FORECASTING THE DEMAND OF CONTAINER THROUGHPUT IN SOUTHEAST ASIA: MULTIVARIATE AUTOREGRESSIVE MODEL

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ABSTRACT

This study was proposed to forecast the demand of container throughput in Southeast Asia. The analysis was carried out in multivariate autoregressive model. Johansen approach was used to find the existence and the number of cointegration relationship. Impulse response function (IRF) was performed to know response to a shock of a variable of other variables. The empirical analysis demonstrated that the estimation model provides indication of goodness-of-fit and of the forecasting potential of the model. Most of the model estimation results follow the long-term development of the actual data series closely. The impulse response of a shock of a variable to itself and other variables disappear certain period. These results verified the stability of all the estimated models. Forecasting of container throughput in Southeast Asian countries demonstrated that Singapore port will still dominates the container throughput at least for next two decades.

KEYWORDS: *Multivariate autoregressive, Forecasting, Container throughput*

1. INTRODUCTION

Southeast Asia has grown to become one of the busiest regions for container shipping. According to WTO, Southeast Asian countries merchandise exports reached $427 billion in 2000, triple the total of 1990. Over the same period, imports rose more slowly but still more than doubled, from $163 billion to $367 billion (*Llyod's Shipping Economist*, August 2002). The number of container handled at Southeast Asia countries has tended to rise. In comparison with the world container traffic, the Southeast Asia overseas shipping traffic accounted for 17.1% of the world container traffic (*Containerisation International Yearbook*, 2004). The significant change of Southeast Asia container trade has become the development of port facilities have been priority issues of the countries in the region. Moreover, this development has become liner shipping companies have to re-evaluate their network structure.

One of the key issues for developing port facilities and evaluating network structure is information about container throughput demand. In port planning and development, estimation of container throughput demand is a necessary step in predicting future revenues for a proposed development project. Hence, analysis of container throughput demand is very important, not only for port management but also for liner shipping company. However, only few studies have concerned on the estimation of the demand of container throughput. One of the studies that concern to the estimation of container throughput demand is study done by Fung (2001). However, his study only concern in estimating the demand for Hong Kong container handling services.

The approaches in estimating demand of trade market are often associated with time series data. The standard classical methods such as the ordinary least squares (OLS) and hypotheses testing are based on the assumption that the time series are stationary. Broadly, a series is stationary if its means and variance are constant over time and the value of the covariance between the two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed (Gujarati, 2003). A non-stationary series is said to be integrated of order *d* or I(*d*) if it must be differenced *d* times to make it stationary. Since the distribution theory in non-stationary series is different from the standard Gaussian asymptotic theory, application of classical estimation methods such as OLS for estimating relationships between non-stationary variables may cause to spurious regressions. The problems with estimation of single equation framework with integrated or non-stationary variables are: non-standard distribution of coefficient estimates, error process not being stationary, explanatory variables generated by processes that display autocorrelation, existence of more than one cointegrating vector and failure of weak exogeneity (Banerjee et al. 1986). To solve the problem of integrated variables, we can use cointegration test and estimation of vector error correction model (VECM) to distinguish between short run and long run relationship. The existence of cointegration can prevent the errors in the long run relationship from becoming larger and larger. This is modeled through the popular econometrics specification of error correction model which integrates the long-run equilibrium analysis and short-run dynamic adjustment by including in the short-run dynamic models a measure of disequilibrium in the last period.

The aim of this study is to estimate the demand of container throughput in Southeast Asian countries by presenting multivariate autoregressive model. Through this study, we can know how container throughputs in one country give significant impact to other countries in the region. The rest of this paper is organized as follows. Section 2 describes data and model limitation. Section 3 describes econometrics model and methodology. Section 4 provides empirical results and discussion. Finally, conclusion is given in section 5. All calculation concerning data analysis and model estimation was performed through TSP software.

2. DATA AND MODEL LIMITATION

Some major Southeast Asian countries that have significant container throughput are included in this study, i.e., Singapore, Indonesia, Malaysia, Thailand, and Philippines. For each country, we select major ports that have high share of container throughput. Those ports are Singapore port of Singapore, Tanjung priok and Tanjung Perak port of Indonesia, Port Klang and Port of Tanjung Pelepas of Malaysia, Bangkok and Leam Chabang port of Thailand, and Manila port of Philippines. Time series data of those ports from 1981 to 2002 are taken from International Containerisation Yearbook. Due to the two new ports, i.e., Laem Chabang port and Port of Tanjung Pelepas, started to operate their port in 1990 and 1999 respectively, time series data of those ports are available from 1991 and 2000 respectively. To accommodate these two ports, dummy variables were introduced in the model, i.e., dummy 1 and dummy 2, for Laem Chabang port and Port of Tanjung Pelepas respectively. The value of these dummy variables is as follows.

$$Dummy\ 1\begin{cases}1 & \text{for time series data from 1991 onward}\\ 0 & \text{otherwise}\end{cases}$$

$$Dummy\ 2\begin{cases}1 & \text{for time series data from 2000 onward}\\ 0 & \text{otherwise}\end{cases}$$

Since the container port characteristic and management policy time series data is difficult to find, the model does not consider the port characteristic and management policy. Hence, in modeling, container throughput in one country is a function of container throughput to itself and other countries.

3. ECONOMETRICS MODEL AND METHODOLOGY

3.1 Unit root test

Before estimating cointegration space and determination of cointegration rank, it is important to test the order of integration of each variable or to check the existence of unit roots, which make the series non-stationary. Testing for unit roots has become a standard tool in modern econometrics data analysis. Conventional statistical analysis assumes that the time series at hand are stationary, and a unit root implies non-stationary (Mills, 1990). Testing for unit roots enables direct inference on the degree of non-stationary and subsequent degree of differencing to transform a time series to stationarity. Several tests are available in the literature. In this study, we restrict to the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979). The basic equation of ADF tests is as follows:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-1} + \varepsilon_t \tag{1}$$

where ε_t is a pure white noise error term and $\Delta Y_{t-1} = (Y_{t-1} - Y_{t-2})$, $\Delta Y_{t-2} = (Y_{t-2} - Y_{t-3})$, etc. β_1, β_2, δ, α_i are parameters and t is the time or trend variable. The number of lagged difference (m) terms to include is often determined empirically, the idea being to include enough terms so that the error term is serially uncorrelated. The null of non-stationarity is equivalent to testing the significance of $\delta = 0$; that is, there is a unit root - the time series is nonstationary. The alternative hypothesis is that δ is less than zero; that is, the time series is stationary.

3.2 Cointegration

Having established unit root test, to find the existence and the number of cointegration relationship, we can perform cointegration test. The fundamental idea of cointegration is that although two series or more are non-stationary, or integrated, such that first difference are required to obtain stationarity, a liner combination of these series can be stationary. This linear combination is known as cointegrating vector or cointegrating relationship. The cointegrating relationship may, therefore, be thought of, as a long-run steady state of dynamic relationship though there can be finite short-run variations around the long-run relationship. The variables comprising the cointegrating relationship would not drift too far apart relative to each other owing to equilibrating forces that tend to keep them together.

The concept of cointegration was introduced by Engle and Granger, 1987, provided the issue of integrating short-run dynamics with long-run equilibria. Although widely used in empirical research, the Engle-Granger (EG) method has several shortcomings such as the size distortion, non-unique sample properties depending on the variable used for normalization and its inability to identify multiple cointegrating vectors (Banerjee et al., 1993). The others methods for estimation of long-run equilibrium relationship have been proposed by Stock (1987) which suggested non-linear least squares (NLS), Engle and Yoo (1991) suggested three steps procedure, maximum likelihood model was proposed by Johansen (1991) and Johansen and Julius (1994). Gonzalo (1994) has shown that Johansen approach has better properties than other estimators and their finite sample properties are consistent with asymptotic results. In this study we concern to the Johansen and Julius (1994) procedure. The Johansen technique proceeds by transforming a vector autoregressive model in levels into an equivalent differenced form, including lagged differences and an implied set of cointegrating vectors as the right hand explanatory variables. The differenced form is then estimated by using maximum likelihood methods. The implied vector cointegrating vectors are extracted using reduced rank regression technique. By Johansen approach, VECM can be estimated in which error correction term is included in each equation. Two types of likelihood ratio test statistics can be derived from Johansen procedure, namely, the trace test statistics,

$$trace(r \mid k) = -T \sum_{i=r+1}^{k} \ln(1-\lambda_i) \tag{2}$$

and max-lamda test statistics,

$$\lambda_{\max} = -T \ln(1-\lambda_{r+1}) \tag{3}$$

where r is cointegration relationship, k is number of variables, T is number of observations, and λ_i is the i-th eigenvalue. If trace test statistics ($r|k$) and λ_{max} greater than c_k, critical value, then reject H(r). H(r) denotes the hypothesis that the rank of Π (see equation 4 for term Π) in H(k) is ≤ r; for example, H(0) states the rank of Π is 0, H(1) states the rank of Π is 0 or 1.

3.3 Vector autoregressive model

A vector autoregressive (VAR) model is a multivariate time series model whose general mathematical form with K-dimensional is given by the following formulation:

$$Y_t = \Pi_1 Y_{t-1} + ... + \Pi_k Y_{t-k} + \Phi D_t + \varepsilon_t \tag{4}$$

where $Y_t = (y_{1t}, ...y_{KT})$, Π_i are K x K coefficient matrix, k is the order of the VAR, ε_t is residual error-term, and $\varepsilon_t \sim N(O, \Sigma)$ (where Σ is a K x K positive definite matrix). The deterministic term D_t can contain a constant, a liner term, seasonal dummies, intervention dummies, or other regressors that we consider fixed and non-stochastic. The Granger representation theorem states, under the hypothesis of cointegration, the VAR can be written as a vector error correction (VEC) model as the following formulation.

$$\Delta Y_t = \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \Pi Y_{t-1} + \Phi D_t + \varepsilon_t \tag{5}$$

The K x K matrix Π can be expressed as $\Pi = \alpha\beta'$ where both α and β' are K x r matrix of full rank. For the model used in study, K = 5, Y_t = container throughput in Indonesia, Singapore, Malaysia, Thailand, Philippines. β' is a matrix representing cointegration relation such that $\beta' Y_t$ is stationary and is interpreted as long run equilibrium relationship between the jointly determined variables. It is important to emphasize that one can not estimate the individual coefficient of β unless one specifies a normalization or identification. There may be stochastic shocks forcing to the system during the short-run, however, with the existence of cointegration relationship, there will be forcing variables which cause the system converge to the long-run relationship. The deviation from equilibrium relations $\beta' Y_t$ form a stationary process and α is the speed of adjustment coefficient for the equation.

3.4 Impulse response function

In applied work, it is often interest to find the response of one variable to an impulse in another variable in a system that involves a number of variables as well. If there is a reaction of one variable to an impulse in another variable we may call the latter causal for the former. IRF trace out the moving average representation of the system and describes how the variable responds over time to a single surprise increase in itself or in any other variables. The variance decomposition tells us how much of the average squared forecast error variance of one variable at the *k*-th step ahead is associated with surprise movements in each variable of the model. Both the innovation accounting tools can be used to make inferences regarding the nature of dynamic interactions between variables and variable exogeneity and Granger non-causality. For, example, if the variance of a particular variable is explained primarily by its own innovations then the variable is weakly exogenous to the system. Let $\Phi_n(\varphi)$ be an integrated term of autoregressive errors. The impulse responses or dynamic multipliers can be obtained from infinite moving average representation of a K-dimensional VAR model (Lutkepohl, 1991) as follows:

$$Y_t = A_1 Y_{t-1} + ... + A_p Y_{t-p} + u_t \tag{6}$$

$$\Phi_n(\varphi_{ik,n}) = \sum_{j=1}^{n} \Phi_{n-j} A_j \tag{7}$$

where n =1,2, ….., ∞, $\Phi_0 = I_K$, A_j represents parameter of moving average. $A_j = 0$ for $j > p$ and $\varphi_{ik,n}$ (the *ik*-th element of Φ_n) represents the response of variable y_i to a shock in variable k, n periods ago. Since the covariance matrix of a VAR, Σ_u, is positive definite, it is essential to transform the innovation of the system into a contemporaneously uncorrelated form.

4. EMPIRICAL RESULT AND DISCUSSION

4.1 Unit root test

Prior to perform unit root test, the natural logarithmic (ln) of the original series have been used in order to reduce the possibility of heteroskedasticity and to make the series more comparable. The results of unit root tests by augmented Dickey-Fuller (ADF) are presented in Table 1. ADF tests were performed on the full sample for the period 1981-2002 both on levels as well as differenced forms to find the order of integration. All the variables are non-stationary at their levels. A non-stationary series can be made stationary by differencing. The variables become stationary at first difference, or integrated order 1 or $I(1)$ since the null of unit root is rejected at first difference.

Table 1 Unit root test by Augmented Dickey-Fuller (ADF)

Series	Level	First difference	Integrated order
ln(Indonesia)	-1.081	-4.136*	I(1)
ln(Singapore)	-1.067	-3.832*	I(1)
ln(Malaysia)	-0.535	-3.768*	I(1)
ln(Thailand)	-3.329	-3.639*	I(1)
ln(Philippines)	-2.678	-3.805*	I(1)

Notes: The Dickey-Fuller regressions include an intercept and a linear trend term (random walk with deterministic trend). The null hypothesis is that the series is non-stationary. This hypothesis is rejected if the statistics is larger in absolute value than the critical value. Critical value for ADF test at 5% level of significance is -3.617. * denotes rejection of the null hypothesis of non-stationary at the 5% significance level.

4.2 Cointegration test

Since all the variables are found to be integrated order one I(1), to find the existence and the number of cointegration relationship among variables, we compute the maximum eigen values (λ_{max}) and the trace statistics by applying Johansen procedure. The number of cointegration relations is established by a sequential likelihood ratio test on the rank of an estimated parameter matrix from VECM. Results of these tests with 95% critical values are reported in Table 2. The λ_{max} and trace test reject the null hypothesis of no cointegration (r = 0) at a 5% significance level. However, neither of the criteria can reject the null hypothesis of r ≤ 4 against the alternative hypothesis of r = 5 at 5% significance level. Hence, we can conclude there exist four cointegration relationships at 5% significance level, and there exist considerable evidence of the existence of long-run relationship.

Table 2 Cointegration test by Johansen procedure

		λ_{max}		Trace test	
Ho Null	H1 (alternative)	Test statistic	95% Critical value	Test Statistic	95% Critical value
r = 0	r = 1	51.62*	33.18	157.04*	68.91
r ≤ 1	r = 2	43.57*	27.17	105.42*	47.18
r ≤ 2	r = 3	41.39*	20.78	61.85*	29.51
r ≤ 3	r = 4	16.19*	14.04	20.46*	15.2
r ≤ 4	r = 5	3.26	3.96	3.26	3.96

Note: 'r' indicates the number of cointegration relationships. The null hypothesis is if there is no cointegration. This hypothesis is rejected if λ_{max} and trace test statistics is larger than the critical value. * denote rejection of null at 5% significance level. The optimal lag length of VAR was selected by AIC. Optimal order of VAR was 2.

4.3 Vector error correction model (VECM)

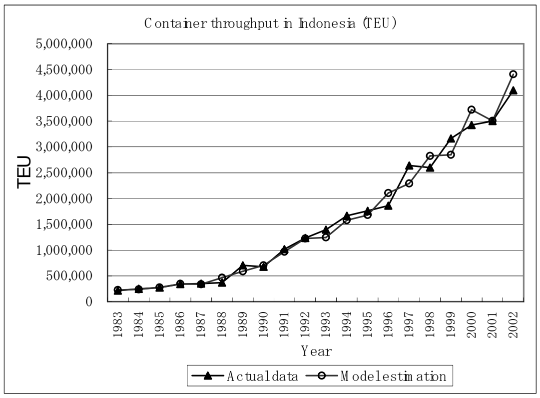
As stated earlier that under the hypothesis of cointegration, the VAR can be written as a vector error correction model (VECM). In this sub-section we show the regression result of vector error correction model based on the Johansen procedure. Coefficient matrix of VECM is given in Table 3. Based on this model we can forecast container throughput in Southeast Asian countries for the future year.

Table 3 Coefficient matrix of vector error correction model

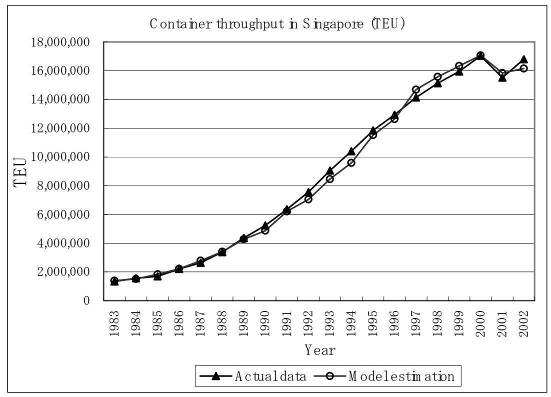
	Coefficient matrix of the lagged variable in difference					Coefficient matrix of the lagged variable in levels							
	ΔI	ΔS	ΔM	ΔT	ΔP	I_{t-1}	S_{t-1}	M_{t-1}	T_{t-1}	P_{t-1}	Constant	Dummy 1	Dummy 2
ΔI	0.6224	-0.5304	-0.4410	0.0468	-0.5072	-2.2250	1.9534	0.5279	-0.0575	-0.2931	-2.0026	0.2210	0.1814
	[0.374]	[0.944]	[0.499]	[1.188]	[0.425]	[0.666]	[1.241]	[0.453]	[0.877]	[0.513]	[2.479]	[0.166]	[0.192]
	{1.663}	{-0.561}	{-0.883}	{0.039}	{-1.193}	{-3.342}	{1.573}	{1.164}	{-0.065}	{-0.571}	{-0.807}	{1.333}	{0.944}
ΔS	0.1496	-0.6423	0.0776	-0.2406	0.2219	-0.1334	-0.2328	-0.1041	0.6907	-0.3738	2.5994	0.0809	-0.1211
	[0.161]	[0.407]	[0.215]	[0.512]	[0.183]	[0.287]	[0.535]	[0.195]	[0.378]	[0.221]	[1.069]	[0.071]	[0.082]
	{0.926}	{-1.576}	{0.360}	{-0.469}	{1.210}	{-0.464}	{-0.434}	{-0.532}	{1.824}	{-1.688}	{2.429}	{1.131}	{-1.461}
ΔM	-0.1539	0.5664	-0.3625	0.5459	-0.5245	0.0177	-0.4339	-0.3460	0.2120	1.0541	-6.3535	0.0114	0.4194
	[0.273]	[0.689]	[0.364]	[0.867]	[0.310]	[0.485]	[0.906]	[0.330]	[0.640]	[0.374]	[1.810]	[0.120]	[0.140]
	{-0.563}	{0.821}	{-0.995}	{0.629}	{-1.691}	{0.036}	{-0.478}	{-1.045}	{0.331}	{2.814}	{-3.509}	{0.094}	{2.990}
ΔT	-0.0037	0.0791	-0.2706	-0.2069	0.1752	0.0388	-0.1515	0.1233	0.1263	-0.2543	2.1293	0.0202	-0.0564
	[0.191]	[0.484]	[0.256]	[0.609]	[0.217]	[0.341]	[0.636]	[0.232]	[0.450]	[0.263]	[1.272]	[0.085]	[0.098]
	{-0.019}	{0.163}	{-1.056}	{-0.339}	{0.803}	{0.113}	{-0.237}	{0.530}	{0.280}	{-0.965}	{1.673}	{0.237}	{-0.572}
ΔP	0.3921	-0.7343	-0.4651	0.5084	0.3052	-1.0215	1.6409	0.3975	-0.3338	-1.0628	2.6815	-0.0269	0.1060
	[0.249]	[0.629]	[0.332]	[0.791]	[0.283]	[0.443]	[0.827]	[0.302]	[0.584]	[0.341]	[1.652]	[0.110]	[0.128]
	{1.572}	{-1.166}	{-1.398}	{0.642}	{1.077}	{-2.302}	{1.983}	{1.315}	{-0.570}	{-3.108}	{1.622}	{-0.243}	{0.827}

Note:
I= Indonesia, S = Singapore, M = Malaysia, T = Thailand, P = Philippines;
[ ] = standard error, { } = t value

To evaluate the accuracy of the model, we generate a series over a sample period and observe how well this estimation series match with the actual data. The process is straightforward; the first and second data in the sample are fed in the model as starting values for the calculation of ΔY_t as given in equation 5. Adding the later to the starting value provides the model estimation Y_t for the third year in the sample. The process is repeated for each year in the sample period. The estimation series (in natural logarithmic) is transformed again to the original value (level). Comparison of the model estimation with the actual data is shown in Figure 1.



(a)



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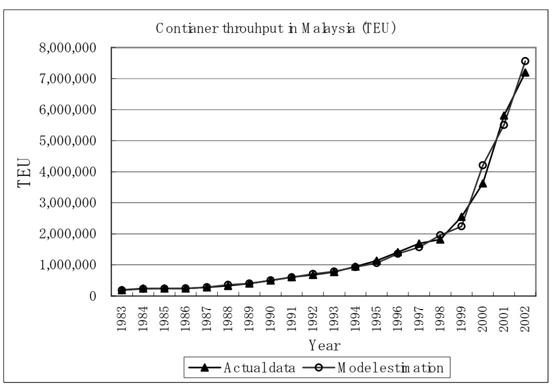

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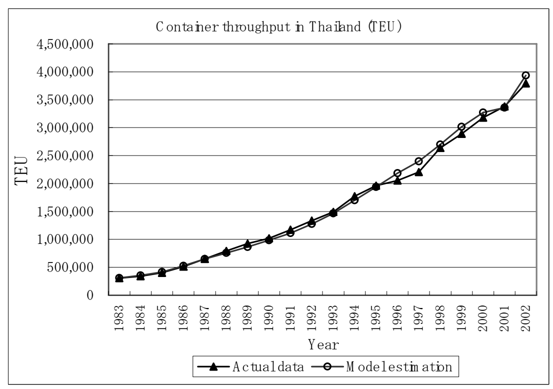

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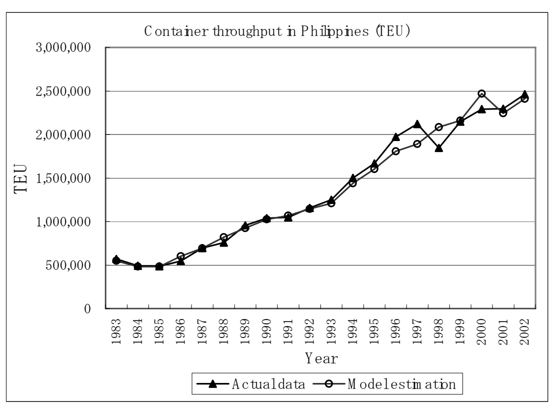


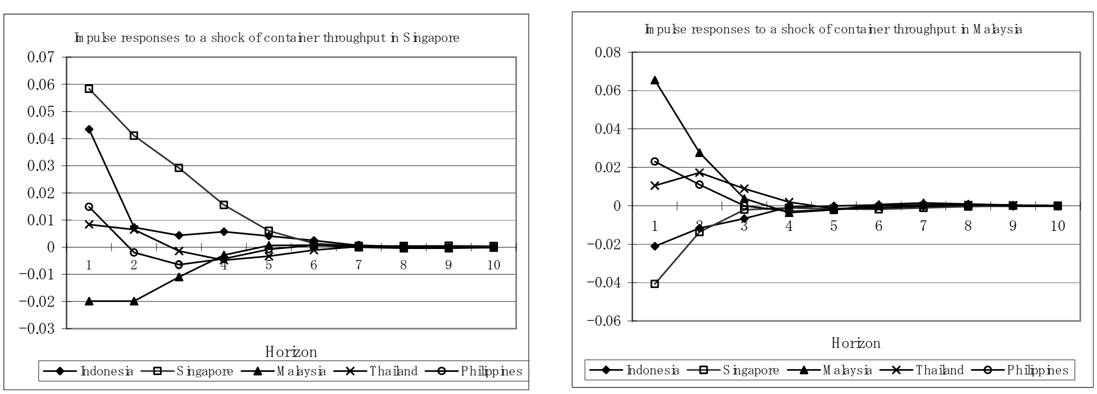
(e)

Figure 1 Comparison of container throughput between actual data and model estimation in (a) Indonesia, (b) Singapore, (c) Malaysia, (d) Thailand, (e) Philippines

The figure provides indication of goodness-of-fit and of the forecasting potential of the model. Most of the model estimation result follows the long-term development of the actual data series closely. The emergence of Port of Tanjung Pelepas has pushed rapid growth of container throughput in Malaysia from 2000 to 2002 with the increasing of container throughput was 3,568,241 TEU as shown in Figure 1 (c). Conversely, the container throughput in Singapore port has been reduced from 17,040,000 TEU in 2000 to 15,520,000 TEU in 2001 as shown in figure 1 (b).

4.4 Impulse response function

In this sub-section we describe the response of a shock of container throughput in a country to other countries reflected by impulse response function (IRF). If a variable does react to the shock of another variable, it is said that the latter causes former. We found the impulse response of a shock of container throughput in each country to it self and other countries disappear after certain period as depicted in Figure 2. This verifies the stability of all the estimated models. Due to the page limitation, we only show IRF of Singapore and Malaysia. A shock of container throughput in Singapore reacts positively to others countries except Malaysia as illustrated in Figure 2 (a). This phenomenon is understandable that around 81.5% of the containers that enter Singapore port are transshipped (PSA Annual Report, 2002). Hence, the rising of container throughput in Singapore actually come from the increasing of container throughput in the regions. The negative response of Malaysia coincides with the negative response of Singapore port of a shock of container throughput in Malaysia as shown in Figure 2 (b). The negative response of Singapore of a shock of container throughput in Malaysia can be interpreted as the severe port competition between these two countries, especially with the emergence of Port of Tanjung Pelepas (PTP) which has the potentiality to become the new ‘hub port’ in the region. Hence, the most important message from this analysis is that Malaysian port is creating a real threat to Singapore port as the Hub port in Southeast Asia.



(a) (b)

Figure 2 Impulse responses of a shock of container throughput in (a) Singapore, and (b) Malaysia

4.5 Forecasting of container throughput

In the context of forecasting of container throughput, we adopt some assumptions of the model as the following:

- Statistical structure of the model will not change substantially in the future.
- Since we only dealt with the major port in each county, we assume no capacity restriction of those ports.

- Liner shipping services network is not change substantially.
- Port characteristics and management policy are not included in the model.

The procedure for forecasting is the same with the procedure to generate a series over a sample period as mentioned earlier. The last known value of time series is used as starting value for the calculation of ΔY_{t+1}. Adding the later to the starting value provides the model estimation Y_{t+1} for the $t+1$ in the forecasting year. The process is repeated for each year up to 2015. The forecasting result is shown in Figure 3. Container throughput in each country in the region tends to increase. In 2015, Container throughput in Indonesia, Singapore, Malaysia, Thailand, and Philippines are 14,891,325 TEU, 28,505,265 TEU, 18,759,650 TEU, 12,164,334 TEU and 5,836,955 TEU respectively with average annual growth are 9.15%, 5.34%, 7.55%, 8.00% and 7.7% respectively. Comparing with the historical data from 1981 to 2002, which the average annual growth of container throughput at major container ports in Indonesia, Singapore, Malaysia, Thailand, and Philippines are 19.73%, 14.42%, 21.02%, 14.18% and 8.74% respectively; the forecasting result seems to be reasonable. The important massage from this forecasting result is, at least for next two decades, Singapore port will still dominates the container throughput in the Southeast Asia. However, if we see from average annual growth of container throughput in Singapore as mentioned above is only 5.34%, the domination of Singapore port, as the "hub-port", will decline.

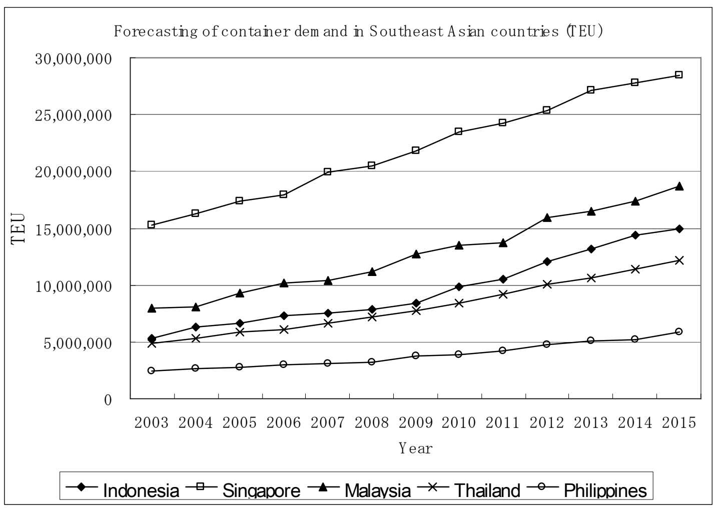


Figure 3 Forecasting of container throughput in Southeast Asian countries

5. CONCLUSION

This paper presented estimation of demand of container throughput in Southeast Asian countries. The analysis was done in multivariate autoregressive model. The empirical analysis demonstrated that the estimation model provides indication of goodness-of-fit and of the forecasting potential of the model. Most of the model estimation result follows the long-term development of the actual data series closely. The impulse response of a shock of a variable to itself and other variables die out after certain period. This verified the stability of all the estimated models. Forecasting of container throughput in Southeast Asian countries demonstrated that Singapore port will still dominates the container throughput in the Southeast Asia at least for next two decades. However, the domination of Singapore port, as the "hub-port", will decline.

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