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China Effect in the Dry Bulk Shipping Market[1]

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ABSTRACT

The rapid growth of China's economy has not only dramatically changed the international logistics environments but has also greatly influenced the world shipping market. The so-called China effect made the ocean freight soar to an unprecedented level despite the terror of September 11, the resulting war in Afghanistan and Iraq and worldwide recession. The main purpose of this paper is to analyse the characteristics of the China effect in dry bulk market and show how long the effect lasts. This paper employs GPH co-integration test since the structural model must be stationary to get the accurate predicted values. The empirical results show that the model is mean-reverting. This paper also applies variance decompositions and impulse-response functions to the structural model, indicating that freights are endogenous to the trade variable. The rolling regression coefficients and impulse-response functions suggest that the China effect decays very slowly and lasts long.

Key Words：China effect, dry bulk shipping market, rolling regression, GPH

[1] The Korean version of this paper was published in *the Journal of Shipping and Logistics*, Vol. 49, June, 2006, issued by the Korean Association of Shipping and Logistics.

Ⅰ. Introduction

There is no doubt that the rapid growth of China's economy will greatly determine the future direction of the shipping market. The so-called China effect, which is caused by the rapid increase of exports to and imports from China, has worked as an important factor in the shipping market since late 2003.[2]

After the MRI general freight index reached a peak of 325 in May 1995, it underwent a long-term depression until late 2002, but it began to rise from 232 in October 2002 and reached 464 in April 2005. In particular, due to the shock of the terror of September 11, 2001 in which the world trade center was destroyed by airplane, the shipping business suffered from depression. However, it lasted for only 4 months. The indexes representing shipping business such as the MRI general freight index and the BDI(Baltic Dry Index) began to show a sharp rise from January 2002, reaching 469 in December 2004. It is known that the China effect contributed to such a rise.

The BDI also began to rise from 882 on January 2, 2002 and soared to 6,208 on December 6, 2004 showing an increase rate of 604% for 35 months. The BDI increased from 1,006 on August 14, 2002 to 2,011 on April 7, 2003-meaning that the BDI increased by 1,000 in eight months. It again increased to 3,138 on October 1, 2003, taking only six months to reach 3000. Furthermore, it reached 4,049 in September 9, 2003, taking only one week to go beyond 4,000 and it took no more than three months to pass 5,000 as it was 5,046 on January 9, 2004.

However, prime minister Wen Jiabao, who has been worried about the overheated growth of Chinese economy, declared new restrictive investment policies on steel, automobiles, cements, real estate and aluminium on April 28, 2004. It caused the BDI to fall sharply from 4,229 to 2,622 in two months, April to June.[3]

We can also find the China effect in the ocean freights such as the BCI(Baltic

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[2] KMI World Shipping Outlook(2006).

[3] KMI Maritime Review(2004)

Capesize Index) and the BPI(Baltic Panamax Index).[4] Specifically, the BCI rose from 6,347 in April 2005 to 5,066 in May but fell to 3,078 in 2,943 in July. The BDI fell by 54% in four months from April to July. Such a phenomenon was also detected in the BPI which decreased by the same magnitude as the BCI during the same period. These phenomena showed the China effect in the world shipping market. Hence, the purpose of this study is to identify the China Effect and show its characteristics using the econometric procedures.

II. Introduction and estimation of model

It is very difficult to detect the China effect using econometric techniques because there is no other study except for Ha and Chung(2005). This paper, hence, models the ocean freight as a function of trading volume as in equation (1) in log-linear form.

$$frt_t = a_0 + a_1 china_t + a_2 seasons_t \qquad (1)$$

where frt refers to the natural logarithm of ocean freight such as MRI, BDI, BCI, and BPI. The variable china represents the trading volume of Korea, Japan and U.S. with China. All series are extracted from the websites of the Korea Maritime Institute[5], the Korea International Trade Association[6], and the Bank of Korea. They span the period January 2000 to October 2005.

This study first examines the univariate time-series properties of the series by testing whether the series are stationary or not. This is because all data series considered must be of the same order of integration to avoid problems of spurious relationships, and incorrect inferences (Phillips, 1986; Ohanion, 1988). Without verifying the order of integration of the variables, evidence of simultaneous correlations rather than long-run relationships may be found. To infer causal long-run relationships between nanstationary data requires the application of cointegration analysis. As a preliminary

4 KMI Maritime Review(2005)

5 http://www.kmi.re.kr

6 http://stat.kita.net

step to this analysis it is, therefore, necessary to test the stationarity of the variables.

Existence of unit root means that a series is not stationary. The augmented Dickey-Fuller (ADF) test for unit roots (Dickey and Fuller, 1979, 1981) indicates whether an indicates whether an individual series, X, is stationary by estimating the following regression using ordinary least squares:

$$\Delta X_t = c_0(Time) + b_1 X_{t-1} + \sum_{i=1}^{p} c_i \Delta X_{t-i} + \varepsilon_t \qquad (2)$$

where X_t is the individual time series, Δ is the first difference operator, ε_t is a serially uncorrelated random term, and p is the number of lags. A series is stationary if the coefficient of the lagged variable (b_1 in Equation 2) is negative and significantly different from zero. We test the null hypothesis of a unit root with a constant and a time trend in the regression by $t\tilde{\alpha}$ statistic.

Table 1. Tests for unit root

Level				First Difference			
MRI	BDI	BCI	BPI	MRI	BDI	BCI	BPI
-1.594(1)	-2.234(1)	-2.418	-3.513(1)	-4.260*	-4.790*	-4.4358*(1)	-4.591*
[0.5008]	[0.5687]	[0.7802]	[0.8994]	[0.4912]	[0.4256]	[0.6987]	[0.8813]

Notes: Numbers in parentheses after these statistics indicate the lag length used in the autoregression to ensure residual whiteness. The null hypothesis is that the series in question is *I*(1). The critical value for ADF is approximately -3.43 at the 5 percent level (See Fuller, 1976). An asterisk denotes significance at the 5 percent level.

Table 1 outlines the unit root test results. The number of lags entering the estimated equation is determined on the performance of the Lagrange multiplier test for serial correlation. It is clear that we cannot reject the null hypothesis of a unit root in each of the level variables at the 5 percent significance level. All of the statistics indicate that the first differences of the variables are stationary. Therefore, it is concluded that the variables are nonstationary in levels and stationary in differences. Based on this result, we test whether variables are cointegrated or whether there is an equilibrium relationship between them.

The next step in the test for cointegration is to estimate the cointegrating regressions. Tests for cointegration often draw on unit root tests that presume the order of integration of the equilibrium error to be an integer. A system of economic variables, however, can be fractionally cointegrated such that its equilibrium errors follow a fractionally integrated process (Granger, 1986).

The Geweke-Porter-Hudak (GPH) fractional differencing test is also performed on freight. The ADF tests often draw on unit root tests that presume the order of integration of the equilibrium error to be an integer. In general, the GPH test appears to have better statistical power against autoregressive alternatives than the ADF test. When testing against fractional alternatives, the GPH test performs even better relative to the ADF test. This is particularly the case when the fractional integration parameter lies between .35 and .65(Cheung and Lai, 1993).

Fractionally differenced processes explored by, e.g., Granger and Joyeux (1980) and Hosking (1981) can be used to model parametrically long-memory dynamics. Under this approach, whether a series displays long memory depends on a fractional differencing parameter, which is amenable to estimation and hypothesis testing. A general class of long-memory process is described by

$$B(L)(1-L)^d x_t = C(L)u_t \qquad (3)$$

where $B(L)=1-b_1L-\cdots-b_pL^p$ and $C(L)=1-c_1L-\cdots-c_qL^q$ are polynomials in the lag operator L, all roots of $B(L)$ and $C(L)$ are stable, and u_t is a white-noise disturbance term. The fractional parameter, given by d, assumes any real values. This fractional model includes the usual autoregressive moving-average (ARMA) model as a special case in which $d=0$. The extension to have non-integer values of d raises the flexibility in modeling long-term dynamics by allowing for a rich class of spectral behavior at low frequencies. Granger and Joyeux (1980) and Hosking (1981) show that the spectral density function of x_t, denoted by $f_x(w)$, is proportional to w^{-2d} as w becomes small. The fractional parameter thus crucially determines the low-frequency dynamics of the process.

A spectral method suggested by Geweke and Porter-Hudak (1983) can be used to estimate the fractional parameter d . The Geweke-Porter-Hudak (GPH) method provides a semi-non- parametric test for fractional processes that requires no explicit parameterization of the unknown ARMA dynamics. The statistical procedure involves estimating d using a spectral regression:

$$\ln(I(w_i)) = \phi_0 - \phi_1 \ln(4\sin^2(w_j/2)) + \varepsilon_t, \quad j = 1,2,\cdots,n \tag{4}$$

where $I(w_j)$ is the periodogram at the harmonic frequency $w_j = 2\pi j/T$, ε_t is a random error term, and $n = T^\mu$ for $0 < \mu < 1$ is the number of low-frequency ordinates used in the regression. The periodogram $I(w_j)$ is computed as the product of $2/T$ and the square of the exact finite Fourier transform of the series $\{x_1, x_1, \cdots, x_T\}$ at the respective harmonic ordinate. Geweke and Porter-Hudak (1983) show that the least squares estimate of ϕ_1 provides a consistent estimate of d and hypothesis testing concerning the value of d can be based on the usual t-statistic. The theoretical error variance for ε_t is known to be equal to $\pi^2/6$, which is typically imposed in estimation to raise efficiency.

In applying the GPH spectral procedure, the number of low-frequency ordinates, n, used in the spectral regression is a choice variable. The choice necessarily involves judgment. While a too large value of n will cause contamination of the d estimate due to medium- or high-frequency components, a too small value of n will lead to imprecise estimates due to limited degree of freedom in estimation. To balance these two consideration factors, we experiment with a range of μ values used for the sample size function, $n = T^\mu$. The results are for μ =0.500, 0.550, and 0.600.

Table 2 contains the estimates for the fractional parameter d from the GPH spectral regression. The d estimates are reported together with their t-statistics. Table 2 shows that all of the estimates of d lie between 0 and 1, suggesting possible fractional integration behavior.

Moreover, in all cases, the estimates of d are significantly greater less than 1 but and greater than 0.5, meaning that equation (1) is likely to be misjudged as unstable in terms of the Engle-Granger two step cointegration[7] and Johansen multivariate cointegration procedure.[8]

Table 2. Results of the GPH test

		0.500	0.550	0.600
MRI	$d(d=0)$	0.8938(2.331)*	0.9595(3.030)*	0.6488(2.369)*
	$d=1$	0.0098*	0.0012*	0.0089*
BDI	$d(d=0)$	0.8750(2.282)*	0.8891(2.808)*	0.8263(3.017)*
	$d=1$	0.0112*	0.0025*	0.0013*
BCI	$d(d=0)$	0.9985(2.604)*	0.9273(2.928)*	0.8250(3.065)*
	$d=1$	0.0046*	0.0017*	0.0013*
BPI	$d(d=0)$	0.8703(2.269)*	0.8844(2.793)*	0.8438(3.081)*
	$d=1$	0.0116*	0.0026*	0.0010*

Note: The sample size for the GPH is given by $n=T^{\mu}$. An asterisk denotes significance at the 5 percent level. The hypothesis $H_0 : d=1$ is tested against the one-sided alternative of $d<1$. The hypothesis $H_0 : d=0$ is tested against the two-sided alternative of $d \neq 0$. The figures in parentheses are the t –statistics for the corresponding fractional parameter d estimates.

I found that although the individual variables are non-stationary, a linear combination of the variables are stationary. The levels estimates can thus be used. Applying the OLS to equation (1), the estimated equation is as follows.

[7] Engle, R.F., and Granger, C.W.J.(1987), pp. 251-276.

[8] Johansen, S.(1988), pp. 231-254.

Table 3. Freight equation estimates

	constant	*china*	*F*	R^2
MRI	-2.263* (-4.841)	0.853* (17.15)	24.81* (0.000)	0.869
BDI	-9.630* (-8.740)	1.854* (15.82)	21.47* (0.000)	0.851
BCI	-10.93* (-8.921)	2.022* (15.50)	20.68* (0.000)	0.847
BPI	-8.947* (-7.754)	1.781* (14.51)	18.19* (0.000)	0.829

Note: The *t*-values are in parentheses below the coefficients. The significance levels are in parentheses below *F* statistics. An asterisk denotes significance at the 5 percent level.

The estimates of the china variable have the expected (positive) sign in all of four freights and are statistically significant different from zero at 1 per cent level. This paper also models the ocean freight as a function of trading volume and industrial production as in equation (5) in log-linear form.

$$frt_t = a_0 + a_1 china_t + a_2 cip_t + + a_3 seasons_t \tag{5}$$

where *cip* is a Chinese industrial production(seasonally adjusted). Industrial production is used to proxy real income as the analysis is conducted using monthly data (Caporale and Doroodian, 1994). Table 4 presents the estimates for equation (5).

The results for equation (5) are shown in Table 4. Equation (5) is estimated by ordinary least squares. The estimated China elasticities have the expected positive signs and are significantly different from zero at the 1 per cent level in the equations for MRI, BDI, BCI, and BPI. However, with the exception of MRI, the estimated business elasticities are significantly different from zero at the 5 per cent level but carry the wrong signs. I also can not find any significant difference between R^2 of equation (1) and (5). The determination coefficients of equation (1) are not smaller than those of equation (5). Hence I use equation (1) rather than equation (5) for further analysis.

Table 4 Freight equation estimates : equation (5)

	constant	*china*	*cip*	*F*	R^2
MRI	-2.272*	1.021*	-0.260	22.72	0.870
	(-4.835)	(4.465)	(-0.754)	(0.000)	
BDI	-9.724*	3.600*	-2.704*	26.85	0.888
	(-10.05)	(7.649)	(-3.802)	(0.000)	
BCI	-11.04*	3.989*	-3.045*	26.15	0.885
	(-10.30)	(7.646)	(-3.863)	(0.000)	
BPI	-9.046*	3.613*	-2.838*	22.97	0.872
	(-8.939)	(7.336)	(-3.813)	(0.000)	

Note: For explanatory notes, see Table 3.

Next I employ the dynamic rolling regression to show the effects of increased trading volume on the freight as time passes. This has the merit of detecting whether the China effect gets stronger or weaker, and how fast it decays if weaker. Specifically, the structural model in this paper is initially estimated using data through the first forecasting period, 2002:12. The coefficient is then generated. Next, the data for January 2003 are added to the original data set and the model is re-estimated. New coefficient is made. This "rolling regression" process is continued through to the last period, 2005:10.

Table 5 Rolling regression

period	MRI	BDI	BCI	BPI	period	MRI	BDI	BCI	BPI
2003:01	0.167	0.953	1.227	0.917	2004:06	0.806	2.078	2.268	2.036
2003:02	0.218	0.963	1.227	0.928	2004:07	0.807	2.074	2.265	2.027
2003:03	0.254	1.023	1.286	0.973	2004:08	0.823	2.103	2.303	2.054
2003:04	0.285	1.108	1.358	1.068	2004:09	0.836	2.112	2.309	2.062
2003:05	0.323	1.214	1.475	1.172	2004:10	0.851	2.116	2.306	2.069
2003:06	0.357	1.298	1.570	1.252	2004:11	0.867	2.136	2.327	2.091
2003:07	0.393	1.385	1.662	1.342	2004:12	0.884	2.153	2.343	2.108
2003:08	0.443	1.499	1.811	1.443	2005:01	0.893	2.128	2.312	2.081
2003:09	0.482	1.581	1.922	1.503	2005:02	0.905	2.129	2.312	2.082
2003:10	0.534	1.764	2.117	1.705	2005:03	0.914	2.123	2.299	2.080
2003:11	0.586	1.904	2.264	1.847	2005:04	0.921	2.111	2.290	2.062
2003:12	0.639	1.990	2.339	1.934	2005:05	0.926	2.095	2.277	2.039
2004:01	0.675	2.064	2.402	1.997	2005:06	0.925	2.054	2.218	2.004
2004:02	0.714	2.118	2.417	2.053	2005:07	0.915	1.995	2.158	1.935
2004:03	0.752	2.154	2.408	2.105	2005:08	0.890	1.930	2.092	1.868
2004:04	0.777	2.148	2.364	2.113	2005:09	0.870	1.887	2.052	1.820
2004:05	0.796	2.120	2.314	2.084	2005:10	0.853	1.854	2.022	1.781

The estimated rolling coefficient of MRI freight index rose as much as six times from 0.167 in January 2003 to 0.925 in May 2005. The large increase means that the China's influence has been greatly increased. China's influence on the BDI also rose from 0.953 in January 2003 to 2.153 in December 2004. The coefficient of BCI rose from 1.227 in January 2003 to 2.417 in February 2004, and fell back to 2.265 until July 2004, but again started to rise since then. This pattern was applied to the BPI similarly. However all of the BDI, the BCI and the BPI have the common features that the coefficients continue to decline since January 2005. Specifically all freights arrived at a peak in December 2004, which were 2.153, 2.343, and 2.108, decreased continuously, indicating that the China effect was decaying.

We can see these results in figure 5 to figure 8. The solid lines showing the increase rate of coefficient take the left downward shape and have steep slopes. It means that the increase rate is falling fast. These facts suggest that it is difficult to expect further influence from the China effect and the freights will return to the normal level as the China effect diminishes.

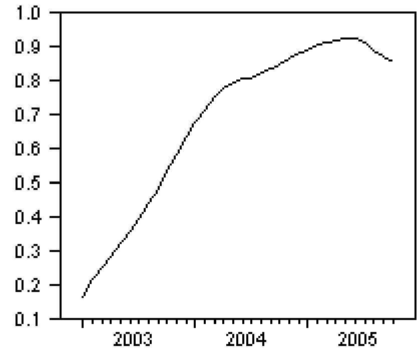

Fig. 1 Rolling coefficients : MRI

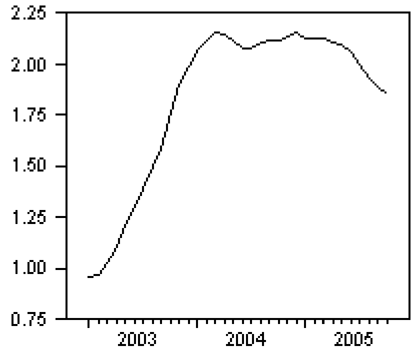

Fig. 2 Rolling coefficients : BDI

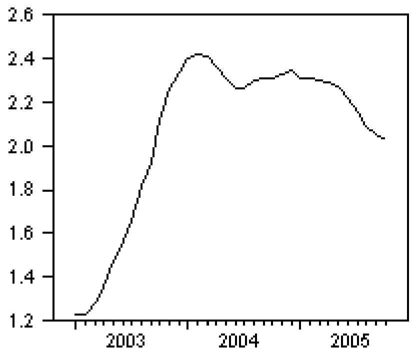

Fig. 3 Rolling coefficients : BCI

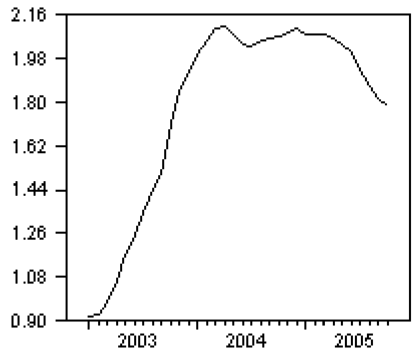

Fig. 4 Rolling coefficients : BPI

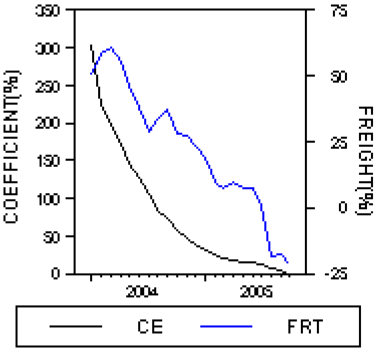

Fig. 5 Growth rate : MRI

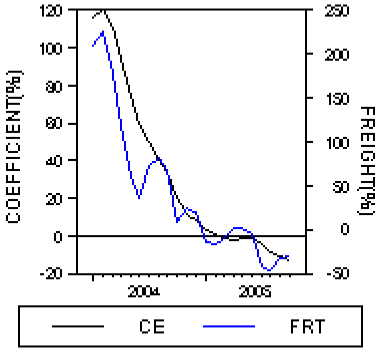

Fig. 6 Growth rate : BDI

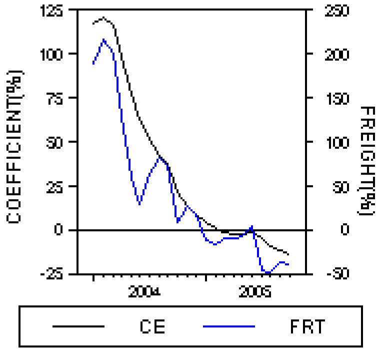

Fig. 7 Growth rate :BCI

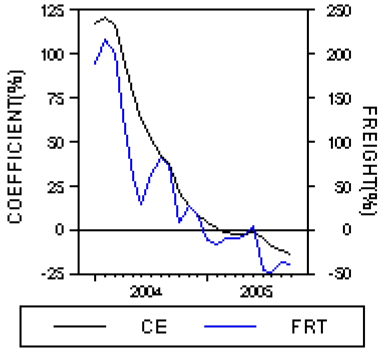

Fig. 8 Growth rate : BPI

Ⅲ. VARIANCE DECOMPOSITION AND IMPULSE RESPONSE

In this section we make use of variance decompositions (VDC) and impulse response functions (IRF). Both were initially prescribed by Sims (1980), and have now been widely used to examine how much movement in one variable can be explained by innovations in different variables and how rapidly these fluctuations in one variable can be transmitted to another. The VDC measures the contribution of each innovation in the vector autoregression (VAR) to the k-step ahead forecast error variance of the dependent variables. A variable that is optimally forecast from its own lagged values will have all its forecast error variance accounted for by its own disturbances (Sims

1982). IRFs essentially map out the dynamic response path of a variable due to a one-period standard deviation shock to another variable.

Table 6. variance decomposition for freights

steps	MRI				BDI			
	case 1		case 2		case 1		case 2	
	frt	*china*	*china*	*frt*	*frt*	*china*	*china*	*frt*
1	100.000	0.000	1.852	98.148	100.000	0.000	7.029	92.971
3	98.902	1.098	5.240	94.760	99.959	0.041	7.525	92.475
6	88.530	11.470	19.477	80.523	91.910	8.090	20.026	79.974
9	69.650	30.350	38.639	61.361	66.559	33.441	39.134	60.866
12	53.914	46.086	51.814	48.186	51.116	48.884	46.440	53.560

steps	BCI				BPI			
	case 1		case 2		case 1		case 2	
	frt	*china*	*china*	*frt*	*frt*	*china*	*china*	*frt*
1	100.000	0.000	2.009	97.991	100.000	0.000	6.530	93.470
3	99.397	0.603	4.436	95.564	99.976	0.024	6.883	93.117
6	85.374	14.626	21.122	78.878	93.246	6.754	17.625	82.375
9	61.101	38.899	41.542	58.458	70.727	29.273	34.403	65.597
12	49.564	50.436	49.563	50.437	57.012	42.988	40.458	59.542

Table 6 shows that the proportions of the forecast error variance of MRI, BDI, BCI, and BPI explained by itself are 54, 51, 50, 57 per cent after 12 months in case 1, respectively. The proportions of the forecast error variance of ocean freights explained by itself are 48, 54, 50, 60 per cent after 12 months in case 2. As a result, innovations in the trading volume explain 43 to 50 per cent and 40 to 52 per cent of the forecast error variance of the ocean freights in case 1 and 2. All in all, innovation accounting indicates that ocean freight is not exogenous with respect to trading volume.

We also employ the impulse response functions to get additional information regarding the responses of the variables to the shocks in the other variable. These impulse response functions show the effect of a one standard deviation shock applied to one of the equations, on both the short and long-run responses of all variables in the system.[9]

Consider a *p*th order vector autoregressive process

$$\Delta X_t = \sum_{i=1}^{p} A_i \Delta X_{t-i} + \varepsilon_t \tag{6}$$

where X_t is the 2×1 vector(ocean freight and trading volume), and A_i's are estimable parameters. The responses of ocean freights to a shock in the trading volume is presented in Table 7. Table 7 indicates that freights increase sharply before peaking nine to ten months after the shocks to trading volume and declines very slowly to its pre-shock level.

Table 7.　Impulse Response

steps	MRI	BDI	BCI	BPI	steps	MRI	BDI	BCI	BPI
1	0.00439	0.01354	0.01845	0.01349	8	0.01337	0.04158	0.05254	0.04310
2	0.00747	0.02315	0.03104	0.02332	9	0.01347	0.04179	0.05256	0.04333
3	0.00962	0.02991	0.03952	0.03038	10	0.01349	0.04170	0.05226	0.04320
4	0.01109	0.03457	0.04512	0.03536	11	0.01344	0.04138	0.05173	0.04281
5	0.01208	0.03771	0.04870	0.03877	12	0.01335	0.04091	0.05104	0.04223
6	0.01273	0.03973	0.05086	0.04102	13	0.01323	0.04034	0.05026	0.04151
7	0.01314	0.04095	0.05204	0.04239	14	0.01309	0.03969	0.04942	0.04070

This suggests that the China effect has a strong influence on the ocean freight and causes the higher ocean freight to last for a long time.

[9] The results are presented assuming no contemporaneous feedback, although any ordering of these variables does not qualitatively affect the results.

Ⅳ. Conclusion

The increased trading volume with China's economic growth has been known to play a vital role in the shipping market. The China effect made the ocean freight soar to an unprecedented level despite the terror of September 11 and worldwide recession. The object of this paper was to analyse the characteristics of the China effect.

This study modeled the ocean freight as a function of trading volume with China of Korea, Japan and the U.S. in log-linear form and examined the univariate time-series properties of the series by testing whether the series are stationary or not. The ADF test for unit roots indicated that the variables are nonstationary in levels and stationary in differences. Based on this result, I tested whether variables are cointegrated. The result of the GPH fractional differencing test found that all of the estimates lie between 0 and 1. Moreover, in all cases, the estimates of d are significantly less than 1 but and greater than 0.5, indicating the presence of fractional cointegration. The levels estimates could thus be used. The estimates of the China variable had the positive sign in all freights and were statistically significant.

This paper also employed the dynamic rolling regression to show the effects of the increased trading volume on the freight as the time passed. The result showed that all the coefficients of freights tended to decline. It means that we cannot expect any additional China effect and the freight will return to the normal level as the China effect diminishes.

I used variance decompositions and impulse response functions. Innovation accounting indicated that ocean freight was not exogenous with respect to trading volume. I also employed the impulse response functions to get additional information regarding the responses of the variables to the shocks in the other variable. The result indicated that freights increased sharply before peaking nine to ten months after the shocks to trading volume and declined very slowly to its pre-shock level. This suggests that China effect has the strong positive influence on the ocean freight and causes the ocean freight to last for a long time.

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