570 | 25.54 |
| 1 | 1 | 0.0489 | 8.3184 | 18.96 |
| 2 | 2 | 0.0227 | 3.8162 | 12.25 |

### 3.4 Parameter Estimation

Since there is no cointegration relation in the result of 3.3, it indicates that the parameter estimation using the VAR model is possible. As the result of parameter estimation using the VAR(1) model, the parameter $\phi_{12,3}$ of AR has p-value of 0.08198, which is not significant at the significance level of 0.05. Otherwise, parameters of constants and others are significant (Table 4).

**Table 4:**Parameter Estimation

| **Equation** | **Parameter** | **Estimate** | **Pr > \|t\|** | **Variable** |
|---|---|---|---|---|
| ∇CPI | CONST1 | 0.11144 | 0.0001 | 1 |
| | AR1_1_1 | 0.27926 | 0.00378 | CPI(t-1) |
| | AR1_1_2 | 0.00139 | 0.00177 | KOSDAQ (t-1) |
| | AR1_1_3 | 0.00073 | 0.00418 | ER(t-1) |
| ∇KOSDAQ | CONST2 | 0.92739 | 0.02904 | 1 |
| | AR1_2_1 | -11.08973 | 0.01427 | CPI(t-1) |
| | AR1_2_2 | 0.00369 | 0.00011 | KOSDAQ (t-1) |
| | AR1_2_3 | -0.09032 | 0.08198 | ER(t-1) |
| ∇ER | CONST3 | 0.71511 | 0.0032 | 1 |
| | AR1_3_1 | -4.60823 | 0.0391 | CPI(t-1) |
| | AR1_3_2 | -0.15249 | 0.0421 | KOSDAQ (t-1) |
| | AR1_3_3 | -0.16748 | 0.0001 | ER(t-1) |

Parameters in Table 4 were estimated again except for parameter $\phi_{12,3}$, but the values of SBC and HQC statistics, which are the minimum information criteria, did not decrease remarkably. Thus, in this study, all parameters were included.The estimating equation of the prediction model using Table 4 is shown in (Equation 12).

$$\hat{Z}_t = \hat{\delta} + \hat{\Phi}_1 + Z_{t-1} + \hat{\varepsilon}_t$$

$$\begin{bmatrix} \nabla CPI_{1t} \\ \nabla KOSDAQ_{2t} \\ \nabla ER_{3t} \end{bmatrix} = \begin{bmatrix} 0.11144 \\ 0.92739 \\ 0.71511 \end{bmatrix} + \begin{bmatrix} 0.27926 & 0.00139 & 0.00073 \\ -11.08973 & 0.00369 & -0.09032 \\ -4.60823 & -0.15249 & -0.16748 \end{bmatrix} \begin{bmatrix} \nabla CPI_{1,t-1} \\ \nabla KOSDAQ_{2,t-1} \\ \nabla ER_{3,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix} \quad (12)$$

### 3.5 Granger Causality Test

We performed a modified Wald test in which the Chi-square test was performed only for the first p coefficients that were optimal time lags. Then, after the first differencing with results, Granger causality test was performed for each time series variable. Since the p-values of the chi-square statistic for Test1, Test2, and Test3 are all less than the significance level of 0.05, each time series variable is identified as having a bidirectional linear dependency that is affected by the past values of itself and two other time series variables, respectively (Table 5) [14-16].

**Table 5:**Granger Causality Test

| Hypothesis | | Chi-Square | Pr > ChiSq |
|---|---|---|---|
| Test1 | $H_{10}: \nabla CPI_t \nleftarrow \nabla KOSDAQ_t, \nabla ER_t$ | 17.02 | 0.0011 |
| | $H_{11}: \nabla CPI_t \leftarrow \nabla KOSDAQ_t, \nabla ER_t$ | | |
| Test2 | $H_{20}: \nabla KOSDAQ_t \nleftarrow \nabla CPT_t, \nabla ER_t$ | 43.34 | <.0001 |
| | $H_{21}: \nabla KOSDAQ_t \leftarrow \nabla CPI_t, \nabla ER_t$ | | |
| Test3 | $H_{30}: \nabla ER_t \nleftarrow \nabla CPI_t, \nabla KOSDAQ_t$ | 10.43 | 0.0133 |
| | $H_{31}: \nabla ER_t \leftarrow \nabla CPI_t, \nabla KOSDAQ_t$ | | |

### 3.6 Impulse Response Function Analysis

The impulse response function was used to analyze the results of dynamic response of other variables over time when one variable in the model was impacted (Table 6). This shows how much other variables are affected when a variable is given an impact with the magnitude of the standard deviation of a unit. The graphs of this are shown in (Figure 2), (Figure 3), and (Figure 4).

**Table 6:**Impulse Response Function Analysis

| Variable Response/Impulse | Lag | CPI | KOSDAQ | ER |
|---|---|---|---|---|
| CPI | 1 | 0.27926 | 0.00139 | 0.00073 |
| | 2 | 0.05918 | 0.00028 | -0.00004 |
| | 3 | 0.01359 | 0.00009 | 0.00002 |
| | 4 | 0.00268 | 0.00002 | -0.00000 |
| | 5 | 0.00059 | 0.00000 | 0.00000 |
| | 6 | 0.00011 | 0.00000 | -0.00000 |
| KOSDAQ | 1 | -11.08973 | 0.00369 | -0.09032 |
| | 2 | -2.72160 | -0.00167 | 0.00674 |
| | 3 | -0.77254 | -0.00483 | -0.00295 |
| | 4 | -0.14858 | -0.00064 | 0.00037 |
| | 5 | -0.03605 | -0.00027 | -0.00011 |
| | 6 | 0.00660 | -0.00003 | 0.00002 |
| ER | 1 | -4.60823 | -0.15249 | -0.16748 |
| | 2 | 1.17594 | 0.01855 | 0.03848 |
| | 3 | -0.05465 | -0.00416 | -0.00727 |
| | 4 | 0.06435 | 0.00102 | 0.00155 |
| | 5 | -0.00046 | -0.00014 | -0.00031 |
| | 6 | 0.00287 | 0.00005 | 0.00006 |

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(Figure 2) shows the responses when the CPI impacts the CPI, the KOSDAQ, and the ER. It had a negative effect until time lag 4 and disappeared on the KOSDAQ index, and affected until time lag 2 and disappeared on the ER.

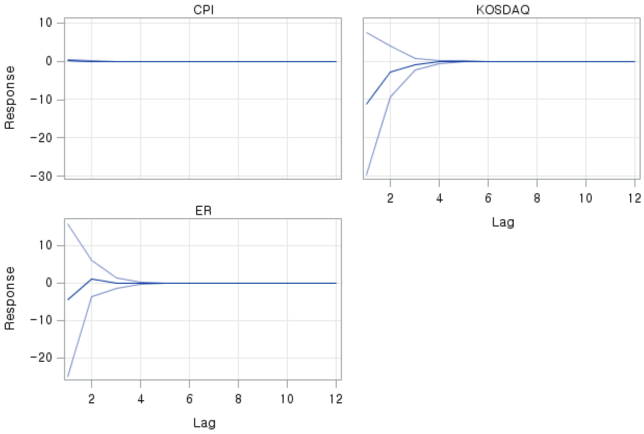


**Figure2:** Responses by CPI Impulse

(Figure 3) shows the responses when the KOSDAQ impacts the CPI, the KOSDAQ, and the ER. It did not affect the CPI, and negatively affected the ER until time lag 1 and disappeared.

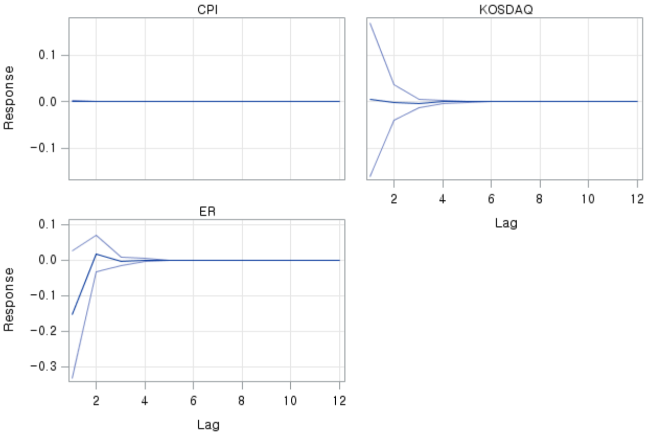


**Figure3:** Responses by KOSDAQ Impulse

(Figure 4) shows the responses when the ER impacts the CPI, the KOSDAQ, and the ER. It did not affect the CPI, and negatively affected the KOSDAQ and the ER until time lag 1 and disappeared.

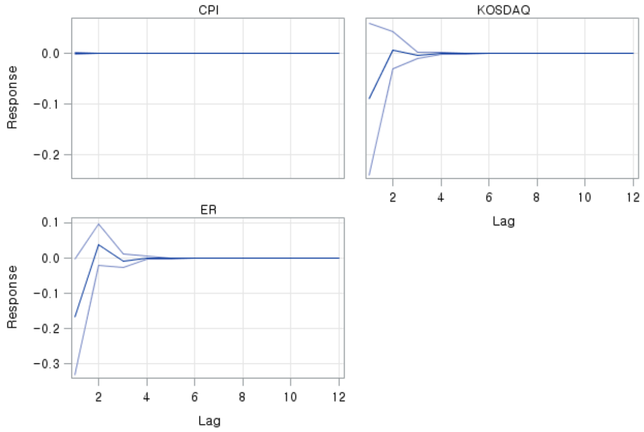


**Figure4:** Responses by ER Impulse

### 3.7 Variance Decomposition Analysis of Prediction Error

(Table 7) is the decomposition of the variance of the prediction error for the model into the ratio of the prediction error caused by the variation of each variable, which is the result of analyzing how much each variable included in the VAR model is explained by other variables. The result shows that, after the sixth lead, the CPI has an explanatory power of about 97% for itself, but other variables have no effect on the CPI. The KOSDAQ has an explanatory power of about 98% for itself, but other variables have no effect on the KOSDAQ. The ER does not affect the CPI, has an explanatory power of about 12% for the KOSDAQ, and about 87% for itself.

**Table 7:**The Ratio of Prediction Error Covariance by Variables

| Variable | Lead | CPI | KOSDAQ | ER |
|---|---|---|---|---|
| CPI | 1 | 1.00000 | 0.00000 | 0.00000 |
| | 2 | 0.97498 | 0.01732 | 0.00770 |
| | 3 | 0.97381 | 0.01849 | 0.00769 |
| | 4 | 0.97372 | 0.01858 | 0.00770 |
| | 5 | 0.97372 | 0.01858 | 0.00770 |
| | 6 | 0.97372 | 0.01858 | 0.00770 |
| KOSDAQ | 1 | 0.00502 | 0.99498 | 0.00000 |
| | 2 | 0.01203 | 0.97959 | 0.00838 |
| | 3 | 0.01251 | 0.97907 | 0.00842 |

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|---|---|---|---|---|
| | 4 | 0.01255 | 0.97902 | 0.00843 |
| | 5 | 0.01255 | 0.97902 | 0.00843 |
| | 6 | 0.01255 | 0.97902 | 0.00843 |
| ER | 1 | 0.00143 | 0.12248 | 0.87609 |
| | 2 | 0.00274 | 0.12493 | 0.87609 |
| | 3 | 0.00281 | 0.12477 | 0.87242 |
| | 4 | 0.00281 | 0.12477 | 0.87242 |
| | 5 | 0.00281 | 0.12477 | 0.87242 |
| | 6 | 0.00281 | 0.12477 | 0.87242 |

## 4. CONCLUSION

This study used a vector autoregressive model, which is one of the vector time series models, to analyze the relationship between variables using monthly data of CPI, KOSDAQ, and Won-Dollar ER. We performed Granger causality analysis, cointegration test, impulse response function analysis, and variance decomposition analysis of prediction error using the vector autoregressive model. The main results are as follows.

As the result of Granger causality analysis, since the p-values of the chi-square statistic are all less than the significance level of 0.05, each time series variable is identified as having a bidirectional linear dependency that is affected by the past values of itself and two other time series variables, respectively

The order of the vector autoregressive model was determined to the VAR(1) model by Schwarz Bayesian Criterion (SBC) statistic and Hannan-Quinn Criterion (HQC). The cointegration test using Trace and Maximum Eigenvalue statistics showed no cointegration relationship. The impulse response function analysis showed that the impulse of the CPI affected the KOSDAQ index and the ER, the impulse of the KOSDAQ affected the ER, and the impulse of the ER affected the KOSDAQ and the ER itself. As the result of the variance decomposition analysis of prediction error, the CPI had an explanatory power of about 97% for itself and the KOSDAQ index about 98% for itself. The ER had an explanatory power of about 12% for the KOSDAQ index and about 87% for the ER itself.

These results indicate that the CPI, the KOSDAQ index, and the ER are influencing each other. Therefore, the results of this study are expected to provide useful information for the monetary policy of government and the Bank of Korea, the portfolio policy of the Korea Exchange in charge of the securities market and domestic and foreign investors, and the government's price stability economic policy.

## ACKNOWLEDGEMENT

This Researchwas supported by Seokyeong University in 2019.

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