Examining the Impact of the World Crude Oil Price on China's Agricultural Commodity Prices: The Case of Corn, Soybean, and Pork

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Abstract

This study investigates effects of the world crude oil price on feed grain prices and pork prices in China. The results from time series techniques show the influences of crude oil price are not significant over the study period. The pork demand and supply result in the skyrocketing pork price.

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Introduction

China's food prices have been rising drastically since 2006 due to short supply and high production costs. The price for pork, a staple of the Chinese diet, surged nearly 86 percent in China last year. The skyrocketing pork price contributed to a 15.4% year-on-year increase in food costs. The outbreak of blue ear disease, also known as Porcine Reproductive and Respiratory Syndrome (PRRS), which caused many pig deaths and significant culling, was an immediate cause of the short supply. Some argue that the main and long-term reason for the pork price hike is that feed grain prices are very high. Due to the soaring crude oil price and heightened environmental concerns, the production of biofuels, which rely mainly on corn and soybean production, has increased dramatically in the past few years. China's economists underline concerns that biofuel production is driving up rapidly the costs of corn and other feed grains which contribute to the rise of pork prices. For example, despite a bumper crop in China in 2006, corn prices have risen by nearly 30 percent over the past nine months on the Dalian Commodities Exchange. The Chinese government slowed corn-based ethanol production and may ban its production to keep domestic feed grain and pork prices stable. However, with upward-trending oil prices, the U.S. and Brazil have promoted the international production of ethanol and kept the world feed grain prices high. Upward pressure on feed grain and pork prices is likely to continue despite the Chinese government going all out to ensure the supply of feed grains and pork in the domestic market.

On the other hand, the soaring Chinese pork prices may be a significant chance for U.S. feed grain and livestock exports to China. In order to cover the domestic shortage of pork, China has to either import feed grains to reduce its production cost or directly import pork. China has been the world's largest importer of soybeans since 2002. Even though China is a major corn exporter in the world market with government supports, corn prices in China are mostly higher than those in the world market. The Chinese government has issued permits for importing biotech corn from the U.S. since 2006. In August 2007, China signed an agreement with Smithfield Foods Company for the purchase of 60 million pounds of Paylean-free pork for delivery by the end of December.

Some previous studies have attempted to investigate the dynamic relationships among the world crude oil price and agricultural commodity prices. Yu et al. (2006) examine the dynamic relationships among world vegetable oil and crude oil prices. However, they did not find a significant impact of crude oil price shocks on changing vegetable oil prices. Elobeid et al. (2006) analyze the long-run impact of corn-based ethanol on the U.S. grain, oilseed, and livestock sectors. They find pork and poultry producers who do not own shares in ethanol plants would lose as the U.S. ethanol industry expands. Campiche et al. (2007) investigate the relationship between petroleum prices and corn, sorghum, sugar, soybeans, soybean oil, and palm oil prices during the 2003-2007 time period using a vector error correction model. They find only corn prices and soybean prices were cointegrated with petroleum prices for the 2006-2007 time period in the study.

The general objective of this study is to investigate the impact of the world crude oil price on China's agricultural commodity prices using time series techniques. The specific objectives of this study are to investigate the dynamic relationship among the world crude oil price and China's corn, soy meal, and pork prices, to find the magnitude of the direct and indirect impacts of crude oil, corn, and soy meal prices on pork prices in China. Through this study, we can identify whether the changes in the world crude oil price are the main reason for rising food prices in China.

Methodology

Multivariate time series models are employed in this study to estimate the dynamic relationships among the variables. The first part focuses on the analysis of Vector ARMA models for the world crude oil price, corn price, soy meal price, and pork price in China. Three steps will be employed in this part: (1) a description of model selection, identification, estimation, and diagnostic checking for model adequacy, (2) investigating the causality among the variables based on the model in the first step, (3) analyses of impulse response functions and variance decompositions. The second part conducts cointegration analysis using the Johansen-Juselius method among the variables and will establish an appropriate vector error correlation model, if necessary.

First, The VARMA model is a very popular tool for analyzing the dynamic relationships for multivariate time series. The d - time series $(Z_{1t,} Z_{2t}, ..., Z_{dt})$ can be jointly modeled as $\phi(B) Z_t = \theta_0 + \theta(B) a_t$,

Where $Z_t = (Z_{1t,} Z_{2t}, ..., Z_{dt})^T$, $a_t = (a_{1t,} a_{2t}, ..., a_{dt})^T$, $\phi(B) = I - \phi_1 B - .... - \phi_p B^p$, $\theta(B) = I - \theta_1 B - .... - \theta_q B^q$, $\phi_i = (\phi_{i,jk})$ is an mXm matrix, and $\theta_i = (\theta_{i,jk})$ is an mXm matrix. a_t is a vector white noise process with $a_t = (a_{1t,} a_{2t}, ..., a_{dt})^T$ such that $E(a_t) = 0, E(a_t a_t^T) = \sum$, and $E(a_t a_s^T) = 0$ for $t \neq s$. The VAR (p) model can be considered as a seemingly unrelated regression (SUR) model with lagged variables and deterministic terms as common regressors. Second, cointegration analysis should be performed because if there are cointegrating relationships between the series, the VECM should be more appropriate to analyze time series. The Johansen-Juselius (1990) method is used for cointegration rank test. Both the trace statistic and maximum eigenvalue statistic are used to test the null hypothesis that the series are cointegrated.

Data

Data for the analysis are based on monthly prices from January 2000 to October 2007. The world crude oil price is the NYMEX futures price which is quoted in U.S. dollars per gallon collected from the Energy Information Administration. The corn, soy meal, and pork prices are the wholesale prices in Shanghai which are quoted in Chinese Yuan per kilogram collected from the Chinese agricultural information website. The world crude oil prices are converted into Chinese Yuan based on the average exchange rate collected from the Federal Reserve Bank of St. Louis. Figure 1-5 plot four prices variables.

Empirical Analysis

1. **Primary Time Series Analysis**

It is necessary to investigate the time series properties of the variables. First, there are three methods to check for stationary of the variables: analyzing time plot, examining autocorrelations, and performing unit root test by using Dickey-Fuller test. 1). Time Plot. All four series tend to move upward with time during the period of 2000-2007. The upward trend patterns suggest that all four series are likely to be non-stationary in mean. 2). Autocorrelation. Test to see whether autocorrelation $\rho_k = 0$ can be carried out by comparing r_k with $2SE(r_k) = 2/\sqrt{94} = 0.20$. The autocorrelations for each series are dying out but are doing very slowly. It can be concluded that all the series are non-stationary in mean. 3). Unit root. The estimated coefficients and standard errors of β_i along with the calculated test statistics, are shown in Table 1. The test statistic is calculated using t-value: $(b_i - 1)/SE(b_i)$ and the following hypothesis to be tested: H_0: β_1=1, and Ha: β_1<1. Dickey-Fuller value for n=94 and probability = 0.05 is equal to -2.90. Since the calculated value for every series is not less than the critical value the null hypothesis cannot be rejected, indicating the presence of a unit root and that the series is non-stationary in mean. This is further evidence that the series are all non-stationary.

Differencing is an effective way of eliminating non-stationary in mean and rendering the series stationary. Also, above three tests are employed to see if the transformed data is stationary. Table 2 lists the estimated coefficients and standard errors along with the calculated test statistics. Since the calculated value for every series is less than the critical value the null hypothesis can be rejected, indicating no presence of a unit root and that the series is likely stationary in mean.

2. Model Identification and Building for the VARMA model

Model Identification

To determine the orders of p and q for the stationary VARMA (p, q) model, it is necessary to analyze the lag auto- and cross-correlation matrices, $R(k)$ and the partial autoregression matrices, $P(k)$, at lag one through ten.

1) Lag Auto- and Cross-Correlations**.** The joint significance of these elements in each matrix can be tested by using the Q-test. The test hypotheses formula is given below:

$H_0: \ R(k) = 0, \ \ H_a: R(k) \neq 0.$

$Q = (n-k)\sum_{ij}[r_{ij}(k)]^2$

Where $r_{ij}(k)$ are the elements in the lag k matrix in the i^{th} row and j^{th} column. Q is the Chi-square distribution with degree of freedom of 16 in this case. At the 5% level of significance, the critical value of Chi-square with degree of freedom 16 is 26.3. The null hypotheses may be rejected if the test statistic is greater than 26.3.

2) Lag Partial Autocorrelation Coefficients.

The likelihood Ratio test is approximated by the M-test using the follow the hypotheses and formula:

$H_0: \ R(k) = 0, H_a: \ R(k) \neq 0.$

$$2(L_u - L_c) \cong M = -(n - \frac{1}{2} - km)\ln\{\frac{|S(k)|}{|S(k-1)|}\}$$

Where n is the number of the observations, k is the order, and m is the number of variables. $S(k)$ and $S(k-1)$ are determinants of variance-covariance matrix of the residuals. M is distributed Chi-sq with degree of freedom equal to m^2. The critical value at 5% significance is 26.3. Table 3 shows the calculated values for Q and M test. Intuitively, it might to say that autocorrelations tails off and partial autocorrelations cut offs at lag 6 by comparing the values of Q-test and M-test. Thus, the VAR (6) with ϕ_1-ϕ_5= 0 is considered as the final model. The parameter estimation and diagnostic checking on the VAR (6) with ϕ_1-ϕ_5= 0 model can be performed.

Model Building

There are three methods to check test the validity of the VARMA model: (1).Significance of the parameter estimates, (2) Multicollinaerruty of the parameters, and (3) White noise of the residuals. First, it is possible to simplify the identified model by comparing the t-value against the cut off rule of 1.00 and eliminating some of the insignificant parameters. The second test is for multicollinearity. The correlation matrix of the parameters needed to be checked, and the parameters which have high correlation with other estimates need to be dropped. No obvious multicollinearity problem appears by checking cross-correlation coefficient. The last diagnostic test of the model is to check if the residual obtained from the model are white noise. If the model is acceptable, its residuals should be white noise. This white noise test needs to rely on the joint test- Q-test at each lag. Table 4 reports the Q values for residual. Since none exceed the critical value at any lag this test supports the suggestion from the individual test that the residuals are white noise. From above diagnostic checking, the VAR (6) with ϕ_1-ϕ_5= 0 model can be considered as an acceptable model in this study.

3. **Causality Test**

In analyzing the causal relationships between the variables, the main interest is in finding the lead/lag relationship between the series. The Granger-causality between world crude oil price and every China's agricultural commodity prices as well as causality between China's corn and soy meal prices and pork price are tested using the likelihood ratio (LR):

$$LR = 2(L_u - L_c) = n\{Ln\,|\hat{\sum}_u| - Ln\,|\hat{\sum}_c|\}$$

$\hat{\sum}_u$ is the residual covariance matrix from the unconstrained model and $\hat{\sum}_c$ is the residual covariance matrix from the constrained model, in which corresponding parameters are imposed to zero. The LR is a Chi-square distributed with a degree of freedom equal to the number of parameters constrained to zeroes. In this case it is Chi-square test with a degree of freedom 1. The null hypothesis can be rejected if the value of LR is greater than the critical value of the Chi-square distribution with a degree of freedom of 1 at 5% level of significance, 3.84 and at 10% level of significance, 2.71. The results are summarized in table 5. The null hypothesis of the Granger-Causality test is that GROUP1 is influenced by itself, and not by GROUP2. The results show the hypotheses that the world crude oil price does not lead China's corn, soy meal, and pork price are not rejected. Also, the Granger-Causality test statistics show that China's pork price is not influenced by China's corn and soy meal prices. The only significant statistics shows that China's soy meal price is influenced by corn price.

The dynamic relationships between the series are examined in this study. The impulse response function shows how a shock to one variable affects itself and the other variables over time while holding all other external effects constant. Based on the orthogonalized impulse response matrices from SAS 9.1 output (available from authors), there is not a strong effect between any variable to the other three. Another way to look at the dynamic relationships between the variables is to consider variance decomposition matrices. From the proportions of prediction error covariance matrices in SAS 9.1 output (available from authors), most of the variances of one variable are explained by its own shocks.

4. Investigation of Cointegration

Johansen-Juselius Method

For this method, it is necessary to check the rank of the Matrix $\Pi = \left[\sum_{i-1}^{p} \phi_i - I\right]$= r. if r is equal to 0, then the series are not cointegrated, and the VARMA model is appropriate. If r is not equal to zero, then the series are cointegrated, and there are r cointegrated relationships among the series and the error correction model is appropriate for the data.

The first step in investigating the possibility of cointegration is to specify the lag p of the basic VAR(p) model for the original non-stationary series. To identify the lag p, the behavior of P(k) matrices is investigated. Since non-stationary series P(k) cannot be interpreted as partial cross-correlation matrix. It only shows the estimated AR(k) coefficients. The Q statistics can be used to test if all AR(k) coefficients are simultaneously zero. On the basis of the estimated Q- statistics (table 6), the lag p of VAR(p) model for the original series can be identified. Because no chi-square statistic is significant, a simplest VAR model, VAR(1) may be appropriate in this study.

Two statistics are used for testing: (1) $\lambda_{trace} = -n\sum_{i=r+1}^{m}\ln(1-\lambda_i)$, which tests the null hypothesis that the number of distinct cointegrating vectors is less than or equal to r against a general alternative; (2) $\lambda_{\max} = -n\ln(1-\lambda_{r+1})$, which tests the null hypothesis that the number of cointegrating vectors is r against the alternative r+1 cointegrating vectors.

The λ_{trace} test, hypothesis of no cointegration to be tested:

H_0: Cointegration is at most of order r=0; H_a: Not H_0

The $\lambda_{\max}$ test, hypothesis to be tested:

H_0: Cointegration is of order r=0; H_a: Cointegration is of order r+1=1

From Table 7-8, the series are not cointegrated and the VEC model is not suitable. Therefore, the VAR(6) with ϕ_1- ϕ_5= 0 is an appropriate model in this study.

Conclusion

China's economists underline concerns whether the volatility in the world crude oil price and the effects of large-scale ethanol production have contributed to China's soaring food prices. Understanding the dynamic relationship among the crude oil and China's agricultural commodity prices, as well as the magnitude of the impact of crude oil and feed grain prices on pork prices in China, is necessary both for Chinese and U.S. producers and policy makers.

This requires an accurate evaluation of the effect the world crude oil price has on feed grain prices and pork prices in China. This study applies the VARMA model, Granger-causality test, analyses of impulse response functions and variance decompositions, and cointegration analysis to investigate these dynamic relationships. Overall, the empirical results presented make a contribution to understanding the reasons behind the hike in pork prices. After applying the above time series techniques, it shows the crude oil price is not the most influential factor for the continuing rise of Chinese feed grain and pork prices. The increases of the corn and soy meal prices are not the major reasons for soaring pork prices.

The skyrocketing pork price is mainly decided by China's pork demand and supply. Pig farmers expanded production when pork profits increased during 2003-2004 due to consumers' switch from poultry to pork when pathogenic influenza broke out. Sow inventory increased considerably and over supply led to low pork prices from fall 2005 to fall 2006. Furthermore, Swine fever occurred in some provinces lowered pork prices and feed grain prices increased. Rising cost of feed and the low pork prices during 2005-2006 have made farmers reluctant to raise pigs. The outbreak of blue ear disease in 2007 has directly reduced the supply of pigs significantly. The reduced pork supplies combined with strong demand drive pork prices up. Given the cycles of pig production, prices should be high for some time. However, Agricultural production is responsive to price movements, so high pork price with government subsidies for feeding pigs should bring supply up and prices down.

Even though the results from time series techniques show the influences of crude oil price are not significant over the study period, higher world crude oil prices during 2006-2007 have increased costs of production, processing, and transportation of commodities.

Furthermore, the sharp movement for the production of biofuels could also put upward pressure on Chinese food prices. Possibly the influence of crude oil price on agricultural commodity prices will grow if high oil prices continue. These factors put upward pressure on inflation in China. Data frequency is an important factor that impacts the empirical results. Monthly data is not enough for dynamic relationship analysis for the world crude oil price and Chinese food prices during the 2006-2007 time period. If possible, a quantitative measure for the dynamic relationship among crude oil, feed grain, and pork prices in China with considering the change of the bilateral exchange rate for this new era will help Chinese producers and traders of feed grain and livestock to plan their business operations and assist the Chinese government in stabilizing food prices through policy adjustments. Furthermore, measuring these impacts will provide U.S. producers, traders, and policy makers with information regarding the future of U.S. feed grain and livestock exports to China.

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Figure 1. World Crude Oil Price

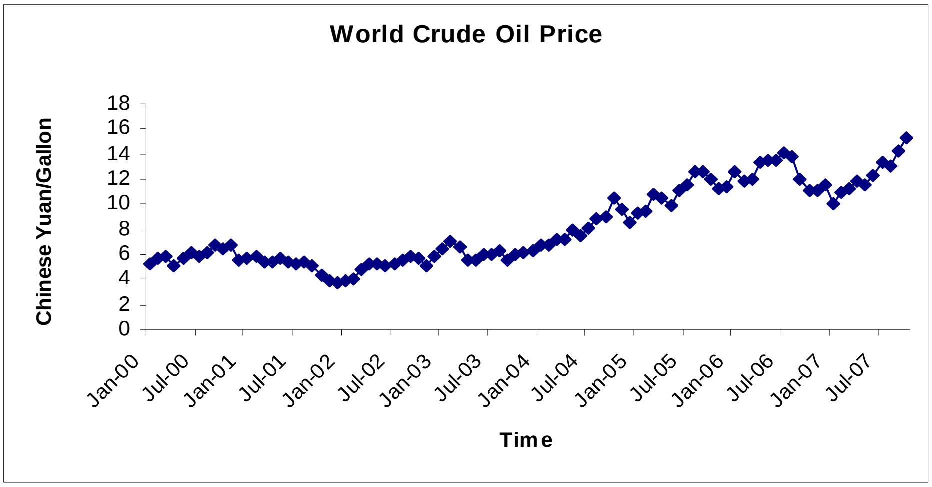

Figure 2. Corn Price in China

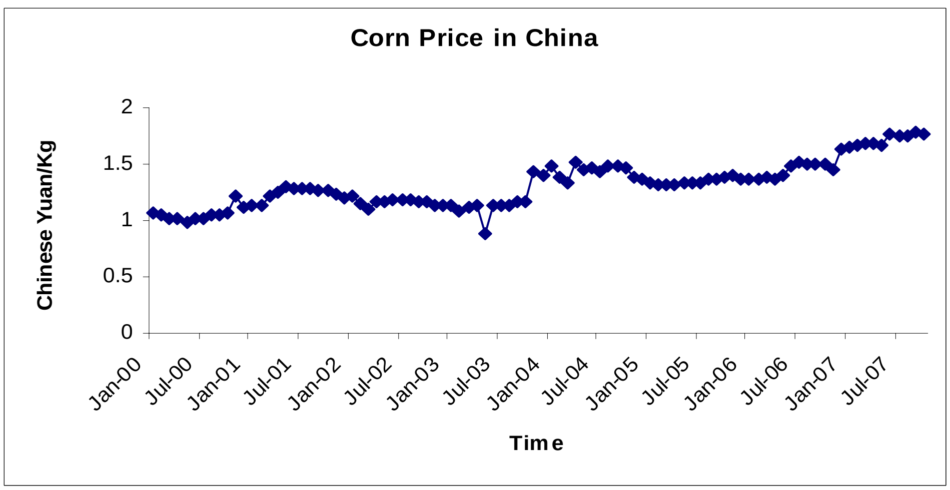

Figure 3. Soy Meal Price in China

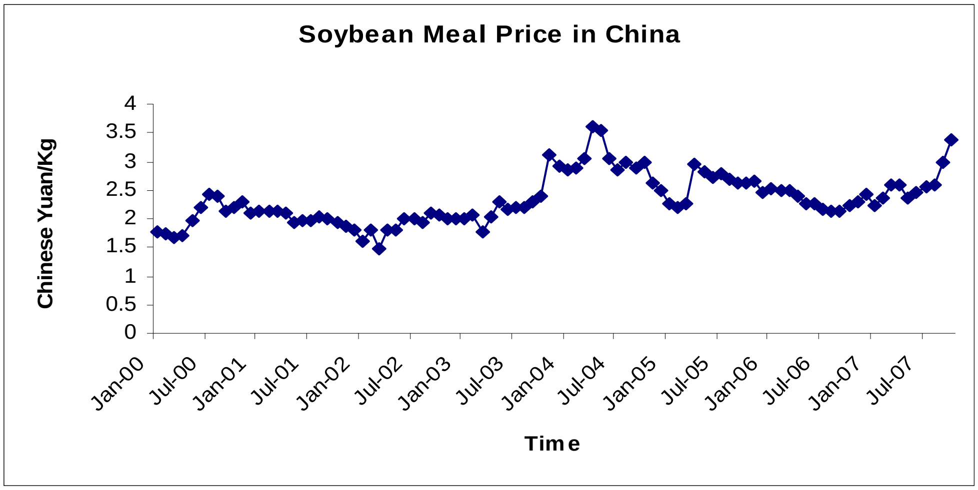

Figure 4. Pork Price in China

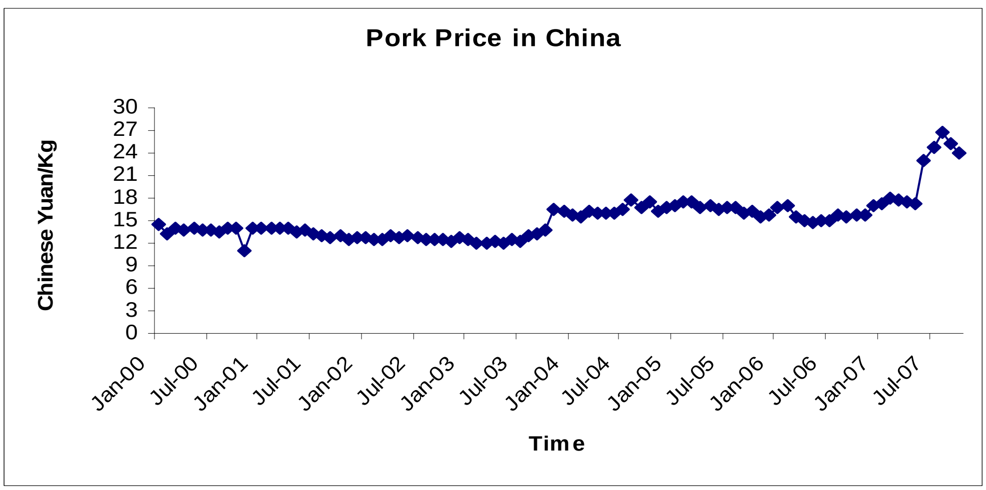

Table 1: Unit Root Test Results for the Original Series

Variable	b_i	Std Err	t-value
Crude Oil Price	1.004	0.023	0.161
Corn Price	0.982	0.036	-0.515
Soy Meal Price	0.912	0.053	-1.647
Pork Price	1.029	0.053	0.548

Table 2: Unit Root Test Results for the First Differences of the Original Series

Variable	b_i	Std Err	t-value
Crude Oil Price	-0.084	0.236	-4.594
Corn Price	-0.419	0.268	-5.304
Soy Meal Price	-0.222	0.247	-4.943
Pork Price	-0.253	0.231	-5.435

Table 3. Q and M test for VARMA model Identification

Lag	1	2	3	4	5	6	7	8	9	10
Q-test.	16.58	15.48	14.07	11.10	15.57	19.08	11.21	12.78	18.54	11.15
M-Test	19.97	18.48	14.17	14.55	15.89	**28.74**	12.92	20.54	12.49	19.44

Table 4. Q test for Checking if the Residual is White Noise

Lag	1	2	3	4	5	6	7	8	9	10
Q-test.	16.58	15.48	14.07	11.10	15.57	19.08	11.21	12.78	18.54	11.15

Table 5: Causality Test Results

Test	Group 1 Variables	Group 2 Variables	Chi-Sq	DF	Prob>Chi-sq
1	Corn Price	Crude Oil Price	0.62	1	0.4312
2	Corn Price	Soy Meal Price	1.96	1	0.1614
3	Corn Price	Pork Price	0.01	1	0.9891
4	Soy Meal Price	Crude Oil Price	0.18	1	0.6691
5	Soy Meal Price	Corn Price	**5.58**	1	0.0182
6	Soy Meal Price	Pork Price	0.48	1	0.4832
7	Pork Price	Crude Oil Price	0.27	1	0.6036
8	Pork Price	Corn Price	0.67	1	0.4138
9	Pork Price	Soy Meal Price	0.22	1	0.6417
10	Pork Price	Corn Price & Soy Meal Price	0.76	2	0.1205

Table 6. Q test for Johansen-Juselius Method

Lag	1	2	3	4	5	6	7	8	9	10
Q-test.	19.67	12.36	15.49	12.38	15.60	19.61	20.48	16.17	18.04	22.94

Table 7. Cointegration Rank Test Using Trace

H_0: Rank=r	H_1: Rank>r	Eigenvalue	Trace	Critical Value
0	0	0.2454	46.41	47.21
1	1	0.1212	20.23	29.38
2	2	0.0789	8.21	15.34
3	3	0.0061	0.57	3.84

Table 8. Cointegration Rank Test Using Max

H_0: Rank=r	H_1: Rank=r+1	Eigenvalue	MaxEigen	Critical Value
0	1	0.2454	26.18	27.07
1	2	0.1212	12.01	20.97
2	3	0.0789	7.64	14.07
3	4	0.0061	0.57	3.76