An Analysis of Co-Movements and Causality of International Interest Rates: The Case of Korea, Japan, and the U.S.

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Abstract In this study, co-movements and causality of international interest rates are analyzed. We use spectral analysis to find co-movements and lead and lag relationships and the transfer function model to examine causality. Using the Granger causality test, we identify unidirectional movements from the interest rates in Japan and the U.S. to those in Korea. The results show that there are dynamic relationships that as exogenous variables, the interest rates in Japan and the U.S. affected those in Korea.

Keywords: Spectral analysis, international interest rates, co-movement, and causality

JEL Classification: C32, E40, F31

Introduction

Forecasting long-term interest rates is very important to financial institutions, especially insurance companies, which hold mostly long-term assets. If the open market interest rate is higher than the assumed interest rate, the life insurance companies can face a reserve problem, and if the open market interest rate is lower than the assumed interest rate, they have difficulty honoring their contracts. Therefore, to reduce the difference between the open market interest rate and the assumed interest rate, an accurate forecast of the long-term interest rate is crucial. To lessen the burden caused by fluctuating interest rates, financial institutions, including insurance companies, have developed products such as variable life insurance and various hedging methods. However, the most significant way to cope with the problem of fluctuating interest rates is to forecast the long-term interest rate more accurately.

Life insurance companies in Korea that sell long-term life insurance with guaranteed interest rates face interest rate risk. The fact that the surrender and lapse ratio in Korea is relatively high would have a smaller impact on insurance companies. The pension that currently has defined benefit, on the other hand, is expected to show the lowest surrender and lapse ratio and will be very sensitive to interest rate changes.

With the liberalization of interest rates due to the open market policy and less regulation on the financial market, interest rates in Korea are expected to decline in the long run and have shown linkage to international interest rates. A great deal of research has been done on international co-movements of interest rates in those countries with the liberalization of interest rates and open financial markets, including Korea. Chinn and Frankel (1995) find that the
interest rate change in Korea has a close relationship with that in Japan. Jung (2000) shows that the interest rate in Japan is the most significant exogenous variable in affecting the interest rate in Korea and finds that there is a one-to-one corresponding relationship for the interest rates between Korea and Japan. Choi (1999) find that, on average, the interest rates of Japan have affected those of Korea more historically, but that after the opening of the Korean financial market, the interest rates of the U.S. have been becoming more influential on those of Korea. Lee (2001) analyzes the dynamic relationship between Korean interest rates and those of the U.S., Japan, and Europe, and finds that before the opening of the Korean financial market, Japanese interest rates were the most highly influential on those of Korea, but that after the opening of the Korean financial market, U.S. interest rates affected Korea’s rates the most. In addition, Lee (2001) finds that after the economic crisis, British interest rates had the largest effect.

Swanson (1987) finds that since 1981, the capital markets in the U.S. and Europe have been integrating more closely. Karfakis and Moschos (1990) show that there is no systematic relationship between the currency systems of Germany and the European Monetary System using a two-variable cointegration test but find that German interest rates have a unidirectional relationship with those of the European Monetary System using a two-variable VAR model. Katsimbris and Miller (1993) show that not only German interest rates but also those of the United States have effects on the European Monetary System’s interest rates. Fung and Isberg (1992) analyze the relationship between the interest rates of U.S. dollar and European dollar using the ESM Model and find that, around 1983, with the expansion of the European dollar market and the increase of swaps and futures contracts, the unidirectional direction from the U.S. to Europe, changed. Lin and Swanson (1993) analyzed the causal relationship between financial markets of Asia and those of Europe and find that there is a strong causality between Singaporean and European interest rates and that there is causality between Singapore’s and Hong Kong’s interest rates in Asia. Bremnes, Gjerde, and Saettem (1997) show in their research of international interest rate co-movements that the more recent data in the sample, the more cointegration vectors are found. The results of their research indicate that international linkages of interest rates are strengthened over time and that it is getting harder for an individual country to adopt and carry out its own policy.

Considering the fact that the international linkage of interest rates is apparent, we should consider other countries’ interest rates as exogenous variables in forecasting future interest rates. Researchers use time domain methods in analyzing the international relationships between economic variables. In analyzing the long-term relationships between macroeconomic variables, cointegration and VECM are used because most of them including interest rates are unstable variables and become stable with first difference. Showing the long-term equilibrium relationship between these time series by the cointegration test is not a sufficient condition to suggest the future movements of these variables.

As a way to make up for the current time-domain analysis method, the spectral analysis method should be considered. The spectral analysis method is very effective in finding the long-term relationship between variables. One of the biggest benefits of spectral analysis is that it can visually show the phenomenon of co-movements of international interest rates.

In this article, by showing such co-movements and the lead and lag relationships among the interest rates of Korea, the United States and Japan using spectral analysis and then inferring the causality between them using a transfer function model, we intend to analyze the causality structure in the interest rates of the three countries. Understanding the exogenous variables affecting domestic interest rates and modeling the causal structure of the interest rates using a
transfer function model are necessary in forecasting future interest rate changes and alleviating the interest rate risk that financial institutions face.

**Data and Methods of Analysis**

**Data**

The data came from the DATABASE of the Bank of Korea. For Korea, the rate of return of a three-year bond is used. For the U.S. and Japan, the rate of return of a ten-year Treasury bond is used. The variables are defined as follows.

- CB3 : the rate of return of a three-year bond (at maturity) in Korea,
- JGB : the rate of return of a ten-year bond (at maturity) in Japan, and
- USGB: the rate of return of a ten-year bond (at maturity) in the United States.

The time series of each variable is shown in Diagram 1.

**Methods of Analysis**

The main purposes of this research are to use spectral analysis to examine the linkage of the Korean, the U.S., and the Japanese interest rates in the frequency domain, apply cross-spectral analysis to grasp the lead and lag relationships of these countries’ interest rates, and to employ the transfer function model to investigate the causality. Before trying to obtain the cyclical periods of the time series, we remove trends in the original time series using the Hodrick-Prescott (1997) Filter (HP Filter). We then conduct harmonic analysis, periodogram analysis, and cross-spectral analysis on the trend-removed time series.

**Spectral Analysis**

**Harmonic Analysis**

If the period of cycle of a time series is known, we can use harmonic analysis to model the cyclical component of the time series. The general equation for harmonic analysis can be expressed as:

\[ x_t = \mu + R \cos(wt + \phi) + \epsilon_t \]  

where
- \( x_t \) : observed value of \( x \) at time \( t \),
- \( \mu \) : the mean value of the time series,
- \( R \) : the amplitude,
- \( w : 2\pi/\tau \) : angular frequency where \( \tau \) is period or cycle length,
- \( \phi \) : phase (the distance from time \( t=0 \) to the first peak), and
- \( \epsilon_t \) : white noise (mean 0, variance \( \sigma^2 \)).
Equation (1) can be written differently to include both a sine and a cosine term as:

\[ x_t = \mu + A \cos(wt) + B \sin(wt) + \varepsilon_t \]  \hspace{1cm} (2)

where \( \cos(wt) \): cosine equation of \( w \) calculated at different times \( t = 0, 1, 2, \ldots \),
\( N \): number of observations \( (N \) is the even number), and
\( \sin(wt) \): sine equation of \( w \) calculated at different times.

Equation (2) is more convenient for the computation of parameters.

**Spectral Analysis**

When the pattern of a time series on a graph does not show the regularity of a cycle length (that is, the period of a time series cycle is not known a priori), we can not use harmonic analysis. Periodogram analysis consists of a composite of harmonic analyses, and spectral analysis is a method of modifying periodogram analysis by utilizing a smoothing technique. Using both periodogram analysis and spectral analysis, we can identify cyclical periods that can be explained by comparatively big variances in a time series. Once such a cyclical period is identified, we can conduct harmonic analysis again using the identified cyclical period to model the cyclical components of the time series. The periodogram model is expressed as the sum of \( N/2 \) \( (i = 1,2,3, \ldots, N/2) \) of periodic components.

\[ x_t = \mu + \sum_i (A_i \cos(w_it) + B_i \sin(w_it)) + \varepsilon_t \]  \hspace{1cm} (3)

Periodogram analysis has sampling error problems. To reduce sampling errors, spectral analysis adopts the smoothing method. Cross-spectral analysis can be used to get information on the relationship between two time series. We can identify the relationship between the two time series visually once the fitted cycle that results from the harmonic analysis on the common cycle of both time series is obtained through spectral analysis.

**Cross-spectral Analysis**

We can get information on the relationship between the time series in each of \( N/2 \) frequency bands using cross-spectral analysis. In certain frequency band, the rate of relationship between the time series can be identified by statistics of the squared coherence, \( S_{x,y}^2(w) \), and the phase relationship or time lag can be identified by statistics of phase, \( \phi_{x,y}(w) \).

Coherency, like \( R^2 \), indicates the percentage of shared variance between the two time series at a particular frequency. Phase, like a time lag, indicates the timing of peaks in the \( y \) series relative to peaks in the \( x \) time series at a given frequency.

Cross-spectral analysis can be used to get information on relationships between two time series. We can identify the relationship between two time series visually, once the fitted cycle that results from harmonic analysis on the common cycle of both time series is found using spectral analysis.

At time lag \( r \), cross-covariance, \( c_{x,y,r} \), can be expressed as:
\[
c_{x,y,r} = \frac{1}{n} \sum_{t=1}^{n} x_t y_{t-r}, \quad r \leq n 
\]

(4)

Then we can find cross-periodogram, \( I_{x,y}(w) \), by the Fourier transformation of cross-covariance as:

\[
I_{x,y}(w) = \frac{1}{2\pi} \sum_{r=0}^{\infty} c_{x,y,r} e^{-i rw}
\]

(5)

By smoothing cross-periodogram, we can get smoothed cross-spectrum. Complex numbers consisting of cross-periodogram and cross-spectrum can be used to calculate coherence and phase of both time series at each frequency. Using each smooth spectrum of time series \( x \) and \( y \) and smoothed cross-spectrum of both time series, we can estimate squared coherence, \( s_{x,y}(w)^2 \), of time series at frequency \( w \):

\[
s_{x,y}(w)^2 = \frac{g_{x,y}(w)^2}{g_{x,x}(w)g_{y,y}(w)}
\]

(6)

where \( g_{x,y}(w) \): smoothed cross-spectrum,
\( g_{x,x}(w) \): smoothed spectrum of time series \( x \), and
\( g_{y,y}(w) \): smoothed spectrum of time series \( y \).

Phase, \( \phi_{x,y}(w) \), of cross-spectrum can be calculated by imaginary (Im) and real (Re) parts of cross-spectrum as follows:

\[
\phi_{x,y}(w) = \arctan \frac{\text{Im} g_{x,y}(w)}{\text{Re} g_{x,y}(w)}
\]

(7)

In equation (7), the imaginary and real parts of the cross spectrum are called the quadrature spectrum and the cospectrum, respectively.

**The Transfer Function Model**

To see whether there is causality between the long-term movements of both identified time series using cross-spectral analysis, we test the causal relationship contained in the variables using the transfer function model, but only after finding the direction of movements using the Granger Causality Test.\(^1\) The transfer function model analyzes the dynamic relationship between the input time series, which can be called the leading indicator, and the output time series.\(^2\) The general transfer function model, with a single input and single output, can be expressed as:

\[
y_t = v(B)x_t + n_t
\]

(8)

where \( v(z) = \sum_{j=0}^{\infty} v_j z^j \),
\( y_t \): output time series,
\( x_t \): input time series,
B: back shift operator,
\( v(z) \): transfer function (the coefficient of the transfer function, \( v_j \), is called impulse
response weight at time lag $j$, and $n_t$: noise satisfying the ARMA model.

A transfer function model that satisfies both stability and causality is given by:

$$y_t = v_0 x_t + v_1 x_{t-1} + v_2 x_{t-2} + \cdots + n_t$$

$$= v(B) x_t + n_t \quad \quad \quad (9)$$

where, $v(z) = \sum_{j=-\infty}^{\infty} v_j z^j$, $\sum_{j=0}^{\infty} |v_j| < \infty$.

In the transfer function model, the input time series data and the noise term data are assumed to be independent of each other. Also, because the transfer function has numerous impulse response weights, a rational function with limited parameters is used. Such a function can be written as:

$$y_t = v(B) x_t + n_t \quad \quad \quad (10)$$

$$v(z) = \frac{\phi_z(z)}{\delta_z(z)} z^b$$

where $\phi_z(z) = \phi_0 - \phi_1 z - \cdots - \phi_r z^r$, $\delta_z(z) = 1 - \delta_1 z - \cdots - \delta_r z^r$, and $b$: delay parameter.

In equation (10), $v(z)$ is called a transfer function with order $(b, r, s)$. While identifying the process of $v(z)$, if the input time series $\{x_t\}$ has no white noise, prewhitening should be done on the series. The prewhitening model is then used to filter the output time series, $\{y_t\}$. We can identify the order of the transfer function model $(b, r, s)$ by using the Box and Jenkins method, after finding the sample-weighted impulse response function using the prewhitening model.

The ARMA model for white noise time series data can be expressed as:

$$\phi(B)n_t = \theta(B)v_t \quad \quad \quad (11)$$

where $\{v_t\}$: white noise process.

Now we can express the rational transfer function model identified through our analyses as follows:

$$y_t = \frac{\phi_z(B)}{\delta_z(B)} x_{t-b} + \frac{\theta(B)}{\phi(B)} v_t \quad \quad \quad (12)$$

In identifying the rational transfer function, one should be very careful about assuming the point at which the output time series $\{y_t\}$, the input time series $\{x_t\}$, and the noise term time series $\{n_t\}$ are stationary. If these time series are not stationary, they should be made stationary.
Empirical Results

Removing Trends

In this article, to find the cyclical period contained in each country’s interest rate time series, spectral analysis is conducted. Trends in time series are removed in advance. To remove trends, the Hodrick-Prescott Filter (HP Filter) is used. The original time series and the HP Filter trend are shown in Diagram 2.

The time series in which trends are removed using the HP Filter are defined as follows:

- DEVCB3 : trend removed three-year bond rate of return for Korea,
- DEVJGB : trend removed ten-year treasury bond rate of return for Japan, and
- DEVUSGB: trend removed ten-year Treasury bond rate of return for the U.S.

The trend removed time series are shown in Diagram 3. In the diagram, it seems that each country’s interest rate time series has a common cyclical period. It is especially apparent that after the movements of the Japanese and U.S. interest rates, the Korean interest rates moved as well.

Analysis of the Cyclical Period and Relationships

The results of the periodogram analysis on the trend-removed time series for each country for the period 1984.01 to 2001.12 (18 years) are shown in Diagram 4. The results of the periodogram analysis show that for Korea and the U.S., the biggest peak is at 36 months (3 years). Therefore, we can say that the cyclical period of interest rates for Korea and the U.S. is 36 months (3 years). For Japan, though, the biggest peak is not at 36 months (3 years), but the second biggest peak appears at this period. Thus, we can argue that, in the long term, there is a 36-month cyclical period and that there is 36-month (3 year) common cyclical period for the interest rates of the three countries.

To find the relationship among the time series with the identified common cyclical period of 36 months, a two-variable cross-spectral analysis, such as coherence analysis or phase analysis, is conducted. The results are shown in Diagrams 5, 6, and 7.

Statistics for the cross-spectral analysis are summarized in Table 1. From the statistics of phase analysis, we find that the interest rates of Japan and the U.S. led those of Korea under the common cyclical period of three years. Also the coherency test results show that there is a closer relationship between the interest rates of Korea and Japan than those of Korea and the U.S.

The results so far show that the relationships of interest rates between countries have changed since 1990, when the capital market was first opened up to other countries. A two-variable cross-spectral analysis on the sub-period of 1990.01 to 2001.12 (12 years) is conducted separately, and the results are shown in Table 2.

The results of the coherency test show that the U.S. interest rates have a closer relationship with those of Korea than those of Japan. These results, which are contrary to the results of the test done on the data for the period 1984.01 to 2001.12 (18 years), indicate that as the capital market is opened up to other countries, U.S. interest rates became more influential to those of Korea than those of Japan.

The phase statistics show smaller numbers than the statistics of the test results on data
from 1984.01 to 2001.12. The sequence of movements among the interest rates does not change. There is still a common cyclical period of three years. The Japanese interest rates led those of Korea by nine months ($=1.10/\pi \times 18$ months) and the U.S. interest rates led those of Korea by six months ($= 1.60/\pi \times 18$ months).

**Results of the Causality Test**

So far, we have found that there is a close long-term relationship between the interest rate time series of the three countries. From the two-variable cross-spectral analysis, we can detect the lead or lag of the interest rate time series under a common cyclical period, but the results do not confirm the sequence of movements from the Japanese interest rates to those of Korea or from the U.S. interest rates to those of Korea.

To identify the existence of causality among these variables, a transfer function model is employed. First, to test the feedback and direction of the time series, a direction test on a first differenced time series is performed using Granger’s causality test. Differenced time series are defined as follows:

- **DCB3**: first differenced three-year bond rate of return for Korea,
- **DJGB**: first differenced ten-year treasury bond rate of return for Japan, and
- **DUSGB**: first differenced ten-year Treasury bond rate of return for the U.S.

To test the stationary feature of the original and differenced time series, the ADF and PP tests are performed. The results are presented in Table 3. The unit root test results show that the original time series of each country’s interest rates are nonstationary and that the differenced series are stationary. Therefore, for the transfer function model, the differenced series are used. Each country’s differenced interest rate time series is shown in Diagram 8.

The results of the Granger causality test on differenced time series are summarized in Tables 4 and 5. Although the Granger test results are known to respond to a lag applied to the model (Gujarati, 1995), test results in this research show that they do not respond to a time lag or coincide with the uni-direction. According to the results of the Granger test, both the results of analysis on the data from January 1984 to December 2001 (18 years) and those on the data from January 1990 to December 2001 (12 years) show that both the interest rates of Japan and the U.S. Granger cause the Korean interest rates and have a uni-directional relationship.

We use the transfer function model to identify the dynamic relationship between two time series. Identifying the rational transfer function model, the output time series $\{y_t\}$, the input time series $\{x_t\}$, and the white noise time series $\{n_t\}$ are assumed to be stationary. Therefore, in this study, we identify the transfer function model using the differenced time series from the original nonstationary time series data.

In identifying the transfer function model, we use the input time series data from 1990.01 to 2001.12 (12 years) for DJGB and DUSGB. Identifying the transfer function, $\nu(z)$, to filter the output time series, prewhitening should be done on the input time series. In this study, the input time series DJGB and DUSGB are prewhitened, and the results are shown in Table 6.

In Table 6, factors in each autocorrelation are prewhitened and are applied to the output time series DCB3 to produce the filtered output time series data $\{\sigma^*_t\}$ and $\{\hat{\sigma}^*_t\}$.

After the time series $\{z_t\}$, $\{\sigma^*_t\}$, $\{z^*_t\}$, $\{\hat{\sigma}^*_t\}$ are produced, we calculate the sample cross-correlation function $\{\rho_{zw}(k)\}$, $\{\rho_{z^*_w}(k)\}$ and estimate the impulse-response weight
function \( v_k \) and \( v_k^* \). Once the impulse-response weight function is estimated, we identify the order of the transfer function model \((b, r, s)\) using the Box and Jenkins (1976) method.

Sample cross-correlation functions with impulse response weight functions \( v_k \) and \( v_k^* \) are shown in Diagrams 9. For the impulse-response weight function and cross-correlation function, when the input variable is DJGB, there is a big spike at lags 0 and 3. At lag 7, the biggest spike appears and gets smaller afterwards. For the input variable of DUSGB, a significantly big spike appears at lags 0 and 3 and gets smaller afterwards.

Based on the Box-Jenkins method that selects the order of the transfer function based on the shape of the sample cross-correlation function, the order \((3, 1, 4)\) for the input variable of DJGB and the order \((3, 0, 0)\) for the input variable of DUSGB are determined. The estimated model fits the time series data. The estimated transfer function is shown in Table 7.

The Portmanteau statistics of the residuals \( v_j \) of the noise time series model of the estimated transfer function model are reported in Table 8. From the above Portmanteau statistics of the residual \( v_j \), we can see that the estimated transfer function fits the given time series well. To find whether the residual of noise time series model \( v_j \) and the prewhitened input time series \( z_t \), \( z_t^* \) are independent of each other, we analyze the cross relationship of the time series. Portmanteau statistics from the cross-correlation function are shown in Tables 9 and 10, which show that the residual of the noise time series model \( v_j \) and the prewhitened input time series \( z_t \), \( z_t^* \) are independent of each other.

**Conclusions**

In this article, we have analyzed co-movements of the interest rates of Korea, Japan, and the U.S. using spectral analysis in frequency domain in order to identify their long-term relationships. We have found that the interest rates of Korea, Japan, and the U.S. have a common cyclical period of three years and that the interest rates of Japan and the U.S. lead that of Korea. The results coincide with previous research results.

Finding co-movements and lead and lag relationships using spectral analysis, we examine causality using a transfer function model. After identifying unidirectional movements from the interest rates of Japan to those of Korea and from the interest rates of the U.S. to those of Korea using the Granger causality test, we estimate their causal structures using the transfer function model. The results with the data from January 1990 to December 2001 (12 years) show that there is a dynamic relationship that as exogenous variables, the interest rates of Japan and the U.S. affected those in Korea.

Finding that foreign interest rates affect domestic interest rates and modeling the causal structure using the transfer function model will help improve the accuracy of forecasting interest rates.

**Footnotes**

1. When modeling non-causal structure that there exists feedback between input time series and output time series, the transfer function model is not appropriate. Therefore, before estimating the transfer function model, Granger Causality Test should be done to test unidirectional movement between two time series.
2. Refer to Yaffee and McGee (2000).

References


Data, the Bank of Korea.


Diagram 1. Interest Rate Trends for Korea, Japan, and the US (1984.01-2001.12)

Diagram 2. Original Time Series and HP Filter Trend

Diagram 3. Trend-Removed Time Series for Each Country’s Interest Rates

Diagram 4. Periodogram Analysis for Common Cyclical Periods
Diagram 5. Results of Coherency and Phase Analysis on Korean and Japanese Interest Rates

Diagram 6. Results of Coherency and Phase Analysis on Korean and American Interest Rates

Diagram 7. Results of Coherency and Phase Analysis on Japanese and American Interest Rates
Diagram 8. First Differenced Time Series Trends

Diagram 9. Sample Cross-Correlation Function with Impulse-Response Weight Function with Input Variables of DJGB, DUSGB
Table 1. Summary of Cross-Spectral Analysis Statistics (1984.01 to 2001.12)

<table>
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<tr>
<th></th>
<th>Coherency</th>
<th>Phase</th>
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<tr>
<td>Korean and Japanese Interest rates</td>
<td>0.65</td>
<td>-1.30</td>
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<tr>
<td>Korean and American Interest rates</td>
<td>0.45</td>
<td>-0.90</td>
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<tr>
<td>Japanese and American Interest rates</td>
<td>0.53</td>
<td>-0.40</td>
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Table 2. Summary of Cross-spectral Analysis Statistics (1990.01 to 2001.12)

<table>
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<th>Coherency</th>
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<tr>
<td>Korean and Japanese Interest rates</td>
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<td>-1.60</td>
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<tr>
<td>Korean and American Interest rates</td>
<td>0.57</td>
<td>-1.10</td>
<td>6 month</td>
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<td>Japanese and American Interest rates</td>
<td>0.66</td>
<td>-0.50</td>
<td>3 month</td>
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Table 3. Results of the Unit Root Test (1984.01 to 2001.12)

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<thead>
<tr>
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<th>PP Test</th>
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<td>CB3</td>
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<td>JGB</td>
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<td>USGB</td>
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<td>-5.8588</td>
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<tr>
<td>DCB3(mod)</td>
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<td>-10.7201</td>
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<td>DJGB</td>
<td>-7.2949</td>
<td>-12.4790</td>
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<tr>
<td>DUSGB</td>
<td>-6.1188</td>
<td>-11.9965</td>
</tr>
</tbody>
</table>

Critical Values 1% : -3.4620; 5%: -2.8750; 10% : -2.5739

Notes 1. Results from estimating model with the intercept.
2. DCB3 (mod) is time series that 4 outliers (1997.12, 1998.02, 1998.07, 1998.10) developed by foreign currency crisis in Korea are removed and is used in this research. The removed parts are substituted by averaged values of observed before and after them.
Table 4. Results of the Granger Causality Tests (1984.01 to 2001.12)

<table>
<thead>
<tr>
<th>Null Hypothesis \ To Lag</th>
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<th>2</th>
<th>3</th>
<th>4</th>
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<td>DJGB does not Granger-cause DCB3</td>
<td>0.04</td>
<td>0.09</td>
<td>0.04</td>
<td>0.08</td>
<td>0.12</td>
<td>0.18</td>
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<td>DCB3 does not Granger-cause DJGB</td>
<td>0.53</td>
<td>0.10</td>
<td>0.27</td>
<td>0.40</td>
<td>0.52</td>
<td>0.60</td>
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<table>
<thead>
<tr>
<th>Null Hypothesis \ To Lag</th>
<th>1</th>
<th>2</th>
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<tbody>
<tr>
<td>DUSGB does not Granger-cause DCB3</td>
<td>0.78</td>
<td>0.05</td>
<td>0.03</td>
<td>0.05</td>
<td>0.11</td>
<td>0.16</td>
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<tr>
<td>DCB3 does not Granger-cause DUSGB</td>
<td>0.99</td>
<td>0.87</td>
<td>0.94</td>
<td>0.99</td>
<td>0.94</td>
<td>0.97</td>
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Table 5. Results of the Granger Causality Tests (1999.01 to 2001.12)

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<thead>
<tr>
<th>Null Hypothesis \ To Lag</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>DJGB does not Granger-cause DCB3</td>
<td>0.05</td>
<td>0.15</td>
<td>0.02</td>
<td>0.04</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>DCB3 does not Granger-cause DJGB</td>
<td>0.66</td>
<td>0.14</td>
<td>0.39</td>
<td>0.39</td>
<td>0.25</td>
<td>0.31</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Null Hypothesis \ To Lag</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>DUSGB does not Granger-cause DCB3</td>
<td>0.66</td>
<td>0.16</td>
<td>0.02</td>
<td>0.03</td>
<td>0.07</td>
<td>0.02</td>
</tr>
<tr>
<td>DCB3 does not Granger-cause DUSGB</td>
<td>0.75</td>
<td>0.94</td>
<td>0.99</td>
<td>0.93</td>
<td>0.80</td>
<td>0.82</td>
</tr>
</tbody>
</table>

Table 6. Results of the ARMA Model

1) DJGB time series: \( (1 - 0.20628 B + 0.22004 B^3)(DJGB_t + 0.03216) = z_t \)

where \( \{ z_t \} \) is the white noise time series with an average of zero and variance \( \sigma^2_z \).

2) DUSGB time series: \( (1 - 0.24284B)(DUSGB_t + 0.01694) = z_t^* \)

where \( \{ z_t^* \} \) is mean zero, variance, \( \sigma^2_z \).
Table 7. Estimated Results of the Transfer Function Model

\[ DCB_3 = -0.0147 + \frac{0.4024 + 0.4867B^4}{1 - 0.4382B} DJGB_{t-3} + 0.47967DUSGB_{t-3} + \]
\[ 1 - 0.2382B - 0.1949B^6 + 0.2090B^7 V_t \]

(AIC = 210.88, SIC = 234.24)

Table 8. Portmanteau Statistics of the Residuals

<table>
<thead>
<tr>
<th>To Lag</th>
<th>Statistics</th>
<th>DF</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>4.36</td>
<td>3</td>
<td>0.225</td>
</tr>
<tr>
<td>12</td>
<td>6.68</td>
<td>9</td>
<td>0.671</td>
</tr>
<tr>
<td>18</td>
<td>21.06</td>
<td>15</td>
<td>0.135</td>
</tr>
<tr>
<td>24</td>
<td>25.37</td>
<td>21</td>
<td>0.232</td>
</tr>
</tbody>
</table>

Table 9. Portmanteau Statistics by Sample Cross-Correlation Function with Input Variable DJGB

<table>
<thead>
<tr>
<th>To lag</th>
<th>( \chi^2 ) statistic</th>
<th>DF</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>0.57</td>
<td>4</td>
<td>0.966</td>
</tr>
<tr>
<td>11</td>
<td>3.34</td>
<td>10</td>
<td>0.972</td>
</tr>
<tr>
<td>17</td>
<td>4.20</td>
<td>16</td>
<td>0.999</td>
</tr>
<tr>
<td>23</td>
<td>7.40</td>
<td>22</td>
<td>0.998</td>
</tr>
</tbody>
</table>

Table 10. Portmanteau Statistics by Sample Cross-Correlation Function with Input Variable DUSGB

<table>
<thead>
<tr>
<th>To lag</th>
<th>( \chi^2 ) statistic</th>
<th>DF</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>3.19</td>
<td>6</td>
<td>0.785</td>
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<tr>
<td>11</td>
<td>11.73</td>
<td>12</td>
<td>0.467</td>
</tr>
<tr>
<td>17</td>
<td>17.07</td>
<td>18</td>
<td>0.519</td>
</tr>
<tr>
<td>23</td>
<td>22.30</td>
<td>24</td>
<td>0.561</td>
</tr>
</tbody>
</table>