CHAPTER 3

RESEARCH METHODOLOGY

To study the relationship of border export, border import and economic growth of Yunnan with the other GMS countries. This study will apply the Panel Data Unit Root Test, Co-integration Test in Panel Data, Granger Causality Test in panel data and Error Correcting Model (ECM) to examine the data.

3.1 The General Growth Model

Generation and estimation all parameters without resulting into unnecessary data, the growth model can be written as:

$$GDP_{i,t}= f(Im_{i,t} ,Ex_{i,t}) \qquad (3.1)$$

Where $GDP_{i,t}$ is gross domestic product, $Im_{i,t}$ is the import value, $Ex_{i,t}$ is the export value. Equation (3.1) is treated as a Cobb-Douglas function with border import and border export as the explanatory variables. It can be expressed in liner form:

$$LnGDP_{i,t}=\beta_0+\beta_1 LnIm_{i,t}+\beta_2 LnEx_{i,t}+\varepsilon_{i,t} \qquad \beta_0 \text{ and} \beta_2>0, \quad \beta_1<0 \qquad (3.1.1)$$

In here, $GDP_{i,t}$ is gross domestic product, $Im_{i,t}$ is the import value, $Ex_{i,t}$ is the export value, $\varepsilon_{i,t}$ is the error term, β_0 represent the intercept, , β_1 andβ_2 are coefficient of regression. The coefficient of regression, β_1 shows that a unit change in the independent variable $Im_{i,t}$ affects on the dependent variable $GDP_{i,t}$, and β_2 indicates that a unit change in the independent variable $Ex_{i,t}$ affects on the dependent variable $GDP_{i,t.}$ The error term $\varepsilon_{i,t}$ is explanted the other factors that may influence $GDP_{i,t.}$ In

Gauss-Markov assumptions the dependent and independent variable are linear correlated, the estimators are unbiased with an expected value zero. E ($\varepsilon_{i,t}$)=0, which means that on average the error terms can canceled with each other.

3.2 The Panel Unit Root Test (stationary test)

In order to avoid the spurious regression, we need to examine the stationary before we apply Co-integration test and Granger causality test. For each individual time series, most macroeconomic data are non-stationary. So we need to prove that data is stationary (unit root) for the order of integration. Panel data unit test normally have six methods: Levin, Lin and Chu (2002), Im, Peasaran and Shin (2003), Breitung (2000), Fisher-type ADF (1999), Fisher-type PP(2001) and Hadri (2000). This study will use 5 methods which are: Levin, Lin and Chu (2002), Im, Peasaran and Shin (2003), Breitung (2000), Fisher-type ADF (1999), Fisher-type PP (2001) to test the panel unit root of data.

In general, the type of penal unit root tests is based upon the augmented Dickey-Fuller (ADF) test on the follow equation:

$$\Delta y_{i,t} = \rho_i y_{i,t-1} + \sum_{L=1}^{p_i} \phi_{iL} \Delta y_{i,t-L} + z'_{i,t}\gamma + u_{i,t} \tag{3.2}$$

Where i=1,2,…,N is the countries, t=1,2,…,T is time series observation are available. y_{it} is dependent variable for i individuals at time t. ρ_i is the coefficient of one period lagged variable. ϕ_{iL} and γ are $k_1\times 1$ and $k_2\times 1$ vectors of exogenous variables. z_{it} is the deterministic components and u_{it} is error term. z_{it} could be 0, 1 or fixed effects.

1) Levin, Lin and Chu (LLC) Test

Individual unit root test have limited power. The power of a test is the probability of rejecting the null when it is false and the null hypothesis is unit root. The hypotheses of Levin, Lin and Chu(LLC) as follows;

H_0: $\rho_i=\rho=0$ (have a unit root) H_1: $\rho_i=\rho < 0$(stationary)

The structure of LLC analysis should be written as:

$$\Delta y_{i,t} = \rho_i y_{i,t-1} + \sum_{L=1}^{p_i} \phi_{iL} \Delta y_{i,t-L} + z'_{i,t}\gamma + u_{i,t} \tag{3.2}$$

We run two auxiliary regressions, and then we can get:

1. $\Delta y_{i,t}$ on $\Delta y_{i,t-L}$ and z_{it} to obtain the residuals $\hat{e}_{i,t}$ and

2. $y_{i,t-L}$ on $\Delta y_{i,t-L}$ and z_{it} to get residuals $\hat{v}_{i,t-1}$.

Then we need to standardization the residuals to get:

$$\tilde{e}_{it} = \hat{e}_{it} / \hat{\sigma}_{\varepsilon i} \tag{3.3}$$

$$\tilde{v}_{i,t-1} = \hat{v}_{it} / \hat{\sigma}_{\varepsilon i} \tag{3.4}$$

Where $\sigma_{\varepsilon i}$ denotes the standard error from each ADF.

At the end we can run the pooled OLS regression:

$$\tilde{e}_{it} = \rho\tilde{v}_{i,t-1} + \tilde{\varepsilon}_{it} \tag{3.5}$$

The null hypothesis is $\rho_i=\rho=0$ which proved that the standard deviation for t-statistics has to be adjusted:

$$t^*_\rho = \frac{t_{\rho=0} - N\tilde{T}\hat{S}_N\hat{\sigma}^{-2}_{\tilde{\varepsilon}}RSE(\hat{\rho})\mu^*_{m\tilde{T}}}{\sigma^*_{m\tilde{T}}} \rightarrow N(0,1) \tag{3.6}$$

Where $\mu^*_{\tilde{T}}$ is mean adjustment term, and $\sigma^*_{\tilde{T}}$ is standard deviation adjustment term. $\hat{S}_N = \frac{1}{N}\sum_{i=1}^{N}\frac{\hat{\sigma}_{yi}}{\hat{\sigma}_{ei}}$ is the mean of the ratios of the long-run standard deviation and the innovation satandard deviation for each individual and $\tilde{T} = T - \left(\sum_i p_i / N\right) - 1$.

The disadvatage of the LLC test is that it relies critically on the assumption of cross-sectional indepence. And the null hypothesis all cross-sctions have a unit root is very restrictive.

2) Im, Pesaran and Shin (IPS) Test

The Im, Pesaran and Shin(IPS) test, allows for heterogeneous cosfficients, which is not restrictive as the LLC test. It also based on the ADF regression, we can look at the equation(3.2):

$$\Delta y_{i,t} = \rho_i y_{i,t-1} + \sum_{L=1}^{p_i}\phi_{iL}\Delta y_{i,t-L} + z'_{i,t}\gamma + u_{i,t} \tag{3.2}$$

The null hypothesis is all individuals have a unit root:

$$H_0 = \rho_i = 0 \ \forall i$$

The alternative hypothesis is some (but not all) of the individuals to have unit root:

$$H_a : \begin{cases} \rho_i = 0, \ for\ i = 1,2,..., N_1 \\ \rho_i < 0, \ for\ i = N_1,..., N \end{cases}$$

When t_{iT} is the individual t-statistic for testing the null hypothesis ρ_i=0 for all i, then the test is based on avarge individual unit root test: $\bar{t} = \frac{1}{N}\sum_{i=1}^{N} t_{iT}$ IPS test.

assume that t_{iT} are indipendent and identically distrbuted (i.i.d). IPS test requies

N/T→ 0 for N→∞.

3) Breitung's Test

The Breitung's test is very similar to LLC test also basced on ADF regression. First step is same as LLC test, but in Breitung's test not not have deterministic terms. We regress$\Delta y_{i,t}$ on $\Delta y_{i,t-L}$ to obtain the residuals $\hat{e}_{it}$ and $y_{i,t-L}$ on $\Delta y_{i,t-L}$ to get residuals $\tilde{v}_{i,t-1}$. Then we do the forward orthogonalization transformation to get residuals $\hat{e}_{it}$. At the end, to do the pooled regression: $e_{it}^{*} = \rho v_{i,t-1}^{*} + \varepsilon_{it}^{*}$, and e_{it}^{*} have normal distributed with N (0, 1).

4) Fisher-type Test or In Choi Test

The Fisher-type test uses ρ-values from unit root tests for each cross-section i. The null hypothesis of Fisher-type test is having a unit root. The formula of the test as follows:

$$\text{ADF-Fisher } x^2 = -2\sum_{i=1}^{N}\log(\rho_i) \rightarrow x_{(2N)}^2 \quad (3.7)$$

$$\textit{ADP-Chi } Z = \sqrt[1]{n}\sum_{i=1}^{N}\emptyset^{-1}(\rho_i) \rightarrow N(0,1) \quad (3.8)$$

In equation (3.7) and (3.8), the ρ_i is come form the PP test. ϕ^{-1} is the inverse of the normal distributions. The test use the chi-square distributed with 2N degrees of freedom (T_i→∞ for finite N). The advatage of this test is that the test can deal with the unbalanced panels. Furthermore, the augmented Dickey-Fuller test allowed the lag lengths of the individual augmented is different.

3.3 Panel Co-integration Test

For the panel co-integration test have 3 methods in normally. The Kao test (1999) is based on combined Johansen. The Pedroni and Fisher test are based on the Engel-Granger method. This paper will choose Kao test and Pedroni test to exam the panel co-integration.

1) Kao Test (1999)

Kao test (1999) runs the individual fixed effects model with homogenous co-integration by pooled regression, as follows;

$$Y_{i,t} = \alpha_i + \beta X_{i,t} + u_{i,t} \qquad (3.9)$$

Where β and X_{it} respected the row and column vectors and the least squared dummy variable (LSDV) estimator β as:

$$\tilde{\beta} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{Y}_{i,t}\,\tilde{X}'_{i,t}\right)\left(\sum_{i=1}^{N}\sum_{t-1}^{T}\tilde{X}_{i,t}\,\tilde{X}'_{i,t}\right)^{-1} \qquad (3.10)$$

Where $\tilde{Y}_{i,t} = Y_{i,t} - \frac{1}{T}\sum_{s=1}^{T} Y_{i,s}$ and $\tilde{X}_{i,t} = X_{i,t} - \frac{1}{T}\sum_{s=1}^{T} X_{i,s}$, the first stage regression for residual written as $\tilde{u}_{i,t} = \tilde{Y}_{i,t} - \tilde{\beta}\tilde{X}_{i,t}$. The null hypothesis is no co-integration with a unit root. Then we can build up the pooled DF regression as follows:

$$\Delta\tilde{u}_{i,t} = (\rho - 1)\tilde{u}_{i,t-1} + v_{i,t} \qquad (3.11)$$

Where the pooled ordinary least squares (POLS) estimation of (ρ-1) is given by:

$$(\tilde{\rho} - 1) = \left(\sum_{i=1}^{N}\sum_{t=2}^{T}\Delta\tilde{u}_{i,t}\,\tilde{u}_{i,t-1}\right)\left(\sum_{i=1}^{N}\sum_{t=2}^{T}\tilde{u}_{i,t-1}^{2}\right)^{-1} \qquad (3.12)$$

Kao' (1999) Test is based on $\tilde{\rho}$ and the corresponding t-statistic:

$$t_{\tilde{\rho}} = (\tilde{\rho} - 1)\left(\hat{s}_{\tilde{u}}^{2}\left(\sum_{i=1}^{N}\sum_{t=2}^{T}\tilde{u}_{i,t-1}^{2}\right)^{-1}\right)^{-1/2} \qquad (3.13)$$

Where $\hat{s}_{\tilde{u}}^{2} = N^{-1}T^{-1}\sum_{i=1}^{N}\sum_{t=2}^{T}\left(\Delta\tilde{u}_{i,t-1} - (\tilde{\rho}-1)\tilde{u}_{i,t-1}\right)^{2}$, corrected for endogenous and serial correlation. When the panel units are cross- sectional independent, the test statistics are asymptotically normal distributed when N→∞ then T→∞. In this test, if we get the result is $\Delta\tilde{u}_{i,t} \sim I(1)$, we accept the null hypothesis no co-integration. If we get the result is $\Delta\tilde{u}_{i,t} \sim I(0)$, we reject the null hypothesis.

2) Pedoni Test (1999,2004)

The Pedoni Test which introduction of the residual-based panel co-integration test in 1995. In 1999, Pedoni developed his panel co-integration test to exam the models with more than one independent variable. In 2004, Pedoni he study two within-dimension-based (panel-ρ) and (panel-t) and two between- dimension-based (group-ρ) and (group-t) with null hypothesis no co-integration.

The residuals-based panel co-integrating regression given by:

$$y_{i,t} = \alpha_i + \beta_{1i}x_{1i,t} + \beta_{2i}x_{2i,t} + \ldots + \beta_{Mi}x_{Mi,t} + e_{i,t}\ , \ t=1,\ldots,T;\ i=1,\ldots,N \qquad (3.14)$$

Where T is the number of observations over time, N is the number of individuals, M is the number of independent variables, $\beta_{1i},\ldots,\beta_{Mi}$ is the slope and α_i is the intercept for each cross-section.

Within-dimension-based test and between- dimension-based test have the same null hypothesis of no co-integration: $H_0 : \rho_i = 1 \quad \forall i$, where ρ_i is the autoregressive coefficient of estimated residuals under the alternative hypothesis ($\hat{e}_{it} = \rho_i \hat{e}_{it-1} + u_{it}$), alternative hypothesis is different between each other. For within-dimension-based (panel co-integration) test impose a common coefficient under the alternative hypothesis, written as: $H_a^w : \rho_i = \rho < 1 \quad \forall i$, For between-dimension-based (group co-integration) test allowed the heterogeneous coefficients under the alternative hypothesis, written as: $H_a^b : \rho_i < 1 \quad \forall i,$.

To calculate the non-parametric statistic, panel-ρ and group-ρ, use the residuals from the co-integration regression (3.14): $\hat{e}_{i,t} = \hat{\gamma}_i \hat{e}_{i,t-1} + \hat{u}_{i,t}$. Then the long-run variance $\hat{\sigma}^2$ and the contemporaneous variance $\hat{s}_i^2$ of $\hat{u}_{i,t}$ is computed. To calculate the parametric statistic, panel-t and group-t, also use the residuals from the co-integration regression (3.14):

$$\hat{e}_{i,t} = \hat{\gamma}_i \hat{e}_{i,t-1} + \sum_{t=1}^{K_i} \hat{\gamma}_{i,k} \Delta \hat{e}_{i,t-k} + \hat{u}_{i,t}^*$$

and $\hat{u}_{i,t}^*$ the variance of is computed, $\hat{u}_{i,t}^* = \hat{s}_i^{*2}$ Pedroni use the follows expressions to test statistic, as follows;

(a) Panel ν-statistic

$$Z_v = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1} \qquad (3.15)$$

(b)Panel ρ-statistic

$$Z_p = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \left(\hat{e}_{i,t-1} \Delta \hat{e}_t - \hat{\lambda}_i \right) \qquad (3.16)$$

(c)Panel pp-statistic

$$Z_{pp} = \left(\hat{\sigma}^2 \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1/2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \left(\hat{e}_{i,t-1} \Delta \hat{e}_t - \hat{\lambda}_i \right) \qquad (3.17)$$

(d)Panel ADF-statistic

$$Z_t = \left(\hat{S}^{*2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}^{*2}_{i,t-1} \right)^{-1/2} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\hat{L}_{11i}^{-2} \hat{e}^{*}_{i,t-1} \Delta \hat{e}^{*}_{i,t} \right) \tag{3.18}$$

(e)Group ρ-statistic

$$\tilde{Z}_\rho = \sum_{i=1}^{N} \left[\sum_{t=1}^{T} \hat{e}^{2}_{i,t-1} \right]^{-1} \sum_{t=1}^{T} \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right) \tag{3.19}$$

(f)Group pp-statistic

$$\tilde{Z}_{pp} = \sum_{i=1}^{N} \left[\hat{\sigma}^2 \sum_{t=1}^{T} \hat{e}^{2}_{i,t-1} \right]^{-1/2} \sum_{t=1}^{T} \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right) \tag{3.20}$$

(g)Group ADF-statistic

$$\tilde{Z}_t = \sum_{i=1}^{N} \left[\sum_{t=1}^{T} \hat{S}^{*2} \hat{e}^{*2}_{i,t-1} \right]^{-1} \sum_{t=1}^{T} \left(\hat{e}^{*}_{i,t-1} \Delta \hat{e}^{*}_{i,t} \right) \tag{3.21}$$

Where $\hat{S}_i^2 = 1/N \sum_{i=1}^{N} \hat{L}_{11} \hat{\sigma}_i^2$ and $\hat{\lambda}_i = 1/2 \left(\hat{\sigma}_i^2 - \hat{S}_i^2 \right)$

We can use the results to compare with the critical values, if the critical values are exceeded than the null hypothesis (no co-integration), we choose to reject the null hypothesis. It means that the long-run relationship between variables is existed.

3.4 Estimating Panel Co-integration Model

A panel is a set of observations on individuals, collected over time. An observation is the pair of $\{y_{it}, x_{it}\}$, where i subscript represent the individual and t subscript shows the time. In this research we use balanced panel. Balanced panel written as $\{y_{it}, x_{it}\}$: t=1,…, T; i=1,…,N.

3.4.1 Fixed effects regression model

Fixed effects regression model (Zhang Xiaotong 2008) is the most common technique for estimation of non-dynamic linear panel regression which has 3 kinds: 1. Entity fixed effects model, 2. Time fixed effects model and 3. Time and entity fixed effects model. General fixed effects model can written as

$$y_{it}= \alpha_i+x_{it}\beta+ \varepsilon_{it} \quad , \quad i=1,2,\ldots,N;\ t=1,2,\ldots,T \qquad (3.22)$$

Where α_i is arbitrary correlated with x_{it}. x_{it} and β are matrixes with k x 1. ε_{it} is the error term. And E ($\varepsilon_{it} \mid \alpha_i, x_{it}$) =0, i=1,2,…,N.

1) Entity fixed effects model

$$y_{it}= \alpha_1 D_1+ \alpha_2 D_2 +\ldots+\alpha_N D_N+x_{it}\beta+ \varepsilon_{it} \ , \ t=1,2,\ldots,T \qquad (3.23)$$

Where $Di = \begin{cases} 1, & if\ i = 1,2,\ldots,N \\ 0, & else \end{cases}$,

Then the model can be written as

$$\begin{cases} y_{1t}=\alpha_1+X_{1t}\beta+\varepsilon_{1t},\ i=1,\ t=1,\ 2,\ldots,\ T \\ y_{2t}=\alpha_2+X_{2t}\beta+\varepsilon_{2t},\ i=2,\ t=1,\ 2,\ldots,\ T \\ \ldots \\ y_{Nt}=\alpha_N+X_{Nt}\beta+\varepsilon_{Nt},\ i=N,\ t=1,2,\ldots,T \end{cases}$$

2) Time fixed effects model

$$y_{it}= \gamma_0+\gamma_1 W_1+ \gamma_2 W_2 +\ldots+\gamma_T W_T+x_{it}\beta+ \varepsilon_{it} \ , \ i=1,2,\ldots,N \qquad (3.24)$$

Where $Wi = \begin{cases} 1, if\ i = 1,2,\ldots,T \\ 0, else \end{cases}$, Then the time fixed effects model described as

$$\begin{cases} y_{i1}= (\gamma_0+\gamma_1) +X_{1t}\beta+\varepsilon_{i1},\ t=1,\ i=1,2,\dots,N \\ y_{i2}= (\gamma_0+\gamma_2) +X_{2t}\beta+\varepsilon_{i2},\ t=2,\ i=1,2,\dots,N \\ \dots \\ y_{ir}= (\gamma_0+\gamma_r) +X_{Nt}\beta+\varepsilon_{ir},\ t=N,\ i=1,2,\dots,N \end{cases}$$

3) Time and entity fixed effects

$$y_{it}= \alpha_0+ \alpha_1D_1+ \alpha_2D_2 +\dots+\alpha_N D_N+\gamma_1 W_1+ \gamma_2 W_2 +\dots+\gamma_T W_T+x_{it}\beta+ \varepsilon_{it} \quad (3.25)$$

Where $Di = \begin{cases} 1, & if\ i = 1,2,\dots,N \\ 0, & else \end{cases}$

and $Wi = \begin{cases} 1, if\ i = 1,2,\dots,T \\ 0, else \end{cases}$

3.4.2 Individual effects model (random effects model)

$$y_{it}= \alpha_i+x_{it}\beta+ \varepsilon_{it} \quad , \quad i=1,2,\dots,N;\ t=1,2,\dots,T \qquad (3.26)$$

Where α_i is arbitrary which uncorrelated with x_{it}. x_{it} and β are matrixes with k x 1. ε_{it} is the error term. We have two assumptions: α_i~iid $(\alpha, \delta_\alpha^2)$ and ε_{it}~iid$(0,\delta_\varepsilon^2)$. And $E(x_{it}\alpha_i) =0$.

3.5 The Granger Causality Test and Error-Correction Models

Causality is a kind of statistical feedback concept which is widely used in the building of forecasting models. In this study we look at the case of three variables y, x_1 and x_2 the Granger causality approach that developed by Granger C.W.J (1969). The traditional Granger causality test is based on a vector auto-regression model (VAR), given by:

$$y_{i,t} = c_0 + \sum_{j=1}^{p} \alpha_{11} y_{i,t-j} + \sum_{k=1}^{n} \beta_{11} x_{1i,t-k} + \sum_{L=1}^{m} \gamma_{11} x_{2i,t-L} + \varepsilon_1 \qquad (3.27)$$

$$x_{1i,t} = c_1 + \sum_{j=1}^{p} \alpha_{12} y_{i,t-j} + \sum_{k=1}^{n} \beta_{12} x_{1i,t-K} + \sum_{L=1}^{m} \gamma_{12} x_{2i,t-L} + \varepsilon_2 \qquad (3.28)$$

$$x_{2i,t} = c_2 + \sum_{j=1}^{p} \alpha_{13} y_{i,t-j} + \sum_{k=1}^{n} \beta_{13} x_{1i,t-K} + \sum_{L=1}^{m} \gamma_{13} x_{2i,t-L} + \varepsilon_3 \qquad (3.29)$$

In 1988, Granger pointed out that if there is co-integrating vector among variables, there must be at least one unidirectional Granger-causality among these variables. Moreover, when the series are co-integration at I (1), the Granger-causality test should be carried out in the ECM estimation, the VAR equation (3.27), (3.28) and (3.29) should be given as (3.30), (3.31), and (3.32).

$$y_{i,t} = c_0 + \sum_{j=1}^{p} \alpha_{11} y_{i,t-j} + \sum_{k=1}^{n} \beta_{11} x_{1i,t-k} + \sum_{L=1}^{m} \gamma_{11} x_{2i,t-L} + \lambda_1 ecm_1 + \varepsilon_1 \qquad (3.30)$$

$$x_{1i,t} = c_1 + \sum_{j=1}^{p} \alpha_{12} y_{i,t-j} + \sum_{k=1}^{n} \beta_{12} x_{1i,t-K} + \sum_{L=1}^{m} \gamma_{12} x_{2i,t-L} + \lambda_2 ecm_2 + \varepsilon_2 \qquad (3.31)$$

$$x_{2i,t} = c_2 + \sum_{j=1}^{p} \alpha_{13} y_{i,t-j} + \sum_{k=1}^{n} \beta_{13} x_{1i,t-K} + \sum_{L=1}^{m} \gamma_{13} x_{2i,t-L} + \lambda_3 ecm_3 + \varepsilon_3 \qquad (3.32)$$

Where Δ is first difference, n, m and p is the lag time. λ is the coefficient of error correcting term. If the null hypothesis is λ=0 is rejected. The short-run adjustment parameter is existed for all ECM model. In the equation (3.30), if the null hypothesis is $\beta_{11}=\gamma_{11}=0$ is rejected, shows that have the short-run causality relationship from $x_{1i,t}$ and $x_{2i,t}$ to $y_{i,t.}$ In the equation (3.31), if the null hypothesis is $\alpha_{12}=\gamma_{12}=0$ is rejected, which means that have the short-run causality relationship from $x_{2i,t}$ and $y_{i,t}$ to $x_{1i,t.}$ In the equation (3.32), if the null hypothesis is $\alpha_{13}=\gamma_{13}=0$ is rejected, there is short-run causality relationship from $x_{1i,t}$ and $y_{i,t.}$ to $x_{2i,t..}$